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<https://doi.org/10.15760/etd.7239>

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Modeling Spatiotemporal Patterns of PM_{2.5} at the Sub-Neighborhood Scale
Using Low-Cost Sensor Networks

by

Philip Jeffrey Orlando

A thesis submitted in partial fulfillment of the
requirements for the degree of

Master of Science
in
Environmental Science and Management

Thesis Committee:
Linda George, Chair
Meenakshi Rao
Kelly Gleason
Lynne Messer

Portland State University
2019

Abstract

Epidemiological research has demonstrated an adverse relationship between fine particulate matter (PM_{2.5}) and human health. While PM_{2.5} continues to pose a significant global health risk, there is still the need to further characterize exposures at the intra-urban scale. Land use regression is a statistical modeling technique which is used to predict air pollution concentrations at high resolution from a limited number of monitoring sites. However, the existing regulatory monitoring networks are typically not dense enough to apply these techniques. We explored the potential of using low-cost PM_{2.5} sensor networks to overcome the limitations of the existing regulatory monitoring infrastructure, and identified the need to determine sensor-specific correction factors based on the local PM_{2.5} source profile. Once calibrated, a land use regression model ($R^2 = 0.89$) was developed using the low-cost sensor network ($n \approx 20$), alongside several land use and meteorological variables, to predict daily particulate matter concentrations at a 50 m spatial resolution during a two year period within Portland, Oregon. From this model, we assessed the relative strengths of expected sources and sinks of fine particulate matter, focusing specifically on the role that the urban canopy may play in mitigating PM_{2.5} exposure. This model showed a modest but observable spatial pattern in PM_{2.5}, but attributed the majority of PM_{2.5} variation to temporal predictors (e.g. ambient background PM_{2.5}, wind speed, temperature). Neither proxies for traffic-related sources, or vegetation-related sinks were identified as significant predictors of PM_{2.5}. Our research also demonstrated the importance of sensor placement, as a considerably different set of predictors was selected after the inclusion of four additional monitoring

sites. Future work will apply this method to four cities with a varying degree of canopy cover to assess differences in intra-urban gradients of $PM_{2.5}$ and to further characterize the influence of vegetation.

Acknowledgements

First of all, I would like to express my sincere gratitude to my advisor Dr. Linda George for her continuous patience, guidance, and expertise throughout my graduate study and research. I never would have imagined pursuing a graduate degree without her inspiring wisdom and dedication to science.

Besides my advisor, I would like to thank the rest of my thesis committee: Dr. Meenakshi Rao, Dr. Kelly Gleason, and Dr. Lynne Messer for their time, encouragement, and insightful feedback.

My sincere thanks also goes to the remaining members of the Canopy Continuum project: Dr. Vivek Shandas and Dr. Todd Rosenstiel for their helpful comments and support.

Another special thanks goes to Meenakshi Rao, as well as, Dr. Yangdong Pan and Jackson Voelkel for cultivating my appreciation of computer science and for teaching me how to harness it to tackle environmental problems.

I thank my fellow labmates in the Sustainable Atmospheres Research lab: Devin Wilde, Dat Vo, Kirsten Sarle, Modi Raduma, Patrick Léon Gross, and Kellen McInerney for their field and laboratory assistance.

I would like to thank my partner, Judit Takács, for her continual moral support and patience while I was often absorbed by my graduate work.

Last but not least, I would like to thank my parents: Shannon and Jeff Orlando for their endless encouragement and support throughout my entire life.

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Chapter 1

Introduction

1.1 Background

1.1.1 Particulate Matter and Human Health

Epidemiological studies have demonstrated an adverse relationship between ambient particulate matter (PM) exposure and human health (Kloog et al., 2013; Brunekreef and Holgate, 2002; Dockery et al., 1993). Adverse health effects from PM exposure include cardiovascular and respiratory morbidity and mortality (Le Tertre et al., 2002; Schwartz, 1994; Pope and Dockery, 2006). The Global Burden of Disease (GBD) comparative risk assessment conducted by the World Health Organization (WHO) attributed approximately 3.2 million year-2010 deaths to ambient PM_{2.5} (PM with a diameter of 2.5 μm or smaller) exposure, and ranked this pollutant as the sixth largest overall risk factor for shortened life expectancy globally (Lim et al., 2012; Apte et al., 2015; Fann et al., 2012; Cohen et al., 2005). To provide further context, the global health burden from ambient PM_{2.5} is greater than the cumulative health risks of other well-established global health threats including HIV-AIDS and malaria which contributed 1.5 million and 1.2 million year-2010 deaths respectively (Lim et al.,

2012; Apte et al., 2015). While ambient PM continues to pose a significant global health burden, there is the need to further characterize higher granularity PM exposure gradients, specifically at the intra-urban scale. Health studies typically rely on inter-city estimates from a limited number of monitoring sites to develop a single exposure estimate for a given city. These single estimates are then assigned to an entire metropolitan area, despite the potential for intra-city heterogeneity in PM sinks and sources. This likely contributes to the underestimation of PM-related health effects in the vicinity of sources (Ross et al., 2007; Jerrett et al., 2005; Hoek et al., 2002).

1.1.2 Characterizing Particulate Matter Pollution

PM is a mixture of solid and liquid particles suspended in the air that vary in shape, number, chemical composition and size. PM is often described by three major size categories, the largest being coarse respirable PM, or PM_{10} . These are particles with a diameter less than $10\ \mu m$ but greater than $2.5\ \mu m$, and are mostly derived from biogenic or geogenic sources including the suspension or resuspension of dust, soil, windstorms, volcanoes, pollen, mold, spores, and sea salt. PM_{10} is also attributed to anthropogenic sources including agricultural activities and mining (Pope and Dockery, 2006). Smaller than coarse PM are fine PM, or $PM_{2.5}$. These are particles that have a diameter less than or equal to $2.5\ \mu m$. Fine PM are derived primarily from anthropogenic sources, usually the direct result from some form of combustion. This includes vehicle emissions, wood burning, coal burning, and industrial processes (steel mills, cement plants, paper mills). In addition to primary sources of fine PM, there are also

secondary sources, where particles form as the result of some chemical transformation in the atmosphere. Secondary fine PM is often the result of nitrogen and sulfur oxides transforming into nitrates and sulfates, or through the formation of secondary organic aerosols (SOAs) from volatile organic compound emissions (VOCs) (Pope and Dockery, 2006). Even smaller than fine PM are the ultrafine PM. While their definition appears to range slightly throughout the literature, these are typically particles which have an aerodynamic diameter less than $0.1\ \mu\text{m}$ (Pope and Dockery, 2006; Oberdorster, Oberdorster, and Oberdorster, 2005; EPA, 2004). Similar to fine PM, ultrafines are primarily derived from some source of combustion. However, ultrafines have an extremely short lifetime (minutes to hours), and will rapidly coagulate or condense to form larger $\text{PM}_{2.5}$ particles, which can remain suspended in the atmosphere and have much longer residence time (days to weeks). Due to these properties, ultrafine PM are often indicative of freshly-emitted PM from local sources.

The human health impacts from PM exposure have been shown to vary depending on the size of the particle. Generally, the smaller the particles, the deeper into the lungs they can infiltrate, leading to more severe health effects. While ultrafine PM may be more capable than fine PM of transferring from the lung to the blood and other parts of the body, there has been a focus on monitoring only fine and coarse PM throughout regulatory agencies due to the cost and reproducibility of ultrafine measurements. Fine PM, in contrast to larger particles, can remain suspended in the atmosphere for longer periods of time, can be breathed more deeply into the lungs, and are more capable of infiltrating indoor environments. In addition, PM_{10} levels throughout the US are generally

within compliance, whereas $\text{PM}_{2.5}$ remains a regulatory challenge.

1.1.3 Urban Air Quality and Traffic

Air pollution can vary across spatiotemporal scales (Gilliland Frank et al., 2005; Beckerman et al., 2013). Spatially, local-scale variations are the result of primary sources, whereas regional-scale variations occur from secondary reactions and transport mechanisms. The majority of temporal variation is the result of diurnal traffic patterns or meteorology (Beckerman et al., 2013). Generally, pollutants directly emitted from mobile sources (traffic-related emissions), or indirectly via photochemical reactions, still dominate the urban environment despite significant improvements in fuel, engine, and emission control technology over the last few decades (Fenger, 1999; Hoek et al., 2000; Nyberg et al., 2000). It is imperative that we characterize air pollution gradients within cities as population density and traffic emissions are high within these environments and exposure is not expected to be experienced evenly (Vardoulakis et al., 2003; Rao et al., 2014). The spatial variability of primary air pollution is higher near major intersections and busy streets within the built environment, where traffic emissions are higher and ventilation is reduced due to the local topography (Harrison, Jones, and Barrowcliffe, 2004; Vardoulakis et al., 2003). In contrast, the spatial variability of secondary pollutants is driven by meteorology and generally regional in scale. Many studies have identified an increase in respiratory and cardiovascular problems from living near major roadways (Jerrett et al., 2008; Brugge, Durant, and Rioux, 2007; Zhou and Levy, 2007). Identifying intra-urban pollution gradients will become increasingly relevant as rising rates

of urbanization and high density development result in greater human exposure to near-road environments. Currently, roughly 80% of the US population currently live within metropolitan areas (and approximately half of the global population), and the global urban population is expected to increase to approximately 68% by the year 2050 (Bureau, 2012; United Nations, 2018).

A meta-analysis conducted by Karner, Eisinger, and Niemeier, 2010 found that many air pollutants within cities have strong pollution gradients, decaying within 150 m - 200 m from the source, and reaching background levels between 200 m - 1000 m (Karner, Eisinger, and Niemeier, 2010). These fine-scale gradients from road sources are well documented for NO, NO₂, PNC, CO, and PM₁₀ (Karner, Eisinger, and Niemeier, 2010; Rao et al., 2014; Zhou and Levy, 2007). However, patterns in PM_{2.5} mass concentration as distance from road sources increases are less pronounced. While PM_{2.5} is a component of traffic-related emissions, mass-based measurements do not always capture this influence. The spatial patterns of PM_{2.5} are mixed, either decreasing very gradually from traffic sources, or showing no clear trend at all (Karner, Eisinger, and Niemeier, 2010; Kendrick, Koonce, and George, 2015).

1.1.4 Influence of Vegetation on Air Quality

There is an increasing body of evidence that suggests that access to greenery can improve human health. A pioneering study conducted by Ulrich showed that hospital patients recovering from surgery were discharged sooner and required less pain medication if they had a view of greenspace from their hospital bed. This was in comparison to patients whose hospital room window

only provided a view of a brick wall (Ulrich, 1984). Subsequent studies have shown that access to greenspace is associated with reduced morbidity (Maas et al., 2009), mortality (Mitchell and Popham, 2007), and lower obesity rates (Bell, Wilson, and Liu, 2008). In addition, recent studies have shown an association between urban greenery (specifically trees) and air quality, suggesting that the urban canopy has a small yet significant effect on reducing pollutants including NO₂, PM₁₀, O₃, and SO₂ (Donovan et al., 2011; Rao et al., 2014; Nowak, Crane, and Stevens, 2006). While some studies found that vegetation may only improve the average air quality by <1-2%, this statistic accounts for multiple pollutants, and the actual magnitude of pollution mitigation can be substantial, typically on the order of 10² - 10³ metric tons per year in a given city (Nowak, Crane, and Stevens, 2006). Even when focusing on just a single pollutant, for example NO₂, a recent study in Portland, Oregon attributed pollution removal by trees to providing a \$7 million USD annual benefit in reduced occurrences of respiratory complications (Rao et al., 2014). Given that trees are a fundamental component of the urban environment, with a 35% average tree cover in US cities (Nowak and Greenfield, 2012), and that rates of urbanization are expected to rapidly increase over the next several decades, it is crucial that we continue to assess the potential role the urban canopy may play in reducing even more harmful air pollutants such as PM_{2.5}.

Trees can affect atmospheric PM concentrations by removal (Beckett, Freer-Smith, and Taylor, 2000) and emission (e.g. pollen). Particles that physically deposit on the leaf surface can also be resuspended, often by precipitation or when leaves, twigs, and branches fall to the ground. While some of the particles

can be absorbed into the tree, most are confined to the plant surface and are ultimately resuspended. As a result, trees are considered only temporary sinks for many atmospheric particles (Nowak et al., 2013). Most of the studies related to PM and urban trees have focused on PM₁₀ (Nowak et al., 2013), and while some studies have evaluated the removal rate and suspension of PM_{2.5} by specific tree species (Beckett, Freer-Smith, and Taylor, 2000; Freer-Smith, El-Khatib, and Taylor, 2004; Freer-Smith, Beckett, and Taylor, 2005; Pullman, 2008), few have estimated the effect of trees on PM_{2.5} concentrations at the city-scale (Nowak et al., 2013). There is some evidence suggesting PM_{2.5} mitigation by urban trees is considerably lower relative to PM₁₀ in terms of mass, but the health benefits are significantly higher (Nowak, Crane, and Stevens, 2006; Nowak et al., 2013). The benefits the urban canopy provides with PM_{2.5} removal is still not well understood, and only a limited number of studies have attempted to evaluate this effect at the intra-urban scale (Nowak et al., 2013; Jeanjean, Monks, and Leigh, 2016; Tallis et al., 2011). This is due, in part, to the challenges inherent to creating spatially resolved PM_{2.5} exposures surfaces at this resolution.

1.2 Modeling Intra-Urban PM_{2.5}

1.2.1 The Lack of Spatially Resolved PM_{2.5}

The lack of spatially resolved PM_{2.5} at the city-scale is mostly due to the practical constraints of air quality monitoring networks. Due to the high cost, cumbersome design, and the skilled labor required to establish and maintain research-grade air quality instrumentation, the current distribution of monitoring stations is confined to a limited number of near-road and urban background sites

within a given city (Vardoulakis, Solazzo, and Lumbreras, 2011). For example, within our Portland, Oregon study area, approximately 4-6 PM_{2.5} monitoring stations were operational during the two year study period. This network, maintained by Oregon Department of Environmental Quality (ODEQ) consisted of a couple rural ambient background sites, urban ambient background sites, and a single near-road site. Reference monitoring stations, typically maintained by local or regional air quality management agencies, are primarily established to assess regulatory compliance and develop a regional air quality index. However, the use of these monitors in epidemiological research, specifically their use in modeling spatially resolved PM surfaces at sub-neighborhood scales (0.01 - 1.0 km), is largely an afterthought. This focus on compliance ultimately results in the potential lack of representativeness of fixed air quality monitoring sites in epidemiological studies. In order to account for the spatial heterogeneity of air pollution sources in urban areas, several modeling techniques have been developed to spatially interpolate PM_{2.5} in order to better estimate the human health effects from PM_{2.5} exposure (Vardoulakis, Solazzo, and Lumbreras, 2011). These include land use regression (LUR) and dispersion modeling techniques (Briggs et al., 2000; Vardoulakis, Solazzo, and Lumbreras, 2011; Hoek et al., 2008; Zhou and Levy, 2008). For the purpose of this study, we applied LUR techniques to develop spatially resolved PM_{2.5} exposures necessary for assessing the relative power of land use sources and sinks, with a focus on the influence of vegetation.

1.2.2 Land Use Regression Modeling of PM_{2.5}

Land use regression (LUR) is a statistical modeling approach which is used to spatially predict continuous air pollution concentrations at high resolution from a limited number of monitoring sites (Briggs et al., 2000; Rao et al., 2014). Land-use and land-cover (LULC) variables are extracted within an appropriate buffer distance from each monitoring location using spatial analysis software. A multiple linear regression model is then developed using the monitored air pollution data as a response variable. The model is then assessed to see how well it meets its test assumptions. These assumptions include (1) a linear relationship exists between the response variable and predictors, (2) model residuals are normally distributed, (3) variation of observations around the line of best fit is constant (homoscedasticity), (4) and strong multicollinearity among predictors is not observed. This method is rooted in the principles that the environmental conditions for the air pollutant response variable of interest can be determined from a limited number of readily available predictors; and that the relationship between the response variable and predictors can be evaluated using a small sample of 'training' data (Briggs et al., 2000). After validation, the LUR model can be used to make spatial predictions of air pollution in between and beyond the original monitoring network used during the training phase. Briefly, LUR models of air pollutants typically rely on predictors including population density, land use, and traffic-related variables to characterize mean pollutant concentrations within several buffer distances at specific monitoring sites. Typical buffer sizes range between 50 m - 3000 m (Eeftens et al., 2012; Jerrett et al., 2007; Rao et al., 2014; Liu et al., 2016). Once the model performance has been evaluated, this

technique can be used to make air quality predictions without the presence of a monitoring station, essentially extrapolating pollutant exposure throughout the remaining study area by relying on the patterns observed within the predictor variables.

While land use regression models are capable of providing spatially resolved air pollutant surfaces at fine scales, they still rely on observational data from a limited number of monitoring sites for model development, calibration, and validation (Jerrett et al., 2005; Vardoulakis, Solazzo, and Lumbreras, 2011). As a result, the performance of LUR models depends on monitoring locations which provide a representative sample for the remaining study area that is to be predicted. In addition, regression mapping techniques are based on assumptions regarding their predictors, or independent variables.

Numerous LUR studies have been conducted to assess fine-scale spatially resolved NO₂ exposures because low-cost passive sampler technology has enabled the deployment of high-density monitoring networks (Rao et al., 2014; Briggs et al., 2000; Eeftens et al., 2012; Hoek et al., 2008). In contrast, LUR models for particulate matter are less numerous because they necessitate a more intensive monitoring campaign, despite evidence suggesting that adverse health effects are tied more closely to PM exposure than nitrogen oxides (Eeftens et al., 2012; Hoek et al., 2008; Pope et al., 2002; Sarnat et al., 2001). The ESCAPE Project (European Study of Cohorts for Air Pollution Effects), a pioneering LUR study focusing on PM_{2.5}, produced one of the largest spatially resolved PM databases in Europe, and relied on a total of 20 - 40 monitoring sites within

each of the 20 European cities examined (Eeftens et al., 2012). However, existing regulatory monitoring networks throughout our five US cities of interest within this study are not dense enough to develop LUR models predicting intra-urban $\text{PM}_{2.5}$ (e.g. Portland $n = 4$, Boise $n = 2$, Albuquerque $n = 5$, Tacoma $n = 2$, and Sacramento $n = 7$) (according to the EPA's AirData Active $\text{PM}_{2.5}$ Map) (US EPA, 2016). Due to the aforementioned limitations of deploying high-density networks with research-grade monitoring equipment, we opted to explore the potential of commercially available low-cost $\text{PM}_{2.5}$ sensors to achieve the recommended network density of ≥ 20 per city.

Previously developed LUR models of $\text{PM}_{2.5}$ within the ESCAPE project have shown moderate to good explained variance, ranging from $R^2 = 35\%$, to $R^2 = 94\%$, with a median of $R^2 = 71\%$ (Eeftens et al., 2012). This range in variance explained is partially due to limited availability of relevant GIS predictor variables across cities. As a result, no single model could be applied to each city. Instead, area-specific predictors were selected for each city's model due to these differences in available predictors. Better performing models were observed to have local traffic data available, specifically traffic intensity, and models without local or limited traffic data performed below the median variance explained (71%). Traffic variables were selected in 18 of the 20 models developed. Less important predictors included residential land use, population density, industrial land use and ports, and natural land use (Eeftens et al., 2012). The differences between final model R^2 and Leave-One-Out Cross-Validation (LOOCV) R^2 was less than 15% for most models, indicating overall model stability (Eeftens et al., 2012).

1.2.3 Opportunities and Challenges of Low-Cost Sensors

Optical Particle Counters (OPCs), also referred to as photometers, are commonly used for particle monitoring because of their ability to provide continuous data, ease of operation, small size, and relatively low cost. This is in contrast to gravimetric techniques which, despite being the most accurate form of measurement, do not provide continuous data and are costly to routinely operate and maintain. Briefly, gravimetric PM samplers actively pull an air sample at a constant flow rate through a series of impactors to collect size-selected PM (e.g. PM_{2.5} or PM₁₀) on a filter paper over a sample period of ≥ 24 hours. Once a measurable amount of PM_{2.5} has been collected after this sample period, the filters are processed and weighed in a lab. The total PM_{2.5} mass is divided by the total volume of air that was sampled throughout the entire sample interval to determine a mean mass density (e.g. $10 \mu\text{g m}^{-3}$). This method requires a technician to routinely install and collect filters at the beginning and end of each sample period. In contrast to collecting and weighing PM samples, OPCs rely on a laser beam and light receptor (usually a photodiode) to measure the light scattered from an individual illuminated aerosol particle due to Mie scattering (Chun et al., 2001; Kim, 2004; Kohli and Mittal, 2015). The particle number concentration (PNC) is then determined by counting the number of scattered light pulses within a specific time interval. The particle diameter is also determined by measuring the height of these light pulses. The PNC is typically discretized into regulatory or epidemiologically relevant size bins (e.g. PM_{2.5}, PM₁₀). Once discretized, PNC can be used to approximate PM mass density, but these standalone values should be interpreted carefully. OPCs cannot be used to

determine aerosol type and some concessions must be made before PNC can be converted into a mass density measurement. For example, OPCs are not able to account for several aerosol properties, including particle density, shape, refractive index, and absorption. As a result, assumptions are made regarding each of these properties, as OPCs report light-scattering equivalent diameters instead of the true physical diameter and mass density (Kobayashi et al., 2014; Kohli and Mittal, 2015). Examples of some of these assumptions include aerosol particles having an aerodynamic diameter (particles are assumed to be spherical), with a constant density of 1 g cm^{-3} (density of water), and a constant refractive index or absorption. As a result, OPCs may be more adept at approximating PM mass of certain sources than others, which often depends on source of PM used during the factory calibration. This information is often not disclosed by OPC manufacturers, as the exact algorithms used to convert PNC to particle mass are proprietary.

Despite the challenges of using OPCs to derive $\text{PM}_{2.5}$ mass density, the potential of these low-cost sensor networks in producing spatially resolved exposure maps at finer scales relative to the existing monitoring infrastructure is promising. If individual correction factors can be established which correspond to the ambient $\text{PM}_{2.5}$ source profile of a specific urban area, then low-cost sensor networks may provide an advantage over traditional monitoring techniques for LUR modeling.

1.3 Research Objectives

This thesis focuses on the development of (a) an opportunistic ambient calibration method for correcting low-cost $\text{PM}_{2.5}$ sensor networks in order to use them for intra-urban modeling and (b) a LUR modeling technique which relies on this corrected sensor network data to predict spatially resolved $\text{PM}_{2.5}$ throughout Portland, Oregon in order to assess the drivers of $\text{PM}_{2.5}$ intra-urban variability, with focus on vegetation. This thesis is part of a larger epidemiological study entitled the Canopy Continuum Project, funded by the USFS. The method developed within this thesis will be subsequently applied to four additional cities within the USFS Canopy Continuum study (Albuquerque, New Mexico, Boise, Idaho, Sacramento, California, and Tacoma, Washington).

The analytical goal of this study is to develop a predictive model to produce spatially resolved $\text{PM}_{2.5}$ surfaces at a spatial resolution of 50 m and a daily temporal resolution throughout a 2 year period. These fine-scale exposures will be developed for later use in an epidemiological study which characterizes the effects of several environmental stressors, including urban heat, NO_2 , and $\text{PM}_{2.5}$ on prenatal health, and assesses the extent the urban canopy may play in helping mitigate prenatal exposure to these environmental stressors.

Chapter 2

Methodology

2.1 Low-Cost Sensor Selection

2.1.1 Sensor Performance

We selected the PurpleAir-II SD (PurpleAir) for this study due to their previously demonstrated performance and relatively low-cost (\$250). The South Coast Air Quality Management District's (SCAQMD) Air Quality Sensor Performance Evaluation Center (AQ-SPEC) has created both lab and field evaluation reports comparing several PurpleAir monitors against Federal Equivalent Methods (FEM). They observed good correlations with FEMs during lab ($R^2 \approx 0.99$) and field ($R^2 \approx 0.95$) evaluations of PM_{10} and $PM_{2.5}$ (AQ-SPEC South Coast AQMD, 2017b; AQ-SPEC South Coast AQMD, 2017a). AQ-SPEC also observed moderate to good accuracy within the 0-250 $\mu g m^{-3}$ range from the PurpleAir monitors across multiple temperature and relative humidity profiles. The PurpleAir monitors outperformed competing sensors that cost 2-4 times more (MetOne E-Sampler, Alphasense OPC-N2, Dylos). The low-cost and good accuracy of the PurpleAir monitors allowed us to installed a higher density network in each of the five cities. The PurpleAir monitors are also WiFi capable,

and transmit data to the ThingSpeak IoT cloud platform every minute. This enabled the real-time monitoring of the network via a Python script which notified us when a specific sensor lost WiFi connection or power, and data collection was interrupted (Appendix A: `purpleair_watchdog.py`). We could then notify the appropriate volunteer monitor hosts to troubleshoot the device and establish a connection, improving long-term data recovery. The PurpleAir-II SD model also includes local storage in the form of a micro-SD card, providing a backup if the device loses connection to its WiFi network, or was not available at a specific location altogether. While this appeared to be a promising feature, the current firmware version (2.50i) of the PurpleAir-II SD had issues with data logging, and the microcontroller would intermittently lose connection with the SD card module. This produced data gaps and error messages were logged within the main data file, creating further data processing issues during analysis. Upon this discovery, we modified our sensor hosting requirements to require a WiFi connection to avoid local storage issues.

Each PurpleAir monitor contains two Plantower PMS5003 sensors. These are low-cost sensors (\$20-\$40) that approximate PM mass using an optical scattering technique. The sensors record PM mass density concentrations for 1.0 μm , 2.5 μm , 5.0 μm , and 10 μm size categories using a proprietary algorithm and come pre-calibrated from factory. The PMS5003 has additional fields that report number density concentrations of particles ranging in size from 0.3 to 10.0 μm . In addition to the two Plantower PMS5003 sensors, the PurpleAir monitors contain a Arduino ESP8266 microcontroller for wireless data communication and logging, a BME280 pressure, temperature, and humidity sensor, an SD card

reader, and a real time clock to keep time while disconnected from the main power supply. The devices also have an IP68 waterproof rating, and are designed for long-term outdoor use.

2.1.2 PurpleAir Device Ownership and Open Data Philosophy

PurpleAir upholds an open data philosophy that is not matched by competing low-cost air quality sensor manufacturers. Many sensor companies consider data as a service, renting monitors and providing data access via monthly subscription (AirAdvice, Apis Inc, MetOne, Alphasense OPC-N2, etc.). While this may benefit the use-cases of some consumers (device troubleshooting/maintenance is often included within this service), this was disadvantageous for our research purposes. In contrast, any data collected from PurpleAir monitors is freely available to all users, independent of device ownership. Data from third party monitors are accessible via their application program interface (API). After field calibration, this allowed us to incorporate data from additional third party PurpleAir monitors into our existing network.

2.2 Laboratory Evaluations

We conducted laboratory evaluations of 65 PurpleAir monitors within a 25 °C temperature controlled chamber at ambient humidity, and measured their response to multiple PM sources. The low-cost PurpleAir monitors were compared against a TSI DustTrak DRX 8433 Aerosol Monitor (also an optical scattering instrument). PurpleAir monitors were exposed to PM generated from smoke generated from lit matches, and smoke created by snuffing a candle

within the test chamber. Only one specific PM source was evaluated during a given test. Approximately 8-10 PurpleAir monitors were suspended from the lid of the 160L stainless steel test chamber using baling wire. The DustTrak reference monitor was placed on the floor of the chamber to ensure adequate ventilation between itself and the sensors hanging above. During the candle and match smoke tests, a 100 mL beaker was placed on the floor of the chamber, opposite to the sampling inlet of the DustTrak monitor. A match or candle was lit and snuffed inside of the beaker and the chamber lid was immediately closed. The chamber would rapidly saturate with PM well above the maximum effective range reported by the low-cost sensor ($500 \mu\text{gm}^{-3}$) manufacturer. The PM would then slowly decay to zero as it was ventilated with particle-free air (zero-air pushed through a $0.3 \mu\text{m}$ particle filter) at a constant flow-rate (inlet pressure of 30 psi). During this time, the PM levels within the chamber were monitored using the analog port on the DustTrak, an analog to digital convert (A/D converter), and a Python script which provided a real-time 1-second estimate of the $\text{PM}_{2.5}$ mass density. The entire process, from PM saturation to below-ambient concentration, required approximately 1-2 hours per test. The slow and steady decay of the PM within the chamber allowed us to compare each PurpleAir monitor to the DustTrak reference across a wide range of PM concentrations, throughout the entirety of the low-cost sensors' effective range ($0 - 500 \mu\text{gm}^{-3}$). However, since we were primarily interested in sensor performance across an environmentally relevant range, we developed individual linear models for each sensor by comparing 1-minute averages against the reference

instrument between 0 - 150 μgm^{-3} . This method allowed us to capture a near-continuous concentration range instead of just a few discrete points that a typical span calibration would provide. Comparing the low-cost sensors across a continuous PM range from multiple PM sources helped characterize the linearity of the low-cost sensors against our reference monitor.

2.3 PurpleAir Data Acquisition and Storage

PurpleAir provides a lightweight JSON API (<http://www.purpleair.com/json>) for requesting the most recent observation from each monitor, but accessing historical data is not as straightforward. While historical data is stored by PurpleAir and made available via a wagtail which requires a manual download (<http://www.purpleair.com/sensorlist>), they do not provide a programmatic interface for downloading historical data from their platform. Instead, historical data is accessible through the ThingSpeak cloud platform. Programmatically downloading historical data is still free and open, but it is significantly more challenging than accessing the real-time data from the PurpleAir JSON API.

This added difficulty can be explained by two main factors. The primary factor is the API rate limit set by ThingSpeak. The size of each request is limited to a maximum of 8000 observations. This equates to about one week's worth of data from a single node per request. Therefore, accessing historical data from multiple devices over a long period of time (especially in the case of initial database population) required a dynamic method of scheduling a sequence of API requests based on a given start and end date. To overcome this obstacle, we developed a suite of R/Python/Bash/SQL software which dynamically identified

new sensors as they are installed within our study areas, and included them into our data acquisition queue. Our system then iteratively made requests no larger than 8000 observations across the entire lifetime of each monitor within the network. The results from each request were then processed and stored in our PostgreSQL database with the PostGIS extension. This preserved the spatial coordinates associated with each PurpleAir monitor, and allowed us to perform spatial SQL queries throughout analysis. Once our initial database was populated, a similar script was executed from a Linux server (Xubuntu 18.04) each day at 1:00 AM using the 'cron' task-scheduling software. This script would upload the previous day's data into the database, including any new sensors that were installed throughout the network. It is worth noting that there are no API rate limits in terms of request frequency (requests per unit time), and we found success through multi-threading our pull requests. So long as each request was no larger than 8000 observations, we could pull ThingSpeak data from every available processor core simultaneously. This reduced our initial database population time by $1/8^{\text{th}}$ - $1/12^{\text{th}}$ depending on the available hardware (8 cores versus 12 cores).

In addition to the API request size limit, another challenge we encountered was the field encoding and total field limit of the PurpleAir data when stored on the ThingSpeak platform. Relations within the ThingSpeak API are limited to a total of eight fields, and their names are encoded (e.g. 'field1' instead of 'PM1.0 (CF=ATM) ug/m3'). However, the PurpleAir monitors record 32 fields. Therefore, requesting all of the available data from a given PurpleAir monitor required four separate API requests, achieved through a combination of

ThingSpeak primary and secondary API keys included within the PurpleAir JSON API. These four subsets were combined through SQL-like table joins using an R script. A key provided by PurpleAir's technical support team was required before these data could be fully processed (Appendix B). Once these fields were decoded, our suite of R/Python/Bash/SQL software automated the acquisition, processing, and storage of historical PurpleAir data (Appendix A: `purpleair_id_key.py`; `create_observation.sql`; `thingspeakCollect.R`; `uploadDailyThingspeak.R`; `uploadHistoricalThingspeak.R`).

2.4 Opportunistic Ambient Calibration of PurpleAir Networks

Since the response of each PMS5003 sensor is dependent on the PM source (in addition to the intra-model variation observed), an opportunistic ambient calibration method was developed with the goal of applying regionally-specific correction factors to each individual PMS5003 sensor within the PurpleAir network (Portland, OR). Given that $PM_{2.5}$ is not just a single pollutant, but a complex mixture of particles from multiple primary and secondary sources, an ambient field calibration method was required to best reflect the local PM source profile throughout each city. To determine locally relevant correction factors for each PMS5003 sensor in the Portland network, we compiled 5-minute nephelometer-derived $PM_{2.5}$ data provided by the Oregon Department of Environmental Quality (ODEQ) throughout the duration of our study period (September 2017 - March 2019). Nephelometers, being an optical scattering instrument themselves, initially provide only a Bscat value (the extinction of light due to back

scattering), and are subject to the same response issues as any other optical-based PM measurement (e.g. PurpleAir). However, a linear model was developed by ODEQ to correct these Bscat values. Nephelometers and 24 hour PM_{2.5} gravimetric samplers (FRM) were co-located to develop these correction factors. We used the 5-minute PM_{2.5} data provided by the ODEQ's FRM-corrected nephelometers to compare with our low-cost sensor network as a means of quality scaffolding. Depending on the day, there were 4-6 active nephelometers throughout the entire study period. We used these nephelometers to identify periods of time where PM_{2.5} levels were regionally homogeneous. This consisted of 15-minute periods (a total of three 5-minute observations per nephelometer) where the relative standard deviation (RSD) of the ODEQ reference monitors was less than or equal to 10%. Once windows of regionally homogeneous PM were identified, we compared the atmospheric PM_{2.5} channels ('pm2_5_atm' as opposed to 'pm2_5_cf_1' which is recommended for indoor use) from both PMS5003 sensors within a given PurpleAir monitor against the ambient background concentration (the mean of the active nephelometers) using an Ordinary Least Squares regression (OLS) to determine sensor-specific correction factors. These correction factors were stored as a new relation in our Postgres database to be queried during the modeling phase. Sensors with an R² value below 0.90 were deemed faulty or unreliable, and were excluded from the modeling phase. This method incorporated periods of time throughout the entire study duration, allowing us to capture PM across a range of seasonal sources (wildfires, wood heating, traffic, temperature inversions, etc.) and develop comprehensive correction factors that account for all regionally relevant sources.

2.5 Data Recovery and Sensor Lifetime

Between July 2017 and December 2018 data quality issues from 7% of the PurpleAir network were observed. While this was an improvement over the Shinyei sensors (AirAdvice monitors) we have used during previous studies, the PMS5003 within the PurpleAir are not immune to optical contamination and laser diode degradation. PurpleAir's technical support team recommended cleaning the optics with compressed air and/or applying a vacuum to the sample inlets. Compressed air revived one out of three faulty sensors. Data recovery over this period was greater than 90% and the remaining network has shown no signs of further degradation. Plantower now provides a dual-laser model (PMS6003) which has effectively doubled the lifetime of the sensor by alternating diodes between measurements. Modifications to the sensor chassis and sampling path design have also demonstrated improvements to mitigating dust accumulation in the optics in the previous models (PMS1003, PMS3003).

2.6 Sensor Allocation

The Portland, Oregon sensor network was the first in the Canopy Continuum study, and PurpleAir monitors were placed opportunistically. A sensor allocation and volunteer recruitment method was developed for the remaining four cities (Albuquerque, New Mexico, Boise, Idaho, Tacoma, Washington, and Sacramento, California). These cities were previously selected within the Canopy Continuum project because they represent a varying degree of canopy

cover necessary to characterize the potential role of vegetation in mitigating environmental stressors. Our sensor allocation approach first characterized the spatial autocorrelation of the existing Portland PurpleAir network to identify the minimum distance necessary to capture spatially heterogeneous $PM_{2.5}$. In other words, we plotted the R^2 between every sensor pair as a function of distance and observed when the R^2 began to drop below 0.75. We identified a minimum placement distance of 2 km from these results (Figure 2.1). Sensor allocation in the remaining cities relied on a random sampling approach, stratifying by population density. For each city, a population density surface with a spatial resolution of 2 km^2 was derived via areal interpolation of American Community Survey (ACS) data at the census block group level. Census data was retrieved using the `tidycensus` R package (Walker, 2019). In short, a 2 km^2 grid was created using the spatial extent defined by the bounding box of a given city's Metropolitan/Micropolitan Statistical Area shapefile (US Census Bureau, 2015). A spatial intersection was applied to each grid cell and its corresponding census block group(s) to determine area-based weights. For example, if a grid cell encompassed 50% of a given block group, the weight for that block group would be 0.5. If a grid cell was completely within a single block group, the weight would be 1.0. These weights were then applied to each block group's population count, assuming that the population density within a given block group was evenly distributed. The sum of these weighted population counts, determined by the relative area of each block group within that cell, was divided by the total area of the cell (2 km^2) to calculate its population density. We then iterated through each grid cell/block group pair to create population density

surfaces throughout each city.

FIGURE 2.1: Scatter plot of the Portland PurpleAir network spatial autocorrelation as a function of distance.

These gridded population density layers consisted of approximately 200-500 individual 2 km^2 grid cells depending on the study area. With only a limited number of PurpleAir sensors available to deploy in each city (Albuquerque $n = 30$; Tacoma $n = 25$; Boise and Sacramento $n = 20$), a random sampling approach was employed to prioritize areas of interest during network installation. These randomly assigned target areas were stratified by population density deciles.

Given that the primary goal of this study was to generate PM exposure maps for future analysis in an epidemiological study, the majority of the target areas were randomly assigned to the most densely populated deciles. In other words, we attempted to recruit more volunteers to host PurpleAir monitors who lived in more densely populated neighborhoods, and fewer volunteers from suburban and rural neighborhoods. The total number of monitors deployed in a given city was determined by the size of its Metropolitan Statistical Area (MSA), as well as, the number of pre-existing 3rd party PurpleAir monitors. After the random stratified selection process, target areas were manually adjusted for adjacency to other target areas, as well as, any existing 3rd party PurpleAir monitors.

While this method provided a quantifiable approach to sensor allocation, the structure of each city's network was ultimately limited by volunteer availability. We adopted the 'some data is better than no data' philosophy, and placed the majority of our sensors wherever there were willing and able participants. Sensors were typically installed 6-8 ft above ground in the front or backyard of a volunteer residence. Occasionally, sensors were sited outside commercial or government offices. This was especially the case in target areas with relatively low population densities. Sensors were placed at least 30 ft away from hyper-local sources including barbeques, laundry vents, and fireplaces.

Web maps with the gridded population density and sensor target areas (outlined in bold) were developed using leaflet R package (Cheng, Karambelkar, and Xie, 2018). Static maps are included below and hyperlinks to the original web maps are included within the figure captions (Figure 2.2; Figure 2.3; Figure 2.4; Figure 2.5).

FIGURE 2.2: Sensor allocation map developed for Albuquerque, New Mexico. Areas prioritized for sensor allocation are highlighted in bold. The web map can be viewed here: <http://web.pdx.edu/~porlando/albuquerque.html>

FIGURE 2.4: Sensor allocation map developed for Sacramento, California. Areas prioritized for sensor allocation are highlighted in bold. The web map can be viewed here: <http://web.pdx.edu/~porlando/sacramento.html>

FIGURE 2.5: Sensor allocation map developed for Tacoma, Washington. Areas prioritized for sensor allocation are highlighted in bold. The web map can be viewed here: <http://web.pdx.edu/~porlando/tacoma.html>

2.7 Data Compilation

All data compilation and spatial analysis were performed using the R Statistical Programming Language (R Core Team, 2019), and its corresponding spatial libraries. These include ‘sp’ (Pebesma and Bivand, 2005), ‘sf’ (Pebesma, 2018), ‘raster’ (Hijmans, 2019), ‘rgdal’ (Bivand, Keitt, and Rowlingson, 2019), and ‘rgeos’ (Bivand and Rundel, 2019). The following workflow diagram highlights the various data acquisition and processing scripts necessary to develop LUR models with corrected PurpleAir network data (Figure 2.6).

FIGURE 2.6: A workflow diagram highlighting the various data compilation scripts necessary to develop a LUR model with corrected PurpleAir data. All relevant source code is included within Appendix A.

2.7.1 Spatial and Temporal Predictors of $PM_{2.5}$

Several land-use (LU) and meteorological variables were evaluated to predict daily $PM_{2.5}$ surfaces at a spatial resolution of 50 m. Land-use variables were included as surrogates for potential PM sources in attempt to characterize the spatial heterogeneity of PM within the study area. This included proxies of traffic-related PM such as road (freeways, major arterials, streets, etc.) and rail density. Other spatial predictors were included to account for potential area sources (population density, LULC), or sinks (NDVI, EVI). Meteorological variables were included to characterize the temporal variation of PM. For example, PM concentrations typically increase as the planetary boundary layer (PBL) decreases as the effective mixing volume for PM dilution decreases during low boundary height scenarios. In addition, wind speed has been shown to affect PM concentrations. As wind speed increases, PM generated from urban sources

is readily removed, diluting overall PM levels throughout the urban core (Chudnovsky et al., 2014). The network of ODEQ PM monitors (nephelometers) were also included as a temporal scaling factor of PM. This allowed us to capture temporal patterns in PM that would otherwise be unaccounted for by meteorological variables alone (e.g. wildfires).

Road and Rail Density

Road and rail data were obtained from Metro’s Regional Land Information System (RLIS) data resource center (Oregon Metro, 2018). This included GIS shapefiles of the ‘Streets’, ‘Arterials’ ‘Major Arterials’, ‘Freeways’, ‘Railroads’, and ‘Railyards’ feature classes. Originally vector data, each feature class was discretized into a new raster layer with a spatial resolution of 50 m. These data were also reprojected to match the Coordinate Reference System (CRS) of the study area, and clipped by its extent (Appendix A: `processRoads.R`). For Portland, the bounding box was defined by Metro’s urban growth boundary extent (UGB). RLIS data is not available for the other study areas, and a national-scale data sources should be used instead during future modeling endeavors.

NDVI and EVI

Satellite-derived Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data were obtained from the 250 m MODIS 16-day product (MOD13Q1) (Didan, 2015b). These data were programmatically downloaded using the MODIS R package (Mattiuzzi and Detsch, 2019) (Appendix A: `downloadNDVI.R`). The NDVI was determined using red and near

infrared surface reflectances, which has been shown to provide a temporal indication of vegetation cover and its phenological state (Tucker, 1979; Tucker and Sellers, 1986). The EVI layer is more sensitive over densely vegetated areas, explaining further variation in vegetation density beyond the range of the NDVI. Both of these layers are derived from bi-directional surface reflectances, with masking algorithms for water, clouds (and their shadows), and aerosols (Didan, 2015b). Each MODIS layer was reprojected to match the CRS of the study area, clipped by the study extent, and resampled via bilinear interpolation to match the 50 m spatial resolution of the model. Originally, we explored a temporal cubic spline interpolation method to derive daily NDVI/EVI observations from each 16-day MODIS overpass (Fritsch and Carlson, 1980). While this technique produced promising results with the 1 km resolution MODIS product (MOD13A2), (Didan, 2015a), it did not scale to the 250 m resolution product, and our processing script unexpectedly terminated without explanation (Appendix A: `interpolateNDVI.R`). This was likely due to issues with cloud masking and excessive missing values at this resolution. Instead of interpolating daily NDVI/EVI from the 250 m product, we opted to develop annual aggregates (Appendix A: `annualNDVI.R`).

Elevation data were retrieved from NASA's Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) digital elevation map (DEM) product. This is a global DEM with a spatial resolution of 30 m provided in GeoTiff format (NASA, 2009). This layer was reprojected to match the CRS of our study area, clipped by our study extent, and resampled from 30 m to 50 m (Appendix A: `processElevation.R`).

Population Density

Population density data was obtained from NASA's Gridded Population of the World (GPW) collection (version 4) (Doxsey-Whitfield et al., 2015). This product models the distribution of the global human population on a continuous raster layer for use in social, economic, and Earth science disciplines. This is a 30-arc second resolution product (approximately 1 km) provided in GeoTIFF format. This global raster layer was reprojected to match the CRS of our study area, and then clipped by its extent. It was also resampled from 1 km to 50 m via bilinear interpolation (Appendix A: `processPopDensity.R`).

GridMET Meteorological Variables

Meteorological data was obtained from the University of Idaho's Gridded Surface Meteorological Data (GridMET). The GridMET data is a combination of high-resolution spatial data (4 km) from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and the high-temporal resolution data from the National Land Data Assimilation System (NLDAS) which generates spatially and temporally continuous fields of several meteorological variables (Abatzoglou, 2013; Daly, 2006; Mesinger et al., 2006). The GridMET product provides estimates of daily precipitation totals, minimum and maximum air temperature and relative humidity, specific humidity, mean wind direction and mean wind speed. However, the GridMET product was not designed to capture microclimates that occur at more granular resolutions than its native resolution of the two parent data sources (Abatzoglou, 2013). The wind variables are limited to a 32 km spatial resolution and are not capable of capturing any influences

of terrain on wind fields (Abatzoglou, 2013). An R script was developed to programmatically download daily GridMET data via `wget` calls to a HTTP server (Appendix A: `downloadGridMET.R`). As with the previous predictors, the GridMET data was reprojected to match the CRS of our study area, clipped by our study extent, and resampled to 50 m to match the resolution of our modeled surfaces. A bilinear interpolation was applied to all scalar variables, however, wind direction was resampled using the nearest neighbor method because the bilinear method is incapable of vector averaging (Appendix A: `processGridMET.R`).

Land Use and Land Cover

Land Use and Land Cover (LULC) data was obtained from the USGS's National Land Cover Database (NLCD) 2011 product. The NLCD provides a 30 m spatial resolution categorical raster layer with fifteen different LULC attributes. This includes open water, low, medium, and high intensity developed land, deciduous, evergreen, and mixed forest lands (Homer et al., 2015). This raster was reprojected to match the CRS of our study area, clipped by its extent, and resampled from 30 m to 50 m using the nearest neighbor method. This single categorical layer was decomposed into individual presence/absence rasters for each LULC attribute via one-hot encoding. For example, if the 'open water' LULC was observed within a raster cell, a value of 1 would be assigned to this cell. If a LULC was not observed within a cell, then a value of 0 would be assigned. One-hot encoding the NLCD raster into individual layers was necessary for creating focal statistics (Appendix A: `processNLCD.R`).

Planetary Boundary Layer Height

Planetary boundary layer height (PBL) data was obtained from NOAA's NARR product (Mesinger et al., 2006). An R script was used to programmatically download 3-hourly PBL netCDF data throughout the study duration (September 2017 - March 2019) via `wget` calls to NOAA's FTP server (Appendix A: `downloadPBL.R`). The NARR PBL grid resolution is approximately 0.3 degrees, which corresponds to 32 km at the lowest latitudes. Each 3-hourly grid was aggregated into a single mean value throughout the study area. These 3-hour means were then used to determine the daily maximum and minimum PBL height values. The minimum and maximum PBL values were used as temporal scaling factors, and were extrapolated into continuous 50 m resolution spatial grids corresponding to the extent and CRS of our study area (Appendix A: `processPBL.R`).

Nephelometer PM_{2.5}

Nephelometer-derived PM_{2.5} data with a 5-minute temporal resolution were provided by ODEQ. In addition to the use of these data for determining correction factors for our PurpleAir sensor network, these data were also included as a temporal scaling factor to account for changes in the ambient background concentration due to regional sources (e.g. wildfires). The 5-minute PM_{2.5} values from 4-6 active nephelometers were aggregated into daily mean and median values (Appendix A: `processNeph.R`). Similar to the PBL compilation, these values were extrapolated into a continuous 50 m resolution surface corresponding to the extent and CRS of our study area (Appendix A: `interpolateNeph.R`).

Latitude and Longitude

Continuous fields for both latitude and longitude were generated using R and its spatial libraries (*raster*, *rgdal*, *rgeos*, *sp*, *sf*, etc.). These variables were included to account for the potential effects of spatial autocorrelation described by Tobler's 1st law of geography (Tobler, 1970).

2.7.2 Focal Statistics

Focal statistics were determined for each spatial (and temporal-spatial) predictor at 50 m, 100 m, 300 m, 500 m, and 1000 m buffer sizes (Appendix A: *buffer.R*). These buffer distances were adopted from the LUR methods developed by the ESCAPE Project (Eeftens et al., 2012). The population density variable also included 1250 m, 1500 m, 2000 m, and 2500 m focal buffer distances. Briefly, this method iterates through each cell within a given 50 m resolution spatial grid and determines the mean value of all adjacent cells within a prescribed radius (neighborhood). The target cell is then assigned the mean value of this neighborhood. This process is then repeated across the sequence of desired buffer distances. For a graphical representation of the new layers created from applying focal statistics to the 'Streets' layer, see Figure 2.7. For the predictors which are purely spatial (NLCD, Roads and Rail, Elevation) focal statistics at each neighborhood size were performed only once. However, for the temporal spatial-predictors (NDVI, EVI, GridMET), this operation was repeated for each daily observation. This resulted in a total of 33 thousand individual raster layers, stored as GeoTIFFs, which consumed approximately 100 GB of local disk

storage. Despite being rasterized, this method was also computationally expensive. Determining thousands of focal buffers required the use of a high-memory compute server provided by PSU Research Computing, and consumed *geq*500 GB of memory while running on all 24 available processor cores. Processing time was on the order of 4-6 hours depending on the total number of predictors selected for modeling.

The temporal predictors lacking any spatial component (e.g. scaling factors including PBL and Nephelometer PM) were not included in the focal statistics pipeline, as these layers only consisted of a single mean value for each day.

Focal statistics for the GridMET wind direction data were handled differently than the other variables. This layer, with the inclusion of wind speed, was converted from degrees to radians, and then transposed into its respective u (zonal velocity) and v (meridional velocity) components. Focal statistics were then performed on the u and v components (unit-vector averaging), and converting back into degrees using the arc-tangent (Appendix A: `buffer.R`).

FIGURE 2.7: A graphical representation of applying focal buffers to the RLIS ‘streets’ layer. The buffer distances are appended to the layer name in each panel, e.g. the 1 km buffer is named ‘streets.1000m’. The original rasterized RLIS ‘streets’ layer does not have a buffer size appended to its layer name.

2.7.3 Data Extraction

After generating focal statistics across our sequence of buffer distances, variables, and days, we extracted the grid cells values that spatially intersected with the corrected PurpleAir response variable (Appendix A: `extract.R`). Iterating the raster extraction process across each day within our study duration, the end result was a single large matrix (data frame) with the corrected PurpleAir $PM_{2.5}$ response variable and all relevant predictors at each buffer size. This matrix

consisted of 211 variables and 11,546 observations. Additional categorical variables were added to this matrix including ‘Weekday/Weekend’, ‘Day of Week’, ‘Season’, and ‘Month’. This matrix was used during the modeling phase. The study duration consisted of 575 consecutive days and, given the 11,546 unique observations, the average number of active PurpleAir monitors on a given day was approximately 20. This is comparable to the network sizes within the ESCAPE Project (Eeftens et al., 2012). The Portland network did grow overtime as PurpleAir monitors were incrementally added by our research group as well as other 3rd parties. The network size was closer to 10 active nodes during the first few months of the study, and grew to more than 35 nodes by its end. Some of these were active for a short period of time, but most remained active once initially established.

2.8 Predictor Selection

To avoid issues of multicollinearity, only a single focal buffer distance was selected for each predictor variable during the modeling phase. A correlation matrix was produced for each variable against the response data and the focal buffer with the strongest correlation with the response variable was then selected for modeling. If multiple focal buffers had the same correlation coefficient, then the finest spatial resolution buffer was chosen to capture as much spatial heterogeneity as possible. Variables with nonintuitive correlations, e.g. expected sources yielding a negative correlation, or expected sinks yielding a positive correlation, were excluded from the model.

An additional correlation matrix which compared all of the previously selected predictors was generated to explore groups which covaried. A complete linkage hierarchical clustering algorithm, a built-in parameter within the R ‘corrplot’ library (Wei and Simko, 2017), was used to identify clustered predictors (Defays, 1977). Once these groups were identified, only a single predictor within each group was selected for the modeling phase. For example, if the NLCD-derived ‘Deciduous Forest’, ‘Mixed Forest’, ‘Evergreen Forest’ were clustered with ‘NDVI’, then the most generalizeable predictor was selected for the final model (e.g. the NDVI layer can be used to explain all of the other vegetation layers).

These predictor selection criteria were established to meet the multicollinearity assumption of a traditional multiple linear regression. We relied on a Variance Inflation Factor (VIF) below 5 to meet this assumption. VIF scores were determined using the ‘car’ R library to assess multicollinearity (Fox et al., 2007). Although the multicollinearity assumption only applies to multiple linear regression model, the same variable selection procedure was applied to the Random Forest model for direct comparison. Model variables were also tested for significance, and only predictor coefficient’s p-value less than 0.1 were selected for the final model (Appendix A: `modeling.R`).

The initial predictors selected for the modeling phase are included within Table 2.1. This table details the variable description, abbreviation, and respective data sources. The expected source and sink proxies for each predictor are also included.

2.9 Modeling and Validation

For this study, we compared the performance of a traditional LUR model (multiple linear regression) against a decision-tree-based machine learning model (Random Forest) (Liaw and Wiener, 2002; Breiman, 2001). Of the 11,546 total observations, we randomly subset 70% during the training phase for each model. The remaining 30%, or 'test' data, was reserved for model validation. In addition to this 70/30 holdout approach, we also employed a leave-one-out cross-validation (LOOCV) method which has been widely used in previous LUR studies (Yang et al., 2017; Eeftens et al., 2012; Saucy et al., 2018). With this approach, a single PurpleAir node was excluded from the training data and a model was developed using the $n - 1$ remaining sites. The subsequent model was then used to predict all of the observations for this single node, and the model performance was evaluated by observing the cross validation (CV) R^2 and CV RMSE. This process was then repeated for each individual node, excluding nodes with fewer than 100 observations. The LOOCV method allowed us to evaluate how well a given model predicted for a specific sensor over a consecutive period of time, instead of predicting a random subset of days and sensors simultaneously. In addition, this method allowed us to compare an entire ensemble of predictions (a new model was developed for each node that was left out), and identify any locations that a model was consistently under/over predicting.

An ensemble method was used during the LUR model prediction phase. Specifically, each of the $n - 1$ models developed during the LOOCV phase were

used to predict an individual $\text{PM}_{2.5}$ surface. This ensemble of predictions was then aggregated to determine a single mean $\text{PM}_{2.5}$ surface each day. The Random Forest method was too computationally expensive to rely on the LOOCV technique when making predictions. Instead, the results from the single model which included all available monitoring sites generated from the 70/30 holdout process was used during the prediction phase.

Name	Description	Data Source	Proxy
pm2.5.median	Nephelometer PM _{2.5} (median)	ODEQ 2018	Regional temporal variation
fwy	Freeways (length)	RLIS 2019	Traffic emissions
maj_art	Major Arterials (length)	RLIS 2019	Traffic emissions
arterial	Arterials (length)	RLIS 2019	Traffic emissions
streets	Streets (length)	RLIS 2019	Traffic emissions
railroad	Railroad (length)	RLIS 2019	Railroad emissions
railyards	Railyards (area)	RLIS 2019	Railyard emissions
elev	Elevation (m)	ASTER DEM 2009	Potential sink (windflow)
pop_dens	Population (density)	NASA 2015	Area sources
PBL	Planetary Boundary Layer Height	NOAA 2019	Sink (dilution)
pr	Precipitation (daily total)	GridMET 2019	Potential sink (wet deposition)
th	Wind Direction (degrees)	GridMET 2019	Potential sink (dilution)
vs	Wind Speed (m/s)	GridMET 2019	Potential sink (dilution)
tmnx	Maximum Temperature	GridMET 2019	Potential SOA source
tmnn	Minimum Temperature	GridMET 2019	Potential SOA source
rmax	Maximum Relative Humidity	GridMET 2019	Potential source (hygroscopic growth)
rmin	Minimum Relative Humidity	GridMET 2019	Potential source (hygroscopic growth)
ndvi	NDVI	MODIS 2019	Potential sink (deposition)
evi	EVI	MODIS 2019	Potential sink (deposition)
low_dev	Developed Low Intensity LULC (density)	NLCD 2011	Area sources
med_dev	Developed Medium Intensity LULC (density)	NLCD 2011	Area sources
high_dev	Developed High Intensity LULC (density)	NLCD 2011	Area sources
deciduous_forest	Deciduous Forest Cover (density)	NLCD 2011	Potential sink (deposition)
evergreen_forest	Evergreen Forest Cover (density)	NLCD 2011	Potential sink (deposition)
mixed_forest	Mixed Forest Cover (density)	NLCD 2011	Potential sink (deposition)
lat	Latitude	PurpleAir	Spatial variability of sinks and sources
lon	Longitude	PurpleAir	Spatial variability of sinks and sources
season	Season (1,2,3,4)	PurpleAir	Temporal variability of sinks and sources
weekend	Weekday/Weekend (0,1)	PurpleAir	Temporal variability of sinks and sources

TABLE 2.1: Descriptions of the predictor variables selected during LUR model development with their respective data sources and PM_{2.5} proxies.

Chapter 3

Results and Discussion

3.1 Laboratory Evaluations

Strong linear relationships between the low-cost PurpleAir monitors and the reference DustTrak DRX Aerosol Monitor Model 8533 were observed for both the match and candle smoke tests. The mean R^2 of the candle smoke evaluations was 0.958 ± 0.14 , whereas the mean R^2 of the match smoke evaluations was 0.942 ± 0.17 Table 3.1. Despite following the same protocol between tests, some sensors did not perform linearly with the reference instrument (Figure 3.1). However, these cases occurred infrequently and meaningful calibrations with R^2 values greater than 0.90 occurred for more than 80% of all test periods. While the strength of DustTrak-PurpleAir relationship was independent of the PM source, the slopes differed depending on the PM source. The mean slope of the models generated from the match smoke tests was 1.35 ± 0.64 . This was approximately half the value observed from the candle smoke tests which yielded a mean slope of 2.66 ± 0.75 (Figure 3.2). These results indicate two challenges with low-cost PM sensors for LUR. The first was that intra-model

variation does occur with the Plantower sensors, despite the manufacturer's effort to pre-calibrate each sensor. This means that two sensors, when exposed to the same PM sample, will produce a slightly different response. The slopes from the match smoke tests are more narrowly distributed, while the candle smoke tests have a wider distribution ranging from 2-3 and appear bimodal. This was somewhat unexpected because multiple different types of matches were used throughout these laboratory evaluations, whereas only a single candle was used. This could potentially be explained by match smoke PM having similar physical properties as Plantower's PM source during factory calibration (e.g. absorption, profile, shape, etc.). The second challenge presented by these results is that the Plantower/PurpleAir response is dependent on the PM source. This suggests that laboratory calibrations alone, while a reliable screening tool for faulty sensors, are not enough to determine meaningful correction factors for field-deployed sensors necessary to produce epidemiologically relevant $PM_{2.5}$ concentrations. These results support the development of an ambient calibration method of PurpleAir networks for determining field-specific correction factors. Two scatter plots were included to highlight the PurpleAir's response across the entire PM range of a typical test for both the primary and secondary sensors (A and B sensors) (Figure 3.3; Figure 3.4).

PM Source	R^2	R^2 SD	Slope	Slope SD	Intercept	Intercept SD
Candle	0.958	± 0.14	2.7	± 0.78	0.34	± 2.83
Match	0.942	± 0.17	1.35	± 0.64	3.98	± 5.24
Field	0.958	± 0.02	0.46	± 0.06	1.63	± 0.31

TABLE 3.1: Linear model summary statistics of both laboratory and field evaluations. Lab evaluations are comparing the DustTrak against PurpleAir monitors grouping by the PM source (candle and match smoke). The field evaluations are comparing the mean nephelometer $PM_{2.5}$ against PurpleAir monitors. SD = standard deviation.

FIGURE 3.1: Distribution of R^2 values from linear models comparing DustTrak reference instrument against PurpleAir monitors during laboratory evaluations.

FIGURE 3.2: Distribution of Slope values from linear models comparing DustTrak reference instrument against PurpleAir monitors during laboratory evaluations.

FIGURE 3.3: Scatter plot of laboratory evaluation comparing DustTrak reference instrument against PurpleAir primary sensor (Device ID: 68:C6:8E:A3:CA). The "pm2_5_atm" label refers to the $\text{PM}_{2.5}$ mass-density channel of the PurpleAir.

FIGURE 3.4: Scatter plot of laboratory evaluation comparing DustTrak reference instrument against PurpleAir secondary sensor (Device ID: 68:C6:8E:A3:CA). The "pm2_5_atm" label refers to the $\text{PM}_{2.5}$ mass-density channel of the PurpleAir.

3.2 Opportunistic Ambient Calibration

Based on the laboratory calibration findings, we sought a way to calibrate sensors in-situ with ambient particulate matter. Based on other studies (Eeftens et al., 2012; Zhou and Levy, 2007), $PM_{2.5}$ levels can be mainly driven by regional sources thereby limiting small-scale variability. We tested the idea of calibrating the sensors during regional homogeneity events. Homogeneity was assessed using the 4-6 ODEQ nephelometers in the Portland metro area. These nephelometers have been calibrated against the federal reference method. Originally 5-minute resolution data, the nephelometers were aggregated to 15-minute means to identify periods when $PM_{2.5}$ was determined to be regionally homogeneous (the relative standard deviation of all active nephelometers within the Portland metropolitan area was $\leq 10\%$). Once these periods were identified, linear models were generated for each sensor, and those with an $R^2 < 0.90$, or those with < 100 observations were excluded from the modeling phase (Appendix A: `homogeneousPM.R`). Violin plots were created to graphically assess the distribution of R^2 and slope values during the field calibrations. The R^2 values from the field evaluations were not as narrowly distributed below 1.0 relative to the laboratory evaluations, and considerable left-skew of the R^2 distribution was observed. This suggests that the some sensors were affected by local PM sources that were otherwise not captured by the network of nephelometers. Figure 3.5 shows the distribution of R^2 for the 138 sensors with the nephelometers during homogeneity events. We chose an R^2 of 0.90 as our quality filter. After applying the quality filter to the 138 unique sensors observed throughout

the Portland network, a total of 61 (48%) sensors were considered viable for the modeling phase. These 61 sensors corresponded to 35 individual locations. There were 26 nodes which both the primary and secondary sensors passed our quality standards, and there were 9 remaining nodes which only had a single passing sensor. The 35 site total was accumulated throughout the entire 2-year study period, but, on average, there were 20 active sites on any given day. The slopes of the 61 sensors were then graphically assessed via violin plot. The slopes from the field evaluations ranged between 0.31 and 0.80, with a mean of 0.46 (Figure 3.6; Table 3.1). These coefficients are comparable to those determined by other field evaluations, where PurpleAir monitors were co-located with FRM/FEM instruments (AQ-SPEC South Coast AQMD, 2017a).

Scatter plots illustrating the relationship between primary and secondary sensors from a select PurpleAir node against the homogeneous mean $\text{PM}_{2.5}$ ambient background concentration were included to highlight the observed intra-model variation in slopes (Figure 3.6). The 'STAR Lab Creston-Kenilworth' monitor was an extreme example, and exhibited a 30% difference in slopes between the primary and secondary sensors, despite both sensors producing relatively high R^2 values. The primary sensor produced an R^2 of 0.970, a slope of 0.45, and a RMSE of 1.19. A mean $\text{PM}_{2.5}$ range of 0-50 μgm^{-3} was observed from the nephelometer network during the evaluation period, with the majority of observations limited to 0-25 μgm^{-3} . The secondary sensor yielded an R^2 of 0.967, a slope of 0.31, and a RMSE of 1.25, and encompassed a similar range in nephelometer PM as the primary sensor. Model intercepts were 1.3 and 1.2 μgm^{-3} for the primary and secondary sensor respectively (Figure 3.7; Figure

3.8).

FIGURE 3.5: Distribution of R^2 values from linear models comparing PurpleAir network to ODEQ nephelometer-PM during 15-minute periods when PM was regionally homogeneous (Relative Standard Deviation $\leq 10\%$)

FIGURE 3.6: Distribution of slope values from linear models comparing PurpleAir network to ODEQ nephelometer-PM during 15-minute periods when PM was regionally homogeneous (Relative Standard Deviation $\leq 10\%$). Only the PurpleAir monitors with an $R^2 \geq 0.90$ were included within this plot.

FIGURE 3.7: Scatter plot of a select field evaluation comparing mean regional Nephelometer PM_{2.5} against PurpleAir primary sensor (STAR Lab Creston-Kenilworth). The relative point density is captured by the colorscale.

FIGURE 3.8: Scatter plot of a select field evaluation comparing mean regional Nephelometer PM_{2.5} against PurpleAir secondary sensor (STAR Lab Creston-Kenilworth). The relative point density is captured by the colorscale.

3.3 Predictor Selection

The goal of the modeling effort is to predict $\text{PM}_{2.5}$ at high spatial resolution and identify the land-use or physical drivers of variability. The next step for model development was to identify variables for the inclusion in the model. Purposeful variable selection was performed partly by software and partly by hand. We relied on previous literature and our understanding of the physical properties of $\text{PM}_{2.5}$ to derive our set of proxies for expected sources and sinks (Eeftens et al., 2012; Rao et al., 2014; Brokamp et al., 2017; Saucy et al., 2018; Wang and Ogawa, 2015; Chudnovsky et al., 2014). A list of all initial predictors that were considered are outlined in Table 2.1. Only a single buffer for each spatial predictor was selected for the subsequent modeling phases to avoid issues regarding multicollinearity. We then narrowed down our selected predictors by exploring clusters which covaried. Finally, a stepwise Akaike Information Criterion (AIC) reduction method was employed to further narrow the set of predictors into a final parsimonious model, referred to as the ‘final model’. We relied on the hybrid selection method, which is a combination of both forward and backward selection techniques (Venables and Ripley, 2002). Of the 28 predictors initially considered, only 9 were included within our final explanatory model. It is worth noting that the spatial and spatiotemporal variables each had multiple buffer distances, and the total number of initial predictors was considerably higher than 28 prior to the selection of a single buffer per variable. The 9 final predictors were selected based on correlation strength with the response variable, VIF scores below 5, intuitive signs of model coefficients (i.e. potential sinks

have negative coefficients, and potential sources have positive coefficients), and coefficient p-values below 0.10. The majority of the VIF scores of the predictors within the final model were below 2. The ‘Season’ variable exhibited the highest VIF score of 3.50. This was followed by a score of 2.93 for the maximum daily temperature (‘tmmx.50m’) and 2.16 for daily mean wind speed (‘vs.50m’).

TABLE 3.2: Summary table of the VIF scores from the final model predictors.

	GVIF	Df	GVIF ^{1/(2*Df)}
Median Nephelometer PM _{2.5}	1.163	1	1.078
Elevation (50 m)	1.824	1	1.351
Minimum PBL Height	1.923	1	1.387
Maximum Relative Humidity (50 m)	1.466	1	1.211
Maximum Temperature (50 m)	2.934	1	1.713
Mean Wind Speed (50 m)	2.160	1	1.470
Developed Medium Intensity (100 m)	1.900	1	1.378
Season	3.497	3	1.232
Longitude	1.167	1	1.081

3.4 Leave-One-Out-Cross-Validation

Before conducting the LOOCV with the LUR model, the total number of observations for each PurpleAir node (both primary and secondary sensors) was determined. Nodes with fewer than 100 observations were excluded from the LOOCV modeling phase to prevent individual model performance from being unduly influenced by outliers. Overall, 32 of the 34 PurpleAir nodes had more than 100 observations and were used for LOOCV (the primary and secondary sensor data from each node were aggregated). There were 20 nodes which were

established earlier on in the study and captured more than 200 daily observations (Figure 3.9).

The mean R^2 from these 32 LOOCV models was 0.87, and ranged between 0.73 and 0.97. The interquartile range in R^2 was between 0.84 and 0.90. Model RMSE ranged between 1.31 and 3.71 $\mu g m^{-3}$. Model slopes ranged between 0.67 - 1.06 with a mean of 0.87, and the mean intercept was approximately 0 for most models (Table 3.3). The two nodes which produced LOOCV R^2 below 0.80 ('Haig St', 'Upper Multnomah Village') each had fewer than 200 observations. Differences between LOOCV R^2 and final model R^2 were typically below 10%, indicating overall model stability.

FIGURE 3.9: A bar plot assessing the number of observations for each PurpleAir monitor used during LOOCV. Nodes with fewer than 100 observations (bars below the dotted red line) were not included during the LOOCV.

3.5 Model Validation

Individual predictions from each of the $n - 1$ LUR models developed during the LOOCV phase were aggregated to produce a mean ensemble prediction. This ensemble prediction was then compared against the ‘test’ data (the 30% random subset of the corrected PurpleAir data held out during the model training

Stat	R ²	RMSE	Slope	Intercept
Min	0.73	1.31	0.67	-1.23
1 st Quartile	0.84	1.64	0.82	0.73
Median	0.88	2.00	0.88	0.91
Mean	0.87	2.04	0.87	0.95
3 rd Quartile	0.90	2.29	0.94	1.30
Max	0.97	3.71	1.06	2.64

TABLE 3.3: Summary statistics from the LOOCV phase. A validation regression was generated with each LOOCV model and the ‘test’ data to evaluate model stability.

phase) to assess overall model performance. Specifically, a validation regression was generated, modeling the observed $PM_{2.5}$ from the ‘test’ data as a function of the LUR predictions. The LUR model explained 0.89 % of the variance in the observed data and had a root mean squared error (RMSE) of $\pm 2.39 \mu g m^{-3}$. The slope of this model was 0.98, which suggests that the model slightly underpredicts the corrected PurpleAir ‘test’ data. Despite the good model fit, a graphical assessment of the residuals shows that the model appears to perform better at lower PM concentrations, where more training data was available. While a disproportionate number of days with low pollution should generally be considered a benefit, for modeling purposes this left room for improvement when predicting $PM_{2.5}$ above the $20 \mu g m^{-3}$ threshold. At lower concentrations, between $0-20 \mu g m^{-3}$, the residuals were within the $\pm 5 \mu g m^{-3}$ range. However, LUR model performance appeared to decline as the predicted range exceeded this threshold. There are instances where the model both overpredicts and underpredicts $PM_{2.5}$, and this was only exacerbated when concentrations are above $20 \mu g m^{-3}$ (Figure 3.10). Instances when the observed $PM_{2.5}$ levels were much

higher than the predicted levels suggest days when the regional monitoring network was unable to capture some local PM source at a given PurpleAir node.

The test assumptions of the LUR model were graphically assessed and can be viewed in Figure 3.11. The ‘Residuals vs Fitted’ panel shows the red trendline appears to approximate the zero line, which indicates that the linearity assumption is being met. The ‘Normal Q-Q’ panel shows that the residuals are normally distributed between the -2 and 2 theoretical quantiles, but the normality assumption is not met across the entire range of model residuals. The ‘Scale-Location’ panel shows the red trendline increasing as the fitted values increase. This means that the LUR model does not meet the homoscedascity assumption. However, since we were mostly interested in our ability to predict PM_{2.5} concentrations that typically occur within the urban environment (0 - 20 μgm^{-3}), we were willing to move forward with the model prediction phase, acknowledging that the spatial variability of exceptionally high PM events (e.g. forest fires) must be interpreted with caution. Finally, the ‘Residuals vs Leverage’ panel is used to evaluate potentially influential outliers that located beyond Cook’s distance. Despite our lack of normally distributed residuals, no data points were observed to exceed this distance.

In addition to the LUR model, we explored using a random forest (RF) model for its expectedly higher predictive power and its ability to account for some of the limitations inherent to LUR. Land use regression models have difficulty capturing non-linear relationships and complex interactions, but random forests (RF) are resistant to these problems. Random forests are often preferred

in prediction analyses due to their increased accuracy and resistance to multicollinearity and complex interactions relative to linear regression (Brokamp et al., 2017; Hastie et al., 2005). Our RF model performed slightly better than the LUR model, despite the computational limitations which prohibited an ensemble approach. This single model predicted 0.93% of the variance in the observed data and had a RMSE of $\pm 1.84 \mu\text{gm}^{-3}$, or 23% lower than the LUR model (Figure 3.12). The slope of this CV model was 1.0, and the intercept was near zero (-0.07). The residuals from the RF model also appear to be more tightly grouped along the 1:1 line relative to the LUR model. There were still some persistent outliers observed in the residuals of this model. Despite the promising summary statistics generated during the random forest model validation phase, we encountered some limitations while developing spatial predictions and with overall model interpretability that prevented us from relying on this technique instead of LUR. The limitations that we experienced with RF will be discussed in Section 3.9.

FIGURE 3.10: Scatter plot comparing the observed 30% holdout data as a function of the LUR mean ensemble predicted $PM_{2.5}$.

FIGURE 3.11: A graphical assesement of the LUR model's ability to meet multiple linear regression test assumptions.

FIGURE 3.12: Scatter plot comparing the observed 30% holdout data as a function of the Random Forest predicted $PM_{2.5}$

3.6 Standardized Regression Coefficients

3.6.1 Temporal Predictors

Nephelometer $PM_{2.5}$

The final model included the median $PM_{2.5}$ of the nephelometer network (the ODEQ regional monitoring network), elevation, the minimum planetary boundary layer height, the maximum relative humidity and temperature, mean wind speed, developed medium intensity LULC, season, and longitude. The standardized regression coefficients (betas) of the final LUR model show that the median nephelometer $PM_{2.5}$ value ('pm2.5.median') had the strongest association with $PM_{2.5}$ concentrations observed from the PurpleAir network. A one standard deviation increase in median nephelometer $PM_{2.5}$ corresponded to a 0.908 increase in standard deviation of the PurpleAir network. The unstandardized coefficient for the median nephelometer $PM_{2.5}$ indicates a 0.834 increase in PurpleAir $PM_{2.5}$ for every $1.0 \mu g m^{-3}$ increase in the ambient background concentration. The daily median nephelometer $PM_{2.5}$ concentration can be interpreted as a temporal scaling factor, and the variation in the PurpleAir network can largely be explained simply by the variation in the ambient background concentration. This was not surprising, as Karner et al. previously identified little to no spatial variation with intra-urban $PM_{2.5}$ (Karner, Eisinger, and Niemeier, 2010). Instead, meteorology mostly drives the temporal variation, while the spatial variability of this pollutant typically occurs at regional scales (Table 3.4). The association of the remaining 8 predictors and $PM_{2.5}$ was much weaker, each with beta values below 0.10.

Planetary Boundary Layer Height

The minimum planetary boundary layer height ('pbl.min') was shown to have the 7th highest beta value. An increase in one standard deviation in minimum PBL height resulted in a 0.015 decrease in the standard deviation of our response network. This variable corresponds to the minimum atmospheric volume available for dilution of urban sources. PBL was primarily included to capture days when meteorological conditions were stable, and temperature inversions were expected to trap surface-emitted PM_{2.5}, resulting in elevated concentrations during the cold season (Table 3.4). It was surprising that this variable did not have as strong an association with PM_{2.5} as some of the other temporal predictors (e.g. wind speed and maximum daily temperature).

Season

A categorical 'Season' variable was included to account for recurring seasonal patterns in PM_{2.5} variation over the 2 year study period. While the fall season had the fourth highest beta coefficient in the final model, the other two seasons (spring and summer) had some of the lowest associations with the PurpleAir response network (Table 3.4).

Another categorical variable was considered during the initial predictor selection phase to account for patterns in human activity (traffic, area sources) on weekends versus weekdays. This variable was also included to account for the lack of traffic intensity data that has been widely used throughout previous LUR studies. Weekdays were expected to have higher PM_{2.5} levels due to increase traffic intensity during the work week commute relative to weekends.

However, this variable was not determined to be significant during the LUR model development.

3.6.2 Spatiotemporal Predictors

Temperature

The daily maximum temperature at a 50 m resolution had the second highest beta value. A one standard deviation increase in maximum daily temperature at 50 m ('tmmx.50m') resulted in a 0.073 decrease in standard deviation of the PM_{2.5} levels from our response network. Several potential proxies were considered with the inclusion of temperature data in the final LUR model. On the one hand, higher temperatures correspond with a larger mixing volume, providing a surrogate for increased dilution. However, on the other hand, higher temperatures also enable higher rates of secondary organic aerosol formation, potentially leading to higher PM_{2.5} levels in our response network (Wang and Ogawa, 2015). Additionally, higher temperatures are also associated with the wild fire season within the Portland, Oregon, and some of the most polluted days observed within the training data occurred during the warm season. Despite the uncertainties regarding which proxy would potentially drive the association between temperature and PM_{2.5}, we chose to include 'tmmx.50m' in the final LUR model due to its coefficient's significance. Here, we can interpret this negative beta coefficient to be due to the influence from wildfires, and perhaps slightly by SOA formation. It is worth noting that although temperature was the second most important predictor its beta was only 8% of the nephelometer-derived PM_{2.5} beta (Table 3.4). In other words, the majority of the variation in

our PurpleAir data was explained by the ambient background concentration of the nephelometers.

Wind Speed

Wind speed was identified to be somewhat associated with $PM_{2.5}$, and had the 3rd highest beta coefficient. This predictor was included as a surrogate for dilution, as $PM_{2.5}$ from local sources are readily removed from the urban environment as wind speeds increase. As this predictor increased by one standard deviation, the response variable was observed to decrease by 0.063 standard deviations (Table 3.4). During data compilation, wind direction was determined to be too coarse of a spatial resolution and was excluded from the modeling phase.

Relative Humidity

The maximum relative humidity at 50 m ('rmax') was shown to be one of the least associated predictors with the PurpleAir $PM_{2.5}$. An increase of one standard deviation of this variable was associated with only a 0.011 decrease in the response network. Similar to the maximum temperature layer, relative humidity was included to account for multiple potential affects on $PM_{2.5}$ concentrations. Generally, when relative humidity increases, $PM_{2.5}$ mass density is observed to also increase due to hygroscopic growth. However, after a certain relative humidity threshold, $PM_{2.5}$ levels have been observed to decline as hygroscopic growth produces particles which are too large to remain suspended in

the air, ultimately depositing (Wang and Ogawa, 2015). Despite these uncertainties, this variable was included within the final LUR model due to its significant p-value (Table 3.4).

3.6.3 Spatial Predictors

Elevation

Elevation at a 50 m resolution ('elev.50m') was shown to be the most influential spatial predictor within the final LUR model. Most of the spatial variation observed in the model predictions approximated this elevation layer. This predictor had the 5th highest beta value, and an increase by one standard deviation in elevation resulted in a 0.03 decrease in standard deviation of our response network. This variable was a proxy for dilution, as wind speeds are typically higher at higher elevations and less shielded by surface roughness. The inclusion of this variable was an effort to capture some of the finer-scale topographical effects on PM_{2.5} that were unaccounted for by the GridMET wind speed product. The majority of primary urban PM_{2.5} is emitted near the surface, and can become trapped at lower elevations during stable meteorological conditions.

Developed Medium Intensity LULC

The developed medium intensity LULC variable at the 100 m buffer size ('med_dev' or 'developed_medium_intensity.100m') was shown to have the 6th highest beta. A one standard deviation increase in medium developed LULC corresponded to a 0.023 increase in standard deviation of the response network. In other words, the more medium developed LULC observed within 100 m of

a given PurpleAir site, the more likely $PM_{2.5}$ levels were to be slightly higher. This variable was included as a proxy for area sources in effort to characterize the magnitude, however limited, of fine-scale $PM_{2.5}$ gradients. While the ASTER population density layer was originally prioritized over the NLCD predictors as general proxy for all area sources, its coefficient was determined to be insignificant. The inclusion of medium density development LULC was considered only after the population density layer was determined to no longer be a significant predictor. Surprisingly, during the beginning of the predictor selection phase, high density developed land use was not positively associated with $PM_{2.5}$ across the range of buffer sizes, despite the expectation that more area sources would occur within this LULC class. Also, low density developed land use did initially have a positive correlation with our response network, but this variable did not yield a significant coefficient p-value during the first round of modeling. (Table 3.4). While no traffic-related predictors were included within the final model, graphically speaking, the medium density LULC layer appears to approximate the density of major roads throughout the region.

Longitude

Longitude ('lon') was the second least associated with the PurpleAir response network. A one standard deviation increase in longitude resulted in a 0.013 increase in the standard deviation of $PM_{2.5}$ (Table 3.4). This suggests that the variability of various $PM_{2.5}$ sources and sinks have only a weak association with longitude throughout the Portland, Oregon study area.

TABLE 3.4: Coefficients (1) and standardized (beta) coefficients (2) of the final model with standard error in parentheses

	<i>Dependent variable:</i>	
	Y	
	(1)	(2)
Median Nephelometer PM _{2.5}	0.834*** (0.004)	0.908*** (0.004)
Elevation (50 m)	−0.003*** (0.001)	−0.030*** (0.001)
Minimum PBL Height	−0.0003*** (0.0001)	−0.015*** (0.0001)
Maximum Relative Humidity (50 m)	0.007** (0.003)	0.011*** (0.003)
Maximum Temperature (50 m)	−0.058*** (0.005)	−0.073*** (0.005)
Mean Wind Speed (50m)	−0.242*** (0.022)	−0.063*** (0.022)
Developed Medium Intensity (100 m)	0.555*** (0.132)	0.023 (0.132)
Season (Spring)	−0.186** (0.090)	−0.011 (0.090)
Season (Summer)	−0.232* (0.131)	−0.014 (0.131)
Season (Fall)	0.718*** (0.073)	0.051 (0.073)
Longitude	0.00001*** (0.00000)	0.013*** (0.00000)

Constant	11.775*** (2.705)	0.000 (2.705)
Observations	8,082	8,082
R ²	0.874	0.874
Adjusted R ²	0.874	0.874
Residual Std. Error (df = 8070)	2.295	2.295
F Statistic (df = 11; 8070)	5,091.712***	5,091.712***
Note:	*p<0.1; **p<0.05; ***p<0.01	

3.7 Spatial Patterns of Model Residuals

The global Moran's I of the residuals from each predicted raster was evaluated for spatial autocorrelation. On average, this statistic was 0.99 ± 0.0005 , indicating a lack of complete spatial randomness in model residuals. Instead, the model error was significantly spatially clustered (a Moran's I value of 1.0 indicates perfect clustering of similar values). Therefore, some predictors are contributing to the spatially consistent overprediction/underprediction of PM_{2.5} throughout the Portland study area. Specifically, high model standard error was observed at both the global maximum and minimum elevations. Model standard error can also be seen increasing towards the Eastern and Western extents of the study area, suggesting potential edge effects, or an undesirable influence from including longitude as a predictor. Areas with consistently low modeled standard error were observed within the developed medium intensity LULC (Figure 3.13). Most of the PurpleAir monitors were located within this LULC which may explain the lower residuals within the urban core. Overall, the LUR model residuals ranged between 0.05 and $0.25 \mu\text{gm}^{-3}$.

While the Global Moran's I coefficient of 0.99 suggests the omission of specific variables that may contribute to spatially clustered error, or the inclusion of additional variables that may better explain the variation in intra-urban $\text{PM}_{2.5}$, the range in the residuals from the spatially resolved $\text{PM}_{2.5}$ predictions were well below the RMSE of the model (2.39). Therefore, we did not account for spatial autocorrelation of LUR model residuals beyond its initial characterization.

FIGURE 3.13: A map highlighting the spatially clustered standard error from a single LUR model prediction (January 1st, 2018). All remaining days during the study period exhibited similar patterns in residuals.

3.8 The Importance of Sensor Placement

While we were primarily focused on the anthropogenic drivers of fine-scale $\text{PM}_{2.5}$ spatial gradients, and the influence that vegetation may have on mitigating these exposures, ultimately no clear patterns between traffic or vegetation variables could be established. Our assessment of the relative strengths of the various sources and sinks of $\text{PM}_{2.5}$ has shown that the median ambient background concentration provided by the ODEQ nephelometer network had the strongest association with $\text{PM}_{2.5}$, and the remaining variables were only weakly associated. When comparing the relative strengths of the remaining variables, the effect size of the temporal and spatiotemporal predictors was relatively higher compared to the spatial variables, indicating that the spatial variation of urban $\text{PM}_{2.5}$ is primarily driven by meteorology and regional sources at the 50 m scale.

In addition to the observed spatial clustering in our model error, we found the LUR model development to be extremely sensitive to the initial placement of the PurpleAir response network. During the opportunistic ambient calibration phase, we explored several different time aggregations of the nephelometer network in order to identify periods when $\text{PM}_{2.5}$ was regionally homogeneous. While we initially selected a 15-minute time resolution to evaluate the RSD of the nephelometer network, we also explored a 1-hour resolution, which produced another set of reasonable correction factors. By implementing a coarser time resolution during the opportunistic ambient calibration, we observed an additional 9 sensors which passed our quality control criterion ($R^2 > 0.90$ and

$n \geq 50$). This corresponded to approximately 5 additional locations (each node contains both a primary and secondary sensor) and an increase in the total number of sensors from 61 to 70. The number of observations used during model development subsequently rose from 11,546 to 12,388 during model development. A new LUR model was developed with these data, and a different set of predictors was selected (despite following the same predictor selection protocol as with the previous model) (Table 3.5). For example, an additional proxy for an anthropogenic source, railroad density, was determined to be a statistically significant predictor with the new data. The log of the railroad density at 500 m produced a beta of 0.015. In addition, a vegetation variable, deciduous forest cover, was also identified as a significant predictor. The deciduous forest predictor had a beta of 0.008, which was the lowest in this model. The relationship between many of the spatial predictors and $PM_{2.5}$ were weak, often with beta coefficients below 0.05. Due to the spatial predictors being weakly associated with $PM_{2.5}$, the addition or removal of a small subset of our response network can lead to a major difference in the predictors selected for the final model. When there are only a few sensors at each LULC to begin with, it becomes difficult to effectively capture the entire variation in each proxy, and model bias increases. The correlations for many of the proxies for anthropogenic sources, e.g. freeways, major arterials, railroads, developed LULC, and $PM_{2.5}$ were teetering above and below 0. The sign of the correlation coefficients for some predictors were observed to flip depending on whether the 15-minute or 1-hour RSD nephelometer data were used to correct the response network. For example, freeways at the 50 m buffer size flipped from a correlation coefficient of 0.01

for the 15-minute data, to -0.01 for the 1-hour data. In reality, this relationship is effectively null.

Patterns in $PM_{2.5}$ were predominately explained by temporal factors over spatial ones. Spatially, $PM_{2.5}$ only varied by $0-5 \mu g m^{-3}$. Temporally, however, $PM_{2.5}$ levels were observed to increase by tens of micrograms per cubic meter from day to day, especially during wildfire PM events in the summer months, and temperature inversions in the winter months.

If there is a lack of representativeness with the air quality network used to train the model, then model bias for predictions in unrepresented areas will be higher. For example, if only a single sensor is located near railroad that has elevated $PM_{2.5}$ levels, then the model will predict that locations with a similar railroad density will also be elevated, regardless of the train volume on each particular rail.

In addition to the observed spatial clustering in our model error, we found the LUR model development to be extremely sensitive to the initial placement of the PurpleAir response network. During the opportunistic ambient calibration phase, we explored several different time resolutions of the nephelometer network in order to identify periods when $PM_{2.5}$ was regionally homogeneous. While we initially selected a 15-minute time resolution to evaluate the RSD of the nephelometer network, we also explored a 1-hour resolution, which produced another reasonable set of correction factors. By implementing this coarser 1-hour resolution during the opportunistic ambient calibration, we actually observed an additional 9 sensors which passed our quality control criterion ($R^2 > 0.90$ and $n \geq 50$). This corresponded to approximately 5 additional locations

(each node contains both a primary and secondary sensor) and an increase in the total number of observations from 11,546 to 12,388 during model development. With these data, a new LUR model was developed, and a different set of predictors was selected (following the same predictor selection protocol as with the previous model). For example, an additional proxy for anthropogenic emissions, railroad density, was determined to be a statistically significant predictor with this new data. In addition, a vegetation variable, deciduous forest cover, was also identified as a significant predictor. However, the correlations for many of the spatial predictors with $PM_{2.5}$ were non-existent, often with correlation coefficients below 0.05. Therefore, the addition or removal of a small subset of our response network led to a major difference in the predictors selected for the final model. When there are only a few sensors at each LULC to begin with, it becomes difficult to capture the entire extent of the variation with each proxy, and model bias increases. The correlations for many of the proxies for anthropogenic sources, e.g. freeways, major arterials, railroads, developed LULC, and $PM_{2.5}$ were teetering above and below zero. The sign of the correlation coefficient for some predictors was observed to flip depending on whether the 15 minute or 1 hour RSD nephelometer data were used to correct the response network. For example, freeways at the 50 m buffer size flipped from a correlation coefficient of 0.01 for the 15-minute data, to -0.01 for the 1 hour data, when in reality, this is effectively a null correlation.

TABLE 3.5: Coefficients (1) and standardized (beta) coefficients (2) of a second LUR model, with the standard error included within parentheses. This model was developed using the PurpleAir correction factors data developed with hourly nephelometer data (opposed to the 15-minute data).

	<i>Dependent variable:</i>	
	NA	
	(1)	(2)
Median Nephelometer PM _{2.5}	0.983*** (0.004)	0.920*** (0.004)
Elevation (50 m)	−0.003*** (0.001)	−0.020*** (0.001)
Minimum PBL Height	−0.0004*** (0.0001)	−0.016*** (0.0001)
Log Railroad (500 m)	0.018*** (0.006)	0.015*** (0.006)
Maximum Relative Humidity (50 m)	0.009** (0.004)	0.011*** (0.004)
Maximum Temperature (50 m)	−0.062*** (0.006)	−0.062*** (0.006)
Mean Wind Speed (50 m)	−0.219*** (0.027)	−0.044 (0.027)
Season (Spring)	−0.306*** (0.108)	−0.015 (0.108)
Season (Summer)	−0.311** (0.158)	−0.015 (0.158)
Season (Fall)	0.822*** (0.089)	0.045 (0.089)

Deciduous Forest (300 m)	−3.661* (1.933)	−0.008 (1.933)
Developed Medium Intensity (300 m)	0.967*** (0.255)	0.023 (0.255)
Longitude	−0.00001** (0.00001)	−0.009*** (0.00001)
Latitude	0.00001** (0.00001)	0.009*** (0.00001)
Constant	−32.782 (26.091)	0.000 (26.091)
Observations	8,671	8,671
R ²	0.879	0.879
Adjusted R ²	0.879	0.879
Residual Std. Error (df = 8656)	2.878	2.878
F Statistic (df = 14; 8656)	4,500.152***	4,500.152***
Note: *p<0.1; **p<0.05; ***p<0.01		

3.9 Predictions

3.9.1 Land Use Regression

Predictions of a select day, October 10th, 2018, were mapped in order to characterize the differences between the 1-hour RSD network and 15-minute RSD network for both LUR and RF models. The spatial patterns from the 15-minute RSD LUR model appear to approximate the underlying elevation and developed medium intensity LULC predictors, despite the betas of these variables being ranked only the 5th and 6th most associated with PM_{2.5}. Since the general range

of $PM_{2.5}$ levels for any given day is primarily governed by the median nephelometer values, and other temporal scaling factors such as wind speed and temperature, any remaining spatial heterogeneity is typically confined within a $\pm 5 \mu g m^{-3}$ range from the median. For example, the exact range in predicted $PM_{2.5}$ on this day was $6.25 - 8.62 \mu g m^{-3}$, a difference of only $2.37 \mu g m^{-3}$ from the most to least polluted location. The 1-hour RSD LUR model captures similar patterns in elevation as the previous model, but the railroad and deciduous forest variables suggest different hot spots and cold spots. For example, the Western extent of the study area shows elevated $PM_{2.5}$ levels due to the presence of railroads, whereas the previous model indicated this region should have lower levels. In addition, small pockets of low $PM_{2.5}$ concentrations scattered throughout the region correspond to the presence of deciduous forest cover. From the addition of these two spatial variables, the predicted range in $PM_{2.5}$ concentration grew to $5.37 - 9.62 \mu g m^{-3}$, a $4.25 \mu g m^{-3}$ difference between most and least polluted locations (Figure 3.14). The spatial heterogeneity in $PM_{2.5}$ on a given day is further limited when the model RMSE is taken into consideration. The 15-minute RSD model, previously referred to as the ‘final model’, had a RMSE of 2.39. When the RMSE is applied to the range in predicted $PM_{2.5}$, it becomes difficult to interpret most spatial patterns. For example, the cold spots observed on October 10th, 2018 could potentially overlap with the hotspots, and vice versa (e.g. $6.25 + 2.39 \approx 8.62 - 2.39$). In addition to the graphical assessment, we regressed the 1-hour RSD model against the 15-minute RSD model to further assess the relationship between the two models (Figure 3.15). The 15-minute RSD model (‘final model’) explained less than 1% of the variation in

the 1-hour RSD model, indicating that the inclusion of 4 PurpleAir sites has resulted a significantly different set of predictions. Each point within Figure 3.15 represents the two predicted $PM_{2.5}$ values of a single 50 m by 50 m cell within our raster, itself consisting of $1.031e^6$ total cells. The areas where the 1-hour RSD model predicts considerably lower than the 15-minute RSD model are due to the inclusion of the deciduous forest cover LULC. The 1-hour RSD model can also be seen predicting higher than the 15-minute model within the 500 m railroad buffer.

3.9.2 Random Forest

Exposure maps of the random forest (RF) predictions illustrate some of the limitations of using machine learning techniques over traditional LUR models. The range in $PM_{2.5}$ from the 15-minute and 1-hour RSD RF models was 6.63 - 10.78 $\mu g m^{-3}$ and 6.74 - 10.55 $\mu g m^{-3}$ respectively (Figure 3.16). Although the RF model appeared to perform marginally better during the validation phase, with higher validation regression R^2 and lower RMSE, the RF predictions show unrealistic gradients, and appear to overfit on the latitude and longitude variables. Specifically, explicit vertical thresholds in both the 15-minute, and 1-hour RSD models can be seen due to the inclusion of the longitude predictor. A horizontal threshold in the 1-hour RSD model predictions, while less pronounced, is also evident because this model found latitude to be a significant predictor. These RF results stress the importance of understanding the physical processes that drive $PM_{2.5}$ variation, as relying solely on the statistical measures of model performance may be misleading. Unlike the traditional LUR approach, RF models are

essentially a black box and do not provide model coefficients necessary for interpreting the relative strengths of sources and sinks. As with many other machine learning algorithms, random forest is a ‘data hungry’ technique, and relies on a substantial training set in order to develop a robust stable model. While our training set included more than 10,000 observations, these were generated from a limited number ($n \approx 20$) of physical locations which repeated over a 2-year period. In comparison, the study area in which we are attempting to predict includes over $1.031e^6$ individual grid cells at the 50 m resolution. We are likely not capturing enough variation in each of our spatial predictors necessary to develop a meaningful RF model for predicting intra-urban $PM_{2.5}$.

FIGURE 3.14: Spatially resolved PM_{2.5} predictions of Portland, Oregon on October 10th, 2018 from two LUR models that were developed using 15-minute and 1-hour resolution RSD to correct the PurpleAir network. The 1-hour RSD model includes rail density and deciduous forest density predictors that were not selected in the 15-minute model.

FIGURE 3.15: Scatter plot comparing the predicted PM_{2.5} on 2018-10-10 from the 1-hour RSD model as a function of the 15-minute RSD model.

FIGURE 3.16: Spatially resolved PM_{2.5} predictions of Portland, Oregon on October 10th, 2018 from two Random Forest models that were developed using 15-minute and 1-hour resolution RSD to correct the PurpleAir network. The 1-hour RSD model includes rail density and deciduous forest density predictors that were not selected with the 15-minute model.

3.9.3 Final Model Predictions Over Time

We used the 'final model' to predict 573 consecutive days (September 2017 - March 2019) of PM_{2.5} throughout the Portland metropolitan area. An animated figure which cycles through each daily prediction can be viewed at the following hyperlink: <http://web.pdx.edu/~porlando/animated-pm.gif>. This animation allowed us to identify periods of interest, including a forest fire haze event that occurred during August, 2018 and periods with stable meteorology and wood

burning in December, 2017. The spatial pattern appears to be relatively consistent even on the most polluted days (Figures 3.17, 3.18).

FIGURE 3.17: Spatially resolved PM_{2.5} predictions of Portland, Oregon capturing a forest fire haze event that occurred between August 17th - 25th, 2018 from the ‘final model’.

FIGURE 3.18: Spatially resolved PM_{2.5} predictions of Portland, Oregon during stable meteorological conditions and higher rates of wood-burning between December 14th - 22nd, 2017 from the 'final model'.

Chapter 4

Summary and Future Work

4.1 Summary

Spatially resolved $PM_{2.5}$ concentrations at the intra-urban scale are not well defined throughout US cities. This is due to the practical constraints of deploying high-density networks using costly research-grade monitoring equipment, and the focus on compliance at the regional scale from regulatory agencies. Monitoring networks for $PM_{2.5}$ are scarce, typically between 4-6 monitors per city, and are often deliberately placed away from local sources in order to assess the ambient background concentration. The focus on compliance ultimately results in the potential lack of representativeness of fixed air quality monitoring sites for epidemiological studies, and limits studies which aim to characterize the potential role vegetation may play in mitigating $PM_{2.5}$ exposure. Land use regression techniques have been developed to account for the spatial heterogeneity of air pollution sources within urban areas, in an effort to provide spatially resolved exposure maps and identify the relative strengths of various sources and sinks. This thesis explored the potential of using low-cost sensors for modeling spatially resolved $PM_{2.5}$ exposures within Portland, Oregon at a 50 m resolution

during a 2 year period. The low-cost sensor network increased the density of the existing monitoring network by a factor of 5, enabling us to better characterize the potential patterns in sources and sinks throughout the region necessary for producing spatially resolved $PM_{2.5}$ exposures. However, we observed the spatial predictors of $PM_{2.5}$ to be only weakly associated with our response network, relative to temporal scaling factors. This was not entirely surprising based on the lack of fine-scale spatial variability in $PM_{2.5}$ observed by previous studies (Karner, Eisinger, and Niemeier, 2010). In addition, the predicted range of $PM_{2.5}$ on a given day was typically within the RMSE of the LUR model. While many air pollutants within cities have strong pollution gradients, typically decaying within 150 m - 200 m from the source, spatial patterns of $PM_{2.5}$ are not as distinct. As identified by Karner et al., gradients of $PM_{2.5}$ with increasing distance from traffic-related sources are mixed, and either decrease very gradually or show no clear trend altogether (Karner, Eisinger, and Niemeier, 2010; Kendrick, Koonce, and George, 2015). We could not identify a significant association between our PurpleAir response network and any of the proxies for traffic sources. The only anthropogenic source associated with $PM_{2.5}$ was the medium intensity developed LULC. This predictor was observed in both the 1-hour and 15-minute RSD models, which may be a sign of developed land use as a proxy for area sources. In contrast, no clear associations between proxies for vegetation and $PM_{2.5}$ were established during these initial modeling efforts, and only a single vegetation LULC was identified during the additional 1-hour RSD model. We characterized the sensitivity to initial sensor placement when developing LUR models, as an addition of 4 sensors resulted in a considerably

different set of predictions throughout the study period. Despite the challenges inherent to modeling spatially resolved $PM_{2.5}$ with low-cost sensor data, this thesis has developed a method for modeling intra-urban $PM_{2.5}$ that can be generalized to many other cities, and produced a set of exposure maps which are a notable improvement over the alternative exposures generated from spatially interpolating the existing regulatory monitoring sites.

4.2 Future Work

We have developed a method for modeling spatially resolved $PM_{2.5}$ at the sub-neighborhood scale that can be applied to the remaining four cities within the Canopy Continuum project. Future work will explore the associations between a similar set of land use and meteorological predictors with each of the corresponding low-cost $PM_{2.5}$ networks deployed throughout Albuquerque, New Mexico, Boise, Idaho, Sacramento, California, and Tacoma, Washington. Since these cities exhibit a varying degree of urban canopy cover, the development of additional LUR models, and the resulting inter-city comparison may provide further insights regarding the potential role of vegetation as a sink for $PM_{2.5}$. The inclusion of some additional key predictors should also be considered with future models. As outlined by the ESCAPE project, traffic intensity data was shown to be a crucial variable when predicting spatially resolved $PM_{2.5}$ across many European cities, where PM emissions are higher due to higher levels of diesel engines, and study areas without local traffic intensity resulted in poorer models. While we incorporated road density data of several road classes (streets, arterials, freeways, etc.), the average annual daily traffic volume of

each road segment was not accounted for. In addition to traffic-intensity data, the performance of ESCAPE models for predicting PM absorbance, a marker of black carbon, were generally higher than that of $PM_{2.5}$. This suggests that additional monitoring networks may be required in order to characterize anthropogenic sources. While a substantial fraction of European private cars, and nearly all middle and heavy duty vehicles, use diesel instead of gasoline, the inclusion of PM absorbance within our LUR models may better reflect the impact that mobile emissions have on fine-scale PM exposures within the urban environment (Eeftens et al., 2012). The inclusion of particle number concentration, specifically of ultrafine PM, should also be considered in future modeling efforts, as this pollutant is another proxy for emissions from local sources. The two Plantower sensors inside each PurpleAir monitor provide additional mass density measurements for PM_1 and PM_{10} . Plantower sensors are also capable of measuring the number density of particles as small as 300 nm in diameter ($PM_{0.3}$). Future work should consider the inclusion of the various different PM channels recorded by the PurpleAir network in effort to further characterize the land-use and physical drivers of intra-urban PM variability (Appendix B).

Sensor placement, as we previously demonstrated, can have a cascading effect during model development. Two areas of improvement have been identified from these results: (1) a stratified sensor allocation method and (2) an alternative field calibration technique. A stratified sensor allocation method would better approximate the true variation in each of the relevant spatial predictors. The opportunistic placement of the PurpleAir sensors in Portland resulted in a network which overrepresented urban areas near small streets, but lacked data

for both heavily trafficked and heavily vegetated areas, and did not fully capture the extent of the urban-rural gradient. A previous study which developed fine-scale exposure maps of NO_2 throughout Portland, Oregon relied on a stratified random network of 144 passive samplers (Rao et al., 2014). Unfortunately, a $\text{PM}_{2.5}$ monitoring campaign of this caliber still poses many logistical challenges even for low-cost sensors. The PurpleAir monitors are still limited by cost (a PurpleNetwork with 144 sites would cost \$36,000), power and telecommunication. Identifying remote locations that still provide access to an AC power source and a WiFi connection would likely be prohibitive with a stratified random sensor allocation. Our opportunistic ambient calibration method, while a major improvement over using the uncorrected sensor data, recovered only 48% of the PurpleAir network. An alternative field calibration method, for example a pre- and post-study calibration of each individual sensor against a co-located FRM in the field may return a higher data recovery rate, while enabling the assessment of sensor drift overtime. This is especially important as we demonstrated that the inclusion of a just a few sensors can have a significant impact on the predicted spatial variability.

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Appendix A

Source Code

Source/animateStack.R

```

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7
8 p_load(raster, rasterVis, viridis, animation, classInt, pbapply,
9        parallel)
10 mods <- c("lm"
11           , "rf"
12           , "xgb"
13           )
14
15 pblapply(mods, function(mod) {
16
17   s <- stack(list.files("./data/predicted_raster", paste0(mod, "\\."
18     tif$"), full.names = T))
19   r <- s[[1]]
20
21   # breaks <- seq(0,100,5)
22   breaks <- c(seq(0, 50, 1), Inf) # focus on lower level variation
23   # cols <- colorRampPalette(c("darkgreen", "lightgreen", "yellow",
24     "orange", "red", "maroon"))(length(breaks)-1)
25   # cols <- magma(length(breaks)-1)
26   cols <- colorRampPalette(c("darkgreen", "forestgreen", "yellow", "
27     orange", "red", "#A62A2A"))(length(breaks)-1)
28
29
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31
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96
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98
99

```

```

27 # sequence <- seq(0, 100, 5)
28 # n <- length(sequence)
29
30 # Match EPA PM2.5 AQI Palette
31 # pal <- c("#01CC01", "#66CC00", "#FFFF01", "#FE9900", "#FC0200",
32 # "#A62A2A")
33 # n <- length(pal)
34 # sequence <- c(-Inf, 31, 61, 91, 121, 250, 1000)
35 # classes <- classIntervals(values(r)
36 #                               ,n = n
37 #                               ,style = "fixed", precision = 2
38 #                               ,fixedBreaks = sequence
39 #                               ,fixedBreaks = c(5, seq(0, 100, 10))
40 #                               )
41 # brks <- classes$brks
42 # brks <- round(brks, 2)
43 # cols <- plasma(n)
44 # cols <- pal
45
46 saveGIF({
47
48   # ani.options(ani.height = 6
49   #               ,ani.width = 8
50   #               ,ani.res = 300
51   #               ,ani.units = "in"),
52
53   for(i in c(1:nlayers(s))) {
54
55     r <- s[[i]]
56     r[is.na(r)] <- 0
57     r[r<0] <- 0
58
59     l <- levelplot(r
60                     ,at = breaks
61                     ,col.regions=cols
62                     # ,colorkey=list(
63                     #               #at=breaks
64                     #               at = seq(0,50,10)
65                     #               # ,labels=c(as.character(breaks
66                     #               ,labels=c(as.character(seq(0,
67                     50, 10))))
68                     #               )
69                     ,colorkey=list(title = expression(mu*g*m^-3),
70                                   # ,colorkey=list(space = "left")
71                                   ,margin=FALSE

```

```

71             ,main = gsub("^X", "", names(s[[i]]))
72             #,ylab = expression(mu*g/m^3)
73         )
74         # l <- plot(s[[i]]
75         #           ,breaks = brks
76         #           ,col=magma(256)
77         #           ,main = gsub("^X", "", names(s[[i]]))
78         #           ,ylab = "ug/m3"
79         #           )
80         plot(1)
81         rm(r)
82         gc()
83     }
84 }, interval=0.2, movie.name=paste0("/home/porlando/Documents/
purpleairlur/figures/animations/", mod, "_test.gif"))
85 dev.off()
86 }
87 #,cl=detectCores()-1
88 )
89 #

90 # # Use the right pattern for each model type (lm, rf, xgb, se, etc.)
91 # s <- stack(list.files("./data/predicted_raster", "lm\\.tif$", full.
names = T))
92 #
93 # # This is taking forever!
94 # # classes <- classIntervals(values(s), n = 10, style="fisher",
precision = 3)
95 #
96 # r <- s[[1]]
97 # classes <- classIntervals(values(r), n = 10, style = "fixed",
precision = 2
98 #                               ,fixedBreaks = c(0, 5, 10, 15, 20, 25,
30, 40, 50, 75, 100)
99 #                               )
100 #
101 # brks <- classes$brks
102 # brks <- round(brks, 2)
103 #
104 # # Absolute path required by ImageMagick?
105 # saveGIF({
106 #   for(i in c(1:nlayers(s))){
107 #     l <- levelplot(s[[i]], colorkey=list(at=brks, labels=c(as.
character(brks)))
108 #     ,margin=FALSE
109 #     ,main = gsub("^X", "", names(s[[i]]))
110 #     ,ylab = "ug/m3")

```

```

111 #     # l <- plot(s[[i]]
112 #     #         #,breaks = brks
113 #     #         #,col=magma(256)
114 #     #         #,main = gsub("^X", "", names(s[[i]]))
115 #     #         #,ylab = "ug/m3"
116 #     #         )
117 #     plot(l)
118 #   }
119 # }, interval=0.2, movie.name="/home/porlando/Documents/purpleairlur/
    figures/animations/test.gif")
120 #
121 # # pblapply doesn't work...
122 # # saveGIF({
123 # #   pblapply(1:nlayers(s), function(i) {
124 # #     l <- levelplot(s[[i]], colorkey=list(at=brks, labels=c(as.
        character(brks))), margin=FALSE)
125 # #     plot(l)
126 # #   }, cl=detectCores()-1)}, interval=0.2, movie.name="/home/porlando
    /Documents/purpleairlur/figures/animations/test.gif")

```

Source/annualNDVI.R

```

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7 p_load(rgdal
8       ,raster
9       ,sp
10      ,rgeos
11      ,pbapply
12      #,rasterVis
13      ,zoo
14      ,magrittr
15      ,parallel
16      ,lubridate
17      #,greenbrown # sourceforge repo
18 )
19
20 source("../src/init.R")
21 source("../src/functions.R")
22
23 # Set tmpdir for raster data
24 setRasterTempDir()
25

```

```

26 ndvi <- stack(list.files(path = "./output/ndvi/", pattern = ".tif$",
27   full.names = T))
28 #levelplot(ndvi)
29
30 evi <- stack(list.files(path = "./output/evi/", pattern = ".tif$",
31   full.names = T))
32
33 getDates <- function(stack) {
34   names <- names(stack)
35   dates <- gsub("^.*?\\.", "", names)
36   dates <- gsub("\\.", "-", dates) %>% as.Date()
37   return(dates)
38 }
39
40 getVars <- function(stack) {
41   names <- names(stack)
42   # extract variable name (characters before date)
43   vars <- gsub("\\..*$", "", names)
44   return(vars)
45 }
46
47 # Calculate annual median raster for NDVI and EVI
48 annualNDVI <- function(stack, proj = epsg_26910) {
49   # 16 day observations
50   bi_month <- getDates(stack)
51   vars <- getVars(stack)
52
53   # generate daily sequence
54   dates <- seq.Date(from = min(bi_month), to = max(bi_month), by = "
55     day")
56   dates <- gsub("-", "\\.", dates)
57   daily_names <- paste0(vars, ".", dates)
58
59   # Grab the years across our date range
60   years <- seq.Date(from = min(bi_month), to = max(bi_month), by = "
61     year") %>% lubridate::year()
62
63   # Compute annual medial rasters
64   pblapply(years, function(y) {
65     r <- subset(stack, grep(y, names(stack), value = T)) %>% calc(
66       median, na.rm = T)
67     annual_median <- raster::projectRaster(from = r, res = sp_res,
68       method = 'bilinear', crs = proj)
69     names(annual_median) <- paste0(vars[1], ".", y)
70     annual_names <- grep(y, daily_names, value = T)
71     # This isn't efficient, but I don't want to rewrite my buffer/
72     extract scripts...

```



```

67     s <- lapply(annual_names, function(d) {
68         r <- annual_median
69         names(r) <- d
70         return(r)
71     }) %>% stack
72     writeRaster(s, file.path('./data', unique(vars), paste0(names(s),
73         ".tif")),
74                 ,overwrite=T
75                 ,bylayer=T
76                 ,format="GTiff")
77     }
78     ,cl = detectCores()-1
79     )
80 }
81 # Call our annual processing function
82 pblapply(c(ndvi, evi), annualNDVI
83         ,cl = detectCores()-1
84         )
85 # ndvi2 <- stack(list.files("./data/ndvi", full.names = T))
86 # ndvi2 <- readRDS("./data/ndvi_daily_composite.RDS")
87 # names(ndvi2)
88 # plot(ndvi2)
89 # evi2 <- stack(list.files("./data/evi", full.names = T))
90 # evi2 <- readRDS("./data/evi_daily_composite.RDS")
91 # names(evi2)
92 # test <- evi2[[17:32]]
93 # plot(test)
94 #
95 # lapply(1:nlayers(ndvi), function(x) {
96 #     plot(ndvi[[x]], main = paste(names(ndvi)[x]))
97 #     Sys.sleep(0.3)
98 # })
99 #
100 # lapply(1:nlayers(ndvi2), function(x) {
101 #     plot(ndvi2[[x]], main = paste(names(ndvi2)[x]))
102 #     Sys.sleep(0.3)
103 # })
104 #
105 #
106 # lapply(1:nlayers(evi), function(x) {
107 #     plot(evi[[x]], main = paste(names(evi)[x]))
108 #     Sys.sleep(0.5)
109 # })
110 #
111 # lapply(1:nlayers(evi2), function(x) {
112 #     plot(evi2[[x]], main = paste(names(evi2)[x]))
113 #

```

```

114 # Sys.sleep(0.5)
115 # })

```

Source/compareCF.R

```

1 # Compare CF from 1 hour and 15 minute data
2
3 # load the necessary packages
4 if (!require(pacman)) {
5   install.packages("pacman")
6   library(pacman)
7 }
8
9 p_load(dplyr, ggplot2)
10
11 pm_1h <- readRDS("./data/homogenousPM/lm_results_1-hour.RDS") %>%
  dplyr::select(r.squared, slope, id, n_obs, sigma)
12 pm_15m <- readRDS("./data/homogenousPM/lm_results_15-min.RDS") %>%
  dplyr::select(r.squared, slope, id, n_obs, sigma)
13 pm_wide <- full_join(pm_1h, pm_15m, by = "id", suffix = c(".1h", ".15
  m"))
14 pm_wide$slope_diff <- abs(pm_wide$slope.1h - pm_wide$slope.15m)
15
16 ggplot(filter(pm_wide, r.squared.1h >= 0.9 & r.squared.15m >= 0.90),
  aes(x = as.factor(id), y = slope_diff)) + geom_col()
17 pm_wide %>% filter(r.squared.1h >= 0.9 & r.squared.15m >= 0.90) %>%
  dplyr::select(slope_diff) %>% boxplot()
18 pm_wide %>% filter(r.squared.1h >= 0.9 & r.squared.15m >= 0.90) %>%
  dplyr::select(slope_diff) %>% summary()
19 boxplot(pm_wide$slope_diff)
20
21 # Tidy format
22 pm_1h$time_res <- "1_hour"
23 pm_15m$time_res <- "15_min"
24
25 pm <- bind_rows(pm_1h, pm_15m)
26
27 pm_group_summary <- pm %>% filter(r.squared >= 0.90) %>% group_by(
  time_res) %>% summarise(min_r2 = min(r.squared)
28
29   ,q1_r2 = quantile(r.squared, probs = 0.25)
30
31   ,med_r2 = median(r.squared)
32
33   ,mean_r2 = mean(r.squared)
34
35   ,q3_r2 = quantile(r.squared, probs = 0.75)

```

```

32     ,max_r2 = max(r.squared)
33     ,q1_slope = quantile(slope, probs = 0.25)
34     ,med_slope = median(slope)
35     ,mean_slope = mean(slope)
36     ,q3_slope = quantile(slope, probs = 0.75)
37     ,max_slope = max(slope)
38     ,mean_rmse = mean(sigma))
39
40 pm_group_summary
41 saveRDS(pm_group_summary, ". /data/homogenousPM/pm_summary_by_time_res
.RDS")
42 # pm %>% na.omit() %>% ggplot(aes(x = as.factor(id), y = slope, fill
= time_res)) +
43 #   geom_boxplot()

```

Source/downloadGridMET.R

```

1  library(raster)
2
3  # Load global project variables
4  source("./src/init.R")
5
6  # downloads met data for 1 year for 1 variable
7  getGridMetVar <- function(dir = dir
8                             ,year = year
9                             ,var = var) {
10
11    # check if file exists
12    file_name <- paste0(var, "_", year, ".nc")
13    file_path <- paste0("./", dir, "/", file_name)
14
15    # download file if it doesn't exist yet
16    if(file.exists(file_path)) {
17      print(paste0("Overwriting ", file_path))
18      file.remove(file_path)
19      url <- paste0("https://www.northwestknowledge.net/metdata/data/",
file_name)
20      system(paste0("wget --directory-prefix=", dir
21                    , " --load-cookies ~/.cookies --save-cookies ~/.
cookies --no-parent ", url))
22    } else {

```

```

23     print(paste0("Downloading ", file_path))
24     url <- paste0("https://www.northwestknowledge.net/metdata/data/",
25                 file_name)
26     system(paste0("wget --directory-prefix=", dir
27                 , " --load-cookies ~/.cookies --save-cookies ~/.
28                 cookies --no-parent ", url))
29   }
30 }
31 # downloads met data across list of variables for one year
32 getGridMetVars <- function(dir, vars, year) {
33   lapply(vars, function(x) getGridMetVar(dir = dir
34                                       , year = year
35                                       , var = x))
36 }
37
38 # downloads many variables for many years
39 getGridMetYears <- function(dir, vars, years) {
40   lapply(years, function(x) getGridMetVars(dir = dir
41                                       , year = x
42                                       , vars = vars))
43 }
44
45 # call our nested functions to pull all of the data for each variable
46 # for each year
47 getGridMetYears(dir = "gridMET/nc"
48               , vars = c("pr" # precip
49                         , "sph" # specific humidity
50                         , "rmin" # min rh
51                         , "rmax" # max rh
52                         , "vs" # wind speed 10m
53                         , "th" # wind direction 10m
54                         , "tmmn" # min temp
55                         , "tmmx" # max temp
56                         # , years = c(seq(2017, 2019, 1))
57               , years = c(seq(lubridate::year(start_date), lubridate
::year(end_date), 1))
               )

```

Source/downloadNDVI.R

```

1 # load the necessary packages
2 # load the necessary packages
3 if (!require(pacman)) {
4   install.packages("pacman")
5   library(pacman)
6 }

```

```
7
8 p_load(rgdal
9       ,dplyr
10      ,magrittr
11      ,gdalUtils
12      ,raster
13      ,sp
14      ,stringr
15      #,sf
16      ,rgeos
17      ,leaflet
18      ,MODIS
19      #,bowerbird
20      ,parallel
21      ,snow
22      ,ggplot2
23      ,rts
24      #,rLandsat
25      #,wrspathrow
26      #,getlandsat
27      ,pbapply
28      )
29
30 source("../src/functions.R")
31 source("../src/init.R")
32
33 # Working with MODIS data


---


34 # set MODIS options (these can also be passed to '...' in getHdf())
35 MODISOpts(localArcPath = "../", quiet = FALSE, outDirPath = "../")
36
37 # download the data 1km
38 # tfs <- runGdal(product = "MOD13A2", collection = "006"
39 #              ,tileH = 9, tileV = 4
40 #              ,begin = str_replace_all(start_date, "-", ".")
41 #              ,end = str_replace_all(end_date, "-", ".")
42 #              ,job = "temporalComposite"
43 #              #,SDSstring = "100000000010"
44 #              ,overwrite = TRUE)
45
46 # 250 m Terra (Aqua is MYD13Q1)
47 getProduct("MOD13Q1")
48 getProduct("MYD13Q1")
49 print("begin download")
50 tfs <- runGdal(product = "MOD13Q1", collection = "006"
51              ,tileH = 9, tileV = 4
52              #,begin = "2010.01.01"
```

```

53         ,begin = str_replace_all(start_date, "-", ".")
54         ,end = str_replace_all(end_date, "-", ".")
55         #,end = "2019.01.01"
56         ,job = "temporalComposite" # prevents new directory
        with timestamp from being created
57         #,SDSstring = "100000000010"
58         #,outDirPath = "./MODIS/MOD13Q1.006"
59         ,overwrite = TRUE)
60
61 # saveRDS(tfs, "./data/ndvi_tfs.RDS")
62
63
64 # # Working with Landsat data

```

```

65 #
66 # # rLandsat...
67 # if(!require(rLandsat)) {
68 #   devtools::install_github("socialcopsdev/rLandsat", upgrade_
        dependencies=T)
69 #   library(rLandsat)
70 # }
71 #
72 # # devtools::install_github('azvoleff/wrspathrow', upgrade_
        dependencies=T)
73 #
74 # result <- landsat_search(min_date = start_date, max_date = end_date
75 #                           ,row_master = c(28) # had to google this
        ...
76 #                           ,path_master = c(46)
77 #                           )
78 #
79 # result %>% filter(cloudCover <= 10)
80 #
81 # row_id <- 28
82 # path_id <- 46
83 #
84 # downloadLandsat <- function(start_date, end_date, row_id, path_id,
        cloud_cover, dir) {
85 #
86 #   # Create output directory if it doesn't exist yet
87 #   if(!dir.exists(dir)) {
88 #     dir.create(dir)
89 #   }
90 #
91 #   # Create list of download links via rLandsat
92 #   links <- rLandsat::landsat_search(min_date = start_date, max_date
        = end_date

```

```

93 #                                     ,row_master = row_id # had to google this
94 #                                     ,path_master = path_id) %>% filter(
cloudCover <= cloud_cover)
95 # # links <- links[1,]
96 # pblapply(1:nrow(links), function(i) {
97 #   urls <- links$download_links.google[i] %>%
98 #     unlist() %>%
99 #     grep(pattern = '*_B2.TIF|*_B4.TIF|*_B5.TIF', value=T) # NIR
and Red bands
100 #   pblapply(urls, function(url) {
101 #     system(paste0("wget -c --directory-prefix=", dir
102 #       , " --load-cookies ~/.cookies --save-cookies ~/.
cookies ", url))
103 #   }
104 #   #,cl = detectCores()-1
105 #   )
106 #   }
107 #   #,cl = detectCores()-1
108 #   )
109 # }
110 #
111 #
112 # downloadLandsat(start_date = start_date, end_date = end_date, row_
id = c(28), path_id = c(46),
113 #   cloud_cover = 10, dir = "./data/landsat")
114 #
115 # # File is already fully retrieved; nothing to do.
116 # # Is this because of the cookies argument?
117 #
118 # # espa_creds("porlando", scan("batteries.espa", what=""))
119 # # prods = espa_products(result$product_id)
120 # # prods = prods$master
121 # #
122 # # result_order = espa_order(result$product_id
123 # #   ,product = c("sr", "sr_ndvi")
124 # #   ,projection="lonlat"
125 # #   )
126 # #
127 # #
128 # # # get all the product IDs for India, alternatively can define
path and row
129 # # result = landsat_search(min_date = "2018-01-01", max_date =
"2018-01-16", country = "India")
130 # #
131 # # # inputting espa creds
132 # # espa_creds("porlando", scan("batteries.espa", what=""))
133 # #

```

```

134 # # # getting available products
135 # # prods = espa_products(result$product_id)
136 # # prods = prods$master
137 # #
138 # # # placing an espa order
139 # # result_order = espa_order(result$product_id, product = c("sr","sr
    _ndvi"),
140 # #                                     projection = "lonlat",
141 # #                                     order_note = "All India Jan 2018"
142 # #                                     )
143 # # order_id = result_order$order_details$orderid
144 # #
145 # # # getting order status
146 # # durl = espa_status(order_id = order_id, getSize = TRUE)
147 # # downurl = durl$order_details
148 # #
149 # # # download; after the order is complete
150 # # landsat_download(download_url = downurl$product_dload_url, dest_
    file = "./test")
151 # #
152 # # # Download dependencies
153 # # # system("sudo apt-get update")
154 # # # system("sudo apt-get install python-pip python-numpy python-
    scipy libgdal-dev libatlas-base-dev gfortran libfreetype6-dev")
155 # # # system("pip install landsat-util")
156 # #
157 # # # Extract coordinates for each corner of our study extent
158 # # study_area <- readRDS("./study_area/study_area.RDS") %>%
    spTransform(wgs_84)
159 # # min_lon <- study_area@bbox[1]
160 # # min_lat <- study_area@bbox[2]
161 # # max_lon <- study_area@bbox[3]
162 # # max_lat <- study_area@bbox[4]
163 # #
164 # # landsat-utils method, 0 items were returned!
165 # # system(paste0("landsat search --cloud 4"
166 # #               , " --lat ", min_lat
167 # #               , " --lon ", min_lon
168 # #               , " --start ", start_date
169 # #               , " --end ", end_date
170 # #               ))
171 # #
172 # #
173 # # lsat_search(collection="landsat-8", cloud_cover=c(0,20), limit =
    3)$features
174 # #
175 # # "http://landsat-pds.s3.amazonaws.com/L8/003/017/
    LC80030172015001LGN00/index.html"

```



```

176 #

Source/downloadPBL.R

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7 p_load(rgdal
8        ,rgeos
9        ,sp
10       ,raster
11       ,dplyr
12       ,magrittr
13       ,pbapply
14       ,parallel
15       ,snow)
16
17 source("../src/init.R")
18
19 # create a year sequence based on our init start/end data
20 # years <- seq.Date(as.Date(start_date), as.Date(end_date), by = "
21   year") %>% lubridate::year()
22
23 years <- seq(lubridate::year(start_date), lubridate::year(end_date),
24             by = 1)
25
26
27 getPBL <- function(dir = dir
28                   ,year = year
29                   ,var = var) {
30
31   url <- paste0("ftp://ftp.cdc.noaa.gov/Datasets/NARR/monolevel/",
32               var, ".", year, ".nc")
33
34   system(paste0("wget -c --directory-prefix=", dir
35               , " --load-cookies ~/.cookies --save-cookies ~/.
36               cookies ", url))
37
38 }
39
40 getPBLYears <- function(dir, var, years) {
41
42   # Overwrite flag added to wget (have not confirmed that it works
43   ...)
44   # Remove existing files
45   # f <- list.files(path = dir, pattern = paste0("*.nc"), full.names
46   = T)

```

```
39 # lapply(f, file.remove)
40
41 # Add in new files
42 pblapply(years, function(x) getPBL(dir = dir
43                                   , year = x
44                                   , var = var))
45 }
46
47 getPBLYears(dir = "./data/PBL/nc"
48             , var = c("hpbl")
49             , years = years)
```

Source/edaPredictors.R

```
1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2019-02-25
5 # Compare extract values to remainder of the study area for each
  predictor
6
7 # needed for nvim-R
8 if (basename(getwd()) == "src") {
9   setwd("../")
10  getwd()
11 }
12
13 # load the necessary packages


---


14 if (!require(pacman)) {
15   install.packages("pacman")
16   library(pacman)
17 }
18
19 p_load(plyr
20       , dplyr
21       , tidyr
22       , magrittr
23       , tools
24       , rgdal
25       , raster
26       , corrplot
27       , sp
28       , rgeos
29       , ggplot2
30       , stringr
31       , RColorBrewer
32       , pbapply)
```

```
33     ,parallel
34     ,randomForest
35     ,ranger
36     ,sf
37     ,rasterVis
38     #,circular
39     ,scales
40     ,tmap
41     ,shinyjs
42     ,tmaptools
43     ,gridExtra
44     #,ggsflabel
45     #,gghighlight
46     ,ggrepel
47 )
48
49 # this script is used to compare against a specific modeling session
    by its clean_time
50
51 # Load in global variables
52 source("../src/init.R")
53
54 # Load in misc function
55 source("../src/functions.R")
56
57 clean_time <- readRDS("../models/clean_time/clean_time.RDS")
58
59 # The following functions are a mirror of the extractBuffer script
    _____
60
61 # create a list of daily predictor variables (abbreviations)
62 vars <- c(
63   "pbl.min"
64   , "pbl.max"
65   #, "pr"
66   #, "vs"
67   #, "th"
68   #, "tmmn"
69   #, "tmmx"
70   , "rmin"
71   , "rmax"
72   #, "sph"
73   , "ndvi"
74   , "evi"
75   #, "pm2.5.mean"
76   #, "pm2.5.max"
77   #, "pm2.5.min"
78   #, "pm2.5.sd"
```

```

79   , "pm2.5.median"
80 )
81
82 #list of static predictors
83 static <- c(
84   "fwy"
85   , "streets"
86   , "maj_art"
87   , "arterial"
88   , "railroad"
89   , "railyards"
90   , "elev"
91   #, "population"
92   #, "point"
93   #, "nonpoint"
94   #, "onroad"
95   #, "nonroad"
96 )
97
98 # Define read functions for static and dynamic variables
99
100 # read functions for daily and static predictors
101 readVar <- function(var, date, study_area) {
102   r <- raster(list.files("./data", pattern = paste0("^", var, "\\.",
103     date, "\\tif$"),
104     , full.names = T
105     , recursive = T)) %>% resample(study_area,
106     method = 'ngb')
107 }
108
109 readStatic <- function(var, study_area) {
110   r <- raster(list.files("./data", pattern = paste0("^", var, "\\.",
111     "$"),
112     , full.names = T
113     , recursive = T)) %>% resample(study_area,
114     method = 'ngb')
115 }
116
117 # Focal Buffer functions
118
119 # focal buffers credited to Jackson Voelkel @ SUPR
120 # Buffer sequence
121 # buffers <- c(seq(500,5000,500), seq(6000, 10000, 1000))
122 # buffers <- c(1000, seq(0, 10000, 2500)) # 1km buffer isn't the same
123   as 0km!
124
125 # Read in buffers that matched their creation in extractBuffer.R

```

```

119 buffers <- readRDS(paste0("./data/buffers/", clean_time, "_buffers.
      RDS"))
120
121 # Run a single moving window
122 focalBufferRaster <- function(rast, bufferDist) {
123   # skip wind direction and PBL during buffering
124   if (!grep1("^th|pbl.*|pm2\\.5\\.\\.*", names(rast))) {
125     buf <- focal(rast
126                  ,focalWeight(rast, bufferDist, type="circle")
127                  # assigns NA instead of 0 to edge effects
128                  ,na.rm = T
129                  )
130     names(buf) <- paste0(names(rast), ".", bufferDist, "m")
131     return(buf)
132   }
133 }
134
135
136 # Wind Vector Averaging Function
137 focalBufferWind <- function(stack, bufferDist) {
138
139   # grab the wind direction and speed layers from stack
140   wd <- raster::subset(stack, grep('^th\\.\\.*', names(stack), value = T
141   ))
142   ws <- raster::subset(stack, grep('^vs\\.\\.*', names(stack), value = T
143   ))
144
145   # determine u & v components
146   u <- ws * sin(2*pi*wd/360)*(-1)
147   v <- ws * cos(2*pi*wd/360)*(-1)
148
149   # fun focal on each component
150   mean_u <- focal(u, focalWeight(u, bufferDist, type = "circle"))
151   mean_v <- focal(v, focalWeight(v, bufferDist, type = "circle"))
152
153   # convert back to degrees
154   mean_wd <- (atan2(mean_u, mean_v) * 360/2/pi) + 180
155
156   # assign wd buffer name to output
157   names(mean_wd) <- paste0(names(wd), ".", bufferDist, "m")
158   return(mean_wd)
159 }
160
161 # apply focalBufferRaster to entire stack

```

```

162 focalBufferStack <- function(stack, bufferDist, date) {
163
164   s <- pblapply(1:nlayers(stack), function(x) {
165     focalBufferRaster(rast = stack[[x]], bufferDist)}
166     #,cl = floor((detectCores()-1)/2)
167   ) %>% unlist %>% stack
168
169   # wind direction buffering (requires wd and ws)
170   if ('^th\\.\\.*' %in% names(stack) & '^vs\\.\\.*' %in% names(stack)) {
171     wd <- focalBufferWind(stack, bufferDist)
172     s %>% stack(wd)
173   }
174
175   return(s)
176   # stackApply(stack, indices = 1:nlayers(stack), fun = function(x) {
177   #   focalBufferRaster(rast = x, bufferDist = bufferDist)
178   # })
179 }
180
181 # function resamples and combines all GIS predictors into single
182   raster stack _____
183
184 stackPredictors <- function(date, crs, study_area, static, vars) {
185
186   # Study Area Extent Raster used for resampling...
187   a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>% raster(
188     res = sp_res, vals = 0)
189
190   # read daily predictors
191   r <- lapply(vars, function(x) {
192     readVar(var = x, date = date, study_area = a)
193   })
194   #,cl=detectCores()-1
195   ) %>% stack()
196
197   # read static predictors
198   y <- pblapply(static, function(x) {
199     readStatic(var = x, study_area = a)
200   })
201   #,cl=detectCores()-1
202   ) %>% raster::stack()
203
204   # combine them
205   s <- raster::stack(r, y)
206
207   return(s)
208   gc()
209 }

```

```

208 # End mirror


---


209
210 # Run all of the focal buffers at once!


---


211 createBuffers <- function(stack, buffers, date) {
212   # clear buf dir before writing new files?
213   # try(system(paste0("rm ./data/buf/", date, "*", bufferDist, "m.tif"), silent=T))
214   # file.remove(paste0("./data/buf/", date, "*", bufferDist, "m.tif"), showWarnings=F)
215   # file.remove(paste0("./data/buf/", date, ".*", bufferDist, "m\\.tif"), showWarnings=F)
216   # f <- list.files(path = "./data/buf", pattern = paste0(date, ".*.tif"), full.names = T)
217   # lapply(f, file.remove)
218
219   pblapply(buffers
220     ,function(x) {
221       focalBufferStack(stack, bufferDist = x, date = date)
222     }
223     ,cl = ceiling((detectCores()-1)/2)
224   )
225 }
226
227
228 # Raster processing functions


---


229
230 # Combine all predictors for a given day
231 extractPredictors <- function(date, crs, study_area, bb, vars, static
232   , pm_df, scale_neph = scale_neph) {
233   # Study Area Extent Raster used for resampling...
234   a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>% raster(
235     res = sp_res, vals = 0)
236
237   # read PurpleAir data
238   pa <- readRDS(pm_df) %>% spTransform(CRSobj = crs)
239
240   # Final bounding box
241   b <- readRDS(bb) %>% spTransform(CRSobj = crs) %>% raster(res = sp_
242     res, vals = 0)
243
244   # Create Raster Stack
245   s <- stackPredictors(date = date
246     , crs = crs

```

```

245         ,study_area = study_area
246         ,vars = vars
247         ,static = static)
248
249 # Buffering


---


250 s_buf <- createBuffers(s, buffers = buffers, date = date) %>%
  unlist %>% stack
251
252 # Add PBL and Neph data (not buffered)
253 pbl <- raster::subset(s, grep('^pbl\\.\\.*', names(s), value = T))
254 # neph <- raster::subset(s, grep('^pm2\\.5\\.\\.*', names(s), value =
  T))
255 neph <- raster::subset(s, grep('^pm2\\.5\\.\\.median*', names(s),
  value = T))
256 s_buf %>% raster::stack(pbl, neph)
257
258 # strip date from daily predictor layer names
259 names(s_buf) <- gsub(x = names(s_buf), pattern = paste0("\\\\.", date
  ), replacement = "")
260
261 # Rename 0m buffer to match non-buffered layers
262 names(s_buf) <- gsub(x = names(s_buf), pattern = paste0("\\\\0m$"),
  replacement = "")
263
264 # Crop extent to original bounding box (10 times smaller than
  buffer boundary)
265 s_buf %>% raster::crop(b, snap = 'near') %>% resample(b, method =
  'ngb')
266 s_buf %>% raster::mask(b)
267
268 # Extract PurpleAir data


---


269 pa <- pa[which(pa$date == gsub("\\\\.", "\\-", date)),]
270
271 # Simple extract grabs only the intersecting cell value
272 s_extract <- raster::extract(s_buf, pa, method = 'bilinear', sp = T
  , na.rm = T)
273
274 # Convert to data.frame


---


275
276 # df <- raster::as.data.frame(s_extract) %>% na.omit()
277 df_network <- s_extract %>%
278   st_as_sf() %>%

```



```

279     st_drop_geometry() %>%
280     dplyr::select(-node) %>%
281     gather(-date, key = "variable", value = "value")
282 df_network$extent <- "network"
283
284 # Convert entire raster stack to a new dataframe
285 df_region <- as.data.frame(as.matrix(s_buf))
286 # Add the date variable
287 df_region$date <- as.Date(hyphenDate(date))
288 df_region %>%
289     gather(-date, key = "variable", value = "value")
290 df_region$extent <- "region"
291
292 # Combine each tidy dataset
293 df <- bind_rows(df_network, df_region)
294
295 # Create a variable class vector
296 df$variable_group <- sub("\\.\\d+m$", "", df$variable)
297 return(df)
298 gc()
299 }
300
301
302 # wrap our stacking function into a date sequence generator
303
304 extractDailyPredictors <- function(start_date
305                                     ,end_date
306                                     ,crs
307                                     ,study_area
308                                     ,bb
309                                     ,vars # list of vars
310                                     ,static # list of static vars
311                                     ,pm_df
312                                     ,scale_neph
313 ) {
314     dates <- sequenceDates(start_date, end_date)
315
316     df <- Reduce(rbind, pblapply(dates, function(x) {
317         extractPredictors(date = x
318                           ,study_area = study_area
319                           ,bb = bb
320                           ,crs = crs
321                           ,vars = vars
322                           ,static = static
323                           ,pm_df = pm_df
324                           ,scale_neph = scale_neph)})
325     # parallelization takes place within each loop (faster)

```

```

326     ,cl = detectCores()-1
327   ))
328   return(df)
329   gc()
330 }
331
332
333 # Running our function on multiple days


---


334 if (!file.exists(paste0("./data/df_eda_predictors/", clean_time, "_df_eda_predictors.RDS"))) {
335
336   df <- extractDailyPredictors(start_date = start_date
337                               ,end_date =
338                               end_date
339                               # ,end_date =
340                               start_date # for quick profiling
341                               ,crs = epsg_
342                               26910
343                               ,study_area =
344                               study_area
345                               ,bb = bb
346                               ,vars = vars
347                               ,static =
348                               static
349                               ,pm_df = pm_
350                               df
351                               ,scale_neph =
352                               scale_neph)
353   print(paste0("Creating ", clean_time, "df_eda_predictors.RDS"))
354   saveRDS(df, paste0("./data/df_eda_predictors/", clean_time, "_df_eda_predictors.RDS"))
355 } else {
356   df <- readRDS(paste0("./data/df_eda_predictors/", clean_time, "_df_eda_predictors.RDS"))
357 }
358
359 ## Explore spatial heterogeneity of predictors


---


360
361 # Create a violin plot comparing the distribution of each predictor across the network and region
362 pblapply(unique(df$variable), function(x) {
363   p <- df %>% dplyr::filter(variable == x) %>%
364   ggplot(aes(x = extent, y = value, fill = extent)) +
365   geom_violin() +

```

```

361     labs(y = paste0(x)) +
362     theme_minimal() +
363     theme(axis.text.x = element_blank()
364     , axis.title.x = element_blank()
365     )
366     ggsave(filename = paste0("./figures/violin_plots/", x, "_
violin_plot.png")
367     , plot = p
368     , width = 8
369     , height = 6
370     , units = "in"
371     , dpi = 300
372     )
373
374     rm(p)
375     gc()
376     }
377     , cl = detectCores() - 1
378   )
379
380   # Create a violin plot comparing the distribution of each predictor
group across the network and region
381   pblapply(unique(df$variable_group), function(x) {
382     p <- df %>% dplyr::filter(variable_group == x) %>%
383       mutate(variable = factor(variable, levels = c(paste0(x)
384         , paste0(x, ".1000m")
385         , paste0(x, ".2500m")
386         , paste0(x, ".5000m")
387         , paste0(x, ".7500m")
388         , paste0(x, ".10000m")
389         ))) %>%
390     ggplot(aes(x = variable, y = value, fill = extent)) +
391       geom_violin() +
392       labs(y = paste0(x)) +
393       theme_minimal() +
394       theme(axis.title.x = element_blank())
395     ggsave(filename = paste0("./figures/violin_plots/", x, "_
group_violin_plot.png")
396     , plot = p
397     , width = 8
398     , height = 6
399     , units = "in"
400     , dpi = 300
401     )
402
403     rm(p)
404     gc()
405     }

```

```

406     ,cl = detectCores()-1
407 )

```

Source/functions.R

```

1  # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2  # Canopy Continuum Project, USFS
3  # PI Dr. Linda George
4  # 2018-09-10
5  # functions used to download, process, and visualize MAIAC AOD data
6
7
8  # Miscellaneous

```

```

9  getHostName <- function() {
10     hostname <- Sys.info()
11     return(hostname["nodename"])
12 }
13
14 # Set custom raster tempdir for XPS or Tower (hardcode new hostname
    for new machine)
15 setRasterTempDir <- function() {
16     if(getHostName() == "XPS-15-9570") {
17         dir <- "/tmp/"
18     } else if (getHostName() == "Precision-Tower-5810") {
19         dir <- "/media/porlando/My Book/"
20     } else if (getHostName() == "hecate.rc.pdx.edu") {
21         dir <- "/workspace/porlando/tmp"
22     } else if (grepl("himem.*|phi.*|compute.*cluster|login1.*cluster|
        login2.*cluster", getHostName()))
23         dir <- "/scratch/porlando/tmp"
24     else {
25         print(paste0(getHostName(), "is not a valid hostname! Modify
            setRasterTempDir() to accommodate new host."))
26     }
27     if(!dir.exists(dir)) {
28         dir.create(dir)
29     }
30     rasterOptions(tmpdir = dir)
31     print(paste0("Setting raster tempdir ", dir, " for ", getHostName()
        ))
32 }
33
34
35 # Emulate ggplot default color palette
36 gg_color_hue <- function(n) {
37     hues = seq(15, 375, length = n + 1)
38     hcl(h = hues, l = 65, c = 100)[1:n]

```

```

39 }
40
41 # capture object name as a character
42 obj2char <- function(object) {
43   deparse(substitute(object))
44 }
45
46 # remove geometry from sf object, convert to dataframe with only the
  elements/attributes
47 st_drop_geometry <- function(x) {
48   if(inherits(x, "sf")) {
49     x <- st_set_geometry(x, NULL)
50     class(x) <- 'data.frame'
51   }
52   return(x)
53 }
54
55 # convert sfc to x,y coordinates
56 sfc_as_cols <- function(x, names = c("x", "y")) {
57   stopifnot(inherits(x, "sfc") && inherits(sf::st_geometry(x), "sfc_
    POINT"))
58   ret <- sf::st_coordinates(x)
59   ret <- tibble::as_tibble(ret)
60   stopifnot(length(names) == ncol(ret))
61   x <- x[, !names(x) %in% names]
62   ret <- setNames(ret, names)
63   dplyr::bind_cols(x, ret)
64 }
65
66
67 print_clean_time <- function() {
68   str_replace_all(lubridate::now(), " |: ", "_")
69 }
70
71 # Grab p-value from model object
72 lmp <- function(modelobject) {
73   if (class(modelobject) != "lm") stop("Not an object of class 'lm' ")
74   f <- summary(modelobject)$fstatistic
75   p <- pf(f[1], f[2], f[3], lower.tail=F)
76   attributes(p) <- NULL
77   return(p)
78 }
79
80
81 # plot density in ggplot
82 get_density <- function(x, y, n = 100) {
83   dens <- MASS::kde2d(x = x, y = y, n = n)

```

```

84   ix <- findInterval(x, dens$x)
85   iy <- findInterval(y, dens$y)
86   ii <- cbind(ix, iy)
87   return(dens$z[ii])
88 }
89
90 # creating a custom not-in function
91 '%!in%' <- function(x,y) {!( '%in%'(x,y))}
92
93 sequenceDates <- function(start_date, end_date, interval = "day") {
94   dates <- seq.Date(as.Date(start_date), as.Date(end_date), by =
95     interval) %>%
96     as.character() %>%
97     gsub(pattern = "\\-", replacement = "\\.")
98   return(dates)
99 }
100 # Hyphenate dates that are seperated by "."
101 hyphenDate <- function(date) {
102   gsub("\\.", "\\-", date)
103 }
104
105 # Season generator function!
106 getSeason <- function(DATES) {
107   WS <- as.Date("2012-12-15", format = "%Y-%m-%d") # Winter Solstice
108   SE <- as.Date("2012-3-15", format = "%Y-%m-%d") # Spring Equinox
109   SS <- as.Date("2012-6-15", format = "%Y-%m-%d") # Summer Solstice
110   FE <- as.Date("2012-9-15", format = "%Y-%m-%d") # Fall Equinox
111
112   # Convert dates from any year to 2012 dates
113   d <- as.Date(strftime(DATES, format="2012-%m-%d"))
114
115   ifelse (d >= WS | d < SE, 1, # Winter
116     ifelse (d >= SE & d < SS, 2, # Spring
117       ifelse (d >= SS & d < FE, 3, 4))) # Summer and Fall
118 }
119
120
121
122 # downloading script

```

```

123
124 # trying to download MAIAC data from datapool via R
125 getAOD <- function(user = 'porlando'
126   ,pw = scan("./batteries.dppss", what = "")
127   ,dir = 'MAIAC'
128   ,product = 'MCD19A2'

```

```

129         ,date = '2018.08.28'
130         ,tile = 'h09v04'
131         ,collection = "006") {
132
133     # parse date and julian date for url building
134     Date <- lubridate::ymd(date)
135     julianDate <- paste0(lubridate::year(Date)
136                         ,lubridate::yday(Date))
137
138     # check if file exists
139     folder <- paste0("./MAIAC/e4ftl01.cr.usgs.gov/MOTA/MCD19A2.006/" ,
140                     date)
141
142     # download file if it doesn't exist yet
143     if(length(dir(folder , all.files = TRUE, pattern = "*.hdf")) == 0) {
144
145         # extracts hdf files for a given tile across all observation
146         # times
147         pattern <- paste0(product , ".A" , julianDate , "." , tile , "." ,
148                           collection , "*.hdf")
149
150         # base url for wget
151         url <- paste0("https://e4ftl01.cr.usgs.gov/MOTA/" , product , "." ,
152                      collection , "/" , date , "/" )
153
154         # call wget from command line
155         system(paste0("wget -r -A" , pattern , " -L --user=" , user
156                      , " --password=" , pw
157                      , " --directory-prefix=" , dir
158                      , " --load-cookies ~/.cookies --save-cookies ~/.
159                      cookies --no-parent " , url))
160     }
161 }
162
163 # create a list of correctly formatted dates
164 getDates <- function(start_date = "2017-07-01" , end_date = Sys.Date()
165                      , by = "days") {
166     days <- seq.Date(from = as.Date(start_date) , to = as.Date(end_date)
167                     , by = by)
168     stringr::str_replace_all(days , "-" , ".")
169 }
170
171 # delete all hdf files and subfolders CAREFUL!
172 purgeAOD <- function(parent_dir = "./MAIAC") {
173     system(paste0("rm -rf " , parent_dir , "/*"))
174 }

```

```

170 }
171
172 # processing script

```

```

173
174 # process hdf and create raster
175 processAOD <- function(file_path, study_area = portl_buf) {
176
177   cat("\n")
178
179   # extract date from file_path
180   date <- stringr::str_extract(file_path, '
181     [0-9][0-9][0-9][0-9].[0-9][0-9].[0-9][0-9]')
182   date_clean <- stringr::str_replace_all(date, "\\.", "-")
183   # read in hdf
184   sds <- get_subdatasets(file_path)
185
186   # Grab AOD layers
187   Optical_Depth_047 = sds[grepl("grid1km:Optical_Depth_047", sds)]
188   %>% readGDAL %>% stack
189   Optical_Depth_055 = sds[grepl("grid1km:Optical_Depth_055", sds)]
190   %>% readGDAL %>% stack
191
192   # More variables ...
193   # AOD_Uncertainty = sds[grepl("grid1km:AOD_Uncertainty", sds)] %>%
194   readGDAL %>% stack
195   # FineModeFraction = sds[grepl("grid1km:FineModeFraction", sds)]
196   %>% stack
197   # Column_WV = sds[grepl("grid1km:Column_WV", sds)] %>% stack
198   # AOD_QA = sds[grepl("grid1km:AOD_QA", sds)] %>% readGDAL %>% stack
199   # AOD_MODEL = sds[grepl("grid1km:AOD_MODEL", sds)] %>% readGDAL %>%
200   stack
201   # Injection_Height = sds[grepl("grid1km:Injection_Height", sds)]
202   %>% readGDAL %>% stack
203
204   # Note that some variables such as 'RelAZ' are on a different
205   resolution and must be disaggregated to match -
206   # cosSZA = sds[grepl("grid5km:cosSZA", sds)] %>% readGDAL %>% stack
207   %>% disaggregate(5)
208   # cosVZA = sds[grepl("grid5km:cosVZA", sds)] %>% readGDAL %>% stack
209   %>% disaggregate(5)
210   # RelAZ = sds[grepl("grid5km:RelAZ", sds)] %>% readGDAL %>% stack
211   %>% disaggregate(5)
212   # Scattering_Angle = sds[grepl("grid5km:Scattering_Angle", sds)]
213   %>% readGDAL %>% stack %>% disaggregate(5)
214   # Glint_Angle = sds[grepl("grid5km:Glint_Angle", sds)] %>% readGDAL
215   %>% stack %>% disaggregate(5)

```



```

203
204 # aggregate each satellite overpass into a single band (mean, max)
205 Optical_Depth_047_mean = stackApply(Optical_Depth_047, indices =
206     rep(1, nlayers(Optical_Depth_047))
207     ,fun = "mean", na.rm = TRUE)
208 Optical_Depth_047_max = stackApply(Optical_Depth_047, indices = rep
209     (1, nlayers(Optical_Depth_047))
210     ,fun = "max", na.rm = TRUE)
211 Optical_Depth_055_mean = stackApply(Optical_Depth_055, indices =
212     rep(1, nlayers(Optical_Depth_055))
213     ,fun = "mean", na.rm = TRUE)
214 Optical_Depth_055_max = stackApply(Optical_Depth_055, indices = rep
215     (1, nlayers(Optical_Depth_055))
216     ,fun = "max", na.rm = TRUE)
217 # Combine to multi-band raster with 'row' and 'col' and AOD values
218 r = stack(Optical_Depth_047_mean
219     ,Optical_Depth_047_max
220     ,Optical_Depth_055_mean
221     ,Optical_Depth_055_max)
222
223 names(r) = c(
224     "Optical_Depth_047_mean"
225     , "Optical_Depth_047_max"
226     , "Optical_Depth_055_mean"
227     , "Optical_Depth_055_max"
228 )
229
230
231 # transform raster to pdx CRS
232 r <- projectRaster(r, crs = wgs_84)
233
234 # transform our study area
235 study_area <- spTransform(study_area, CRSobj = wgs_84)
236
237 if (identical(crs(study_area), crs(r))) {
238
239     # extract raster cells that intersect with our study area
240     # s <- trim(r) # what does this do?
241     # x <- extract(r, study_area) # what does this do?
242
243     m <- mask(r, study_area)
244     cr <- raster::crop(m, study_area)
245
246     # date sequence (needed for rts)

```

```

247     dates <- lubridate::ymd(rep(date, nlayers(cr)))
248
249     # convert to RasterBrickTS (breaks filterAOD)
250     # cr %>% rts(dates)
251
252     # add dates to Z values instead of using RTS (for now)
253     cr %>% setZ(dates)
254
255     # od47 <- cr[["Optical_Depth_047"]]
256     # leaflet(portl_buf) %>%
257     #   addTiles() %>%
258     #   addRasterImage(od47) %>%
259     #   addPolygons()
260
261     # dynamically assigning output folder and file name breaks in
262     # parallel/snow argh!
263     # location <- deparse(match.call())$study_area)
264     location <- "portl_buf"
265     # determine if the data intersects
266     if (!is.null(cr[[1]])) {
267       # print(paste0("Returning overlapping AOD data for ", date))
268       writeRaster(cr, filename = paste0("./output/aod/", location, "/"
269         , date_clean, "_", location, "_aod.tif")
270         ,format = "GTiff"
271         ,overwrite = TRUE)
272       return(cr)
273     } else {
274       # print(paste0("AOD data does not overlap with study area on ",
275         date))
276       return(NULL)
277     }
278   }
279 }
280
281 # aggregate raster stack by week
282 # weekly_aod <- function(brick) {
283 #   #
284 #   # }
285
286
287
288 # retrieve AOD grid cells within study area

```

```

289 filterAOD <- function(aod_list) {
290   r <- unlist(aod_list)

```

```

291 # works for rasterBrickTS but not rasterBrick
292 # df <- as.data.frame(r@raster@data@values) %>%
293 df <- as.data.frame(r@data@values) %>%
294   dplyr::filter(!is.na(Optical_Depth_047_mean) |
295                 !is.na(Optical_Depth_047_max) |
296                 !is.na(Optical_Depth_055_mean) |
297                 !is.na(Optical_Depth_055_max))
298   return(df)
299 }
300
301
302
303 # get modis tiles for a given shapefile's extent (broken)
304 getTiles <- function(destfile = "../tiles/modis_sin.kmz") {
305   if(!file.exists(destfile)) {
306     url <- paste0("https://modis.ornl.gov/files/", basename(destfile))
307   }
308   download.file(url, destfile = destfile)
309   tiles <- readOGR(destfile, "Features")
310 } else {
311   tiles <- readOGR(destfile, "Features")
312 }
313 return(tiles)
314 }
315 # EDA script

```

```

316 useable_days <- function(input = nrow_day, percent = 75) {
317   p_days <- nrow_day %>% dplyr::filter(p_coverage >= percent) %>%
318     nrow()/nrow(nrow_day) * 100
319   return(p_days)
320 }
321
322 # quickly inspect/visualize the aod coverage for each day
323 rPlot <- function(aod_layer) {
324   plot(aod_layer)
325   Sys.sleep(1)
326 }
327
328 # Pan's correlation matrix function
329 cor.matrix<-function(x, data=NA, cor.method="pearson", add1to1=F,...) {
330   # panel.hist function adds the histogram
331   options(warning=F)
332   panel.hist <- function(x)
333   {
334     usr <- par("usr")
335     on.exit(par(usr))

```

```

335     par(usr = c(usr[1:2], 0, 1.5) )
336     h <- hist(x, plot = FALSE, breaks=30)
337     breaks <- h$breaks
338     nB <- length(breaks)
339     y <- h$counts
340     y <- y/max(y)
341     rect(breaks[-nB], 0, breaks[-1], y, col="lightblue")
342     box()
343   }
344   panel.cor <- function(x, y, digits=2, prefix="", cex.cor)
345   {
346     usr <- par("usr")
347     on.exit(par(usr))
348     par(usr = c(0, 1, 0, 1))
349     r <- cor(x, y, method="pearson")
350     txt <- format(c(r, 0.123456789), digits=digits)[1]
351     txt <- paste(prefix, txt, sep="")
352     if(missing(cex.cor)) cex <- 0.8/strwidth(txt)
353     text(0.5, 0.5, txt, cex = cex * abs(r))
354   }
355   panel.smooth2<-function(x, y, bg = NA, pch = par("pch"), cex = 1,
356     col.smooth = "red", span = 2/3, iter = 3, plot1to1=add1to1)
357   {
358     points(x, y, pch = pch, cex = cex, ...)
359     ok <- is.finite(x) & is.finite(y)
360     if (any(ok)) {
361       lines(stats::lowess(x[ok], y[ok], f = span, iter = iter), col =
362         col.smooth)
363     }
364     if(plot1to1){
365       mn<-min(c(x,y), na.rm=T)
366       mx<-max(c(x,y), na.rm=T)
367       new.x<-seq(mn,mx,length.out=10)
368       points(new.x,new.x,type='l',col="blue",lwd=2)
369     }
370   }
371   if (class(x)=="formula"){
372     x<-model.frame(x, data=data)
373   }
374   pairs(x, upper.panel=panel.smooth2, lower.panel=panel.cor, diag.panel=
375     panel.hist,
376     cex.labels = 1, font.labels=2)
377   options(warning=T)
378 }

```

Source/ggRegression.R

```

1 # Define Test Regression Plot
2
3 scaleFUN <- function(x) sprintf("%.2f", x)
4
5 # This plot is used to compare test observations and predictions from
  ranger/randomForest models
6 # Provide the names of x and y vectors as strings
7 testRegression <- function(df, x, y, outdir, reduced = F, clean_time)
  {
8
9   # Create lm model objects
10  mod <- lm(df[[y]]~df[[x]])
11  mod_sum <- summary(mod)
12
13  # Compute RMSE on test data versus predictions
14  rmse <- sqrt(mean((df[[y]] - df[[x]])^2))
15
16  # Create color palette to display point density
17  d = grDevices::densCols(df[[x]], df[[y]], colramp =
    colorRampPalette(rev(rainbow(10, end = 4/6))))
18
19  # Build our regression plot
20  p <- ggplot(df, aes_string(x = x, y = y)) +
21    # ylab("Predicted PM2.5 (ug/m3)") +
22    # xlab("Measured PM2.5 (ug/m3)") +
23    xlab(expression(~Observed~PM[2.5]~mu*g*m^-3)) +
24    ylab(expression(~Predicted~PM[2.5]~mu*g*m^-3)) +
25    # annotate("text", label = paste("R2 =", round(modr$r.squared, 4)
26    ), x = 25, y = max(c(cvr$x, cvr$y))-10) +
27    # annotate("text", label = paste("p-value =", round(modr$
28    coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y))-20) +
29    # annotate("text", label = paste("Slope =", round(modr$
30    coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y))-20) +
31    # annotate("text", label = paste("Intercept =", round(modr$
32    coefficients[1], 2)), x = 25, y = max(c(cvr$x, cvr$y))-30) +
33    geom_point(col = d, alpha=0.5) +
34    #coord_fixed() +
35    scale_x_continuous(limits = c(min(c(df[[x]], df[[y]])), max(c(df[[
36    x]], df[[y]])))) +
37    scale_y_continuous(limits = c(min(c(df[[x]], df[[y]])), max(c(df[[
38    x]], df[[y]])))) +
39    # scale_x_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
40    # scale_y_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
41    labs(subtitle = paste("Adj R2 = ", signif(mod_sum$adj.r.squared,
42    4),
43    "Intercept = ", signif(mod_sum$coef[[1]], 2)
44    ,

```

```

37         " Slope =", signif(mod_sum$coef[[2]], 2),
38         " p =", signif(as.numeric(broom::glance(
mod)$p.value), 3),
39         " RMSE =", signif(rmse, 3))) +
40     # geom_smooth(se=F, method = "lm", col = "firebrick") +
41     geom_abline(intercept = mod$coef[[1]]
42                 ,slope = mod$coef[[2]]
43                 ,color = "firebrick") +
44     geom_abline(intercept = 0
45                 ,slope = 1
46                 ,color = "black"
47                 ,linetype = "dashed"
48                 ) +
49     theme_bw() +
50     theme(aspect.ratio = 1
51           ,plot.title = element_text(hjust = 0.5, size=12, face = "
bold")
52           ,plot.subtitle = element_text(hjust = 0.5, size=12, face =
"bold")
53           ,axis.text = element_text(size=rel(1.1), face = "bold",
colour = "black")
54           ,axis.title = element_text(size=15)
55     )
56
57     # Assign file name for full/reduced RF model
58     if(reduced) {
59       outfile <- paste0(outdir, clean_time, "-obs-pred-lm-reduced.png")
60     } else {
61       outfile <- paste0(outdir, clean_time, "-obs-pred-lm.png")
62     }
63     print(paste0("Saving plot to ", outfile))
64     ggsave(plot = p
65            ,filename = outfile
66            ,width = 8
67            ,height = 8
68            ,units = "in"
69     )
70     return(p)
71   }
72 }
73
74
75 # -----
76
77 # Same function as above, but adds a date to the title
78 dailyRegression <- function(df, x, y, outdir, reduced = F, date) {
79
80   # Create lm model objects

```

```

81  mod <- lm(df[[y]]~df[[x]])
82  mod_sum <- summary(mod)
83
84  # Compute RMSE on test data versus predictions
85  rmse <- sqrt(mean((df[[y]] - df[[x]])^2))
86
87  # Create color palette to display point density
88  # d = grDevices::densCols(df[[x]], df[[y]], colramp =
      colorRampPalette(rev(rainbow(10, end = 4/6))))
89
90  # Build our regression plot
91  p <- ggplot(df, aes_string(x = x, y = y)) +
92    # ylab("Predicted PM2.5 (ug/m3)") +
93    # xlab("Measured PM2.5 (ug/m3)") +
94    xlab(expression(~Observed~PM[2.5]~mu*g*m^-3)) +
95    ylab(expression(~Predicted~PM[2.5]~mu*g*m^-3)) +
96    # annotate("text", label = paste("R2 =", round(modr$r.squared, 4)
97    #), x = 25, y = max(c(cvr$x, cvr$y))-10) +
98    # annotate("text", label = paste("p-value =", round(modr$
99    # coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y))-20) +
100   # annotate("text", label = paste("Slope =", round(modr$
101   # coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y))-20) +
102   # annotate("text", label = paste("Intercept =", round(modr$
103   # coefficients[1], 2)), x = 25, y = max(c(cvr$x, cvr$y))-30) +
104   # geom_point(col = d, alpha=0.5) +
105   # geom_smooth(se=F, method = "lm", col = "firebrick") +
106   geom_abline(intercept = mod$coef[[1]]
107               ,slope = mod$coef[[2]]
108               ,color = "firebrick") +
109   geom_abline(intercept = 0
110               ,slope = 1
111               ,color = "black"
112               ,linetype = "dashed"
113               ) +
114   geom_point(alpha=0.5) +
115   geom_text_repel(point.padding = 0.30, aes(label = sprintf("%.2f",
116     signif(df[[y]] - df[[x]], 2)))) +
117   #coord_fixed() +
118   scale_x_continuous(labels = scaleFUN, limits = c(min(c(df[[x]], df
119     [[y]])), max(c(df[[x]], df[[y]])))) +
120   scale_y_continuous(labels = scaleFUN, limits = c(min(c(df[[x]], df
121     [[y]])), max(c(df[[x]], df[[y]])))) +
122   # scale_x_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
123   # scale_y_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
124   labs(caption = paste0(date),
125        subtitle = paste("Adj R2 = ", sprintf("%.4f", signif(mod_sum
126     $adj.r.squared, 4)),

```

```

119         "Intercept =", sprintf("%.2f", signif(mod_
sum$coef[[1]], 2)),
120         " Slope =", sprintf("%.2f", signif(mod_sum$
coef[[2]], 2)),
121         " p =", sprintf("%.3f", signif(as.numeric(
broom::glance(mod)$p.value), 3)),
122         " RMSE =", sprintf("%.3f", signif(rmse, 3))
)) +
123   theme_bw() +
124   theme(aspect.ratio = 1
125         ,plot.title = element_text(hjust = 0.5, size=12, face = "
bold")
126         ,plot.subtitle = element_text(hjust = 0.5, size=12, face =
"bold")
127         ,axis.text = element_text(size=rel(1.1), face = "bold",
colour = "black")
128         ,axis.title = element_text(size=15)
129   )
130
131   # Assign file name for full/reduced RF model
132   if(reduced) {
133     outfile <- paste0(outdir, str_replace_all(date, "\\.", "-"), "-
obs-pred-lm-reduced.png")
134   } else {
135     outfile <- paste0(outdir, str_replace_all(date, "\\.", "-"), "-
obs-pred-lm.png")
136   }
137   print(paste0("Saving plot to ", outfile))
138   ggsave(plot = p
139         ,filename = outfile
140         ,width = 8
141         ,height = 8
142         ,units = "in"
143   )
144   return(p)
145 }
146
147
148 # Same function but with different labels
149 nephRegression <- function(df, x, y, outdir, reduced = F, clean_time)
{
150
151   # Create lm model objects
152   mod <- lm(df[[y]]~df[[x]])
153   mod_sum <- summary(mod)
154
155   # Compute RMSE on test data versus predictions
156   # rmse <- sqrt(mean((df[[y]] - df[[x]])^2)) # 1:1 RMSE

```



```

157 rmse <- glance(mod)$sigma # Model RMSE
158 # Create color palette to display point density
159 d = grDevices::densCols(df[[x]], df[[y]], colramp =
    colorRampPalette(rev(rainbow(10, end = 4/6))))
160
161 # Build our regression plot
162 p <- ggplot(df, aes_string(x = x, y = y)) +
163   # ylab("Predicted PM2.5 (ug/m3)") +
164   # xlab("Measured PM2.5 (ug/m3)") +
165   xlab(expression(~PurplAir~PM[2.5]~mu*g*m^-3)) +
166   ylab(expression(~Nephelometer~PM[2.5]~mu*g*m^-3)) +
167   # annotate("text", label = paste("R2 =", round(modr$r.squared, 4)
    ), x = 25, y = max(c(cvr$x, cvr$y)) - 10) +
168   # annotate("text", label = paste("p-value =", round(modr$
    coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y)) - 20) +
169   # annotate("text", label = paste("Slope =", round(modr$
    coefficients[2], 2)), x = 25, y = max(c(cvr$x, cvr$y)) - 20) +
170   # annotate("text", label = paste("Intercept =", round(modr$
    coefficients[1], 2)), x = 25, y = max(c(cvr$x, cvr$y)) - 30) +
171   geom_point(col = d, alpha=0.5) +
172   #coord_fixed() +
173   scale_x_continuous(limits = c(min(c(df[[x]], df[[y]])), max(c(df[[
    x]], df[[y]])))) +
174   scale_y_continuous(limits = c(min(c(df[[x]], df[[y]])), max(c(df[[
    x]], df[[y]])))) +
175   # scale_x_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
176   # scale_y_continuous(limits = c(0, max(c(cvr$x, cvr$y)))) +
177   labs(subtitle = paste("R2 = ", signif(mod_sum$adj.r.squared, 4),
    " Intercept = ", signif(mod_sum$coef[[1]], 2),
    " Slope = ", signif(mod_sum$coef[[2]], 2),
    " p = ", signif(as.numeric(broom::glance(mod
180   )$p.value), 3),
    " RMSE = ", signif(rmse, 3))) +
181   # geom_smooth(se=F, method = "lm", col = "firebrick") +
182   geom_abline(intercept = mod$coef[[1]]
    , slope = mod$coef[[2]]
    , color = "firebrick") +
183   geom_abline(intercept = 0
    , slope = 1
    , color = "black"
    , linetype = "dashed"
184   ) +
185   theme_bw() +
186   theme(aspect.ratio = 1
    , plot.title = element_text(hjust = 0.5, size=12, face = "
187   bold")
    , plot.subtitle = element_text(hjust = 0.5, size=12, face =
    "bold")
188   )

```

```

195         ,axis.text = element_text(size=rel(1.1), face = "bold",
    colour = "black")
196         ,axis.title = element_text(size=15)
197     )
198
199     outfile <- paste0(outdir, clean_time, "-obs-pred-lm.png")
200
201     # Assign file name for full/reduced RF model
202     if(reduced) {
203         outfile <- paste0(outdir, clean_time, "_obs_pred-lm-reduced.png")
204     } else {
205         outfile <- paste0(outdir, clean_time, "-obs-pred-lm.png")
206     }
207
208     print(paste0("Saving plot to ", outfile))
209     ggsave(plot = p
210           ,filename = outfile
211           ,width = 8
212           ,height = 8
213           ,units = "in"
214         )
215     return(p)
216
217 }

```

Source/homogeneousPM.R

```

1  # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2  # Canopy Continuum Project, USFS
3  # PI Dr. Linda George
4  # 2018-09-17
5  # extract regionally homogenous neph PM (+/- 10% of network mean)
6
7  # set up environment
8
9  # load the necessary packages
10 if (!require(pacman)) {
11     install.packages("pacman")
12     library(pacman)
13 }
14
15 p_load(readr
16       ,readxl
17       ,xlsx
18       ,ggplot2
19       ,raster
20       ,plyr

```

```
21     ,dplyr
22     #,multidplyr
23     ,broom
24     ,reshape2
25     ,tidyr
26     ,stringr
27     ,magrittr
28     ,rlist
29     ,grid
30     ,gridExtra
31     ,tidyquant
32     ,scales
33     ,qdapRegex
34     ,sp
35     ,sf
36     #,mapview # ***** with specific leaflet install
37     ,devtools
38     ,RColorBrewer
39     ,classInt
40     ,htmltools
41     ,scales
42     ,htmlwidgets
43     ,httr
44     ,jsonlite
45     ,rgdal
46     ,pbapply
47     ,snow
48     ,parallel
49     ,data.table
50     ,RPostgres
51     ,tsoutliers
52     ,forecast
53     ,MASS
54     ,viridis
55     ,corrplot
56     ,ngeo
57 )
58
59 # define global variables


---


60 source("../src/ggRegression.R")
61 source("../src/init.R")
62
63 # set timezone to UTC/GMT to match postgres
64 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
65 #   PDT!
66 # DEQ only uses PST!
```

```

66 Sys.timezone()
67 Sys.setenv(TZ="GMT")
68 Sys.timezone()
69
70 ## connecting to local db
71 host <- 'pgsql120.rc.pdx.edu'
72 db <- 'canopycontinuum'
73 user <- 'porlando'
74 port <- 5433
75 pw <- scan("./batteries.pgpass", what = "") # in parent dir
76
77
78 # open connection to our db
79 con <- dbConnect(drv = RPostgres::Postgres()
80                  ,dbname = db
81                  ,host = 'pgsql102.rc.pdx.edu' # not sure why object
82                  host isn't working...
83                  ,port = port
84                  ,password = pw
85                  ,user = user)
86
87 # create unanimous time resolution for all data
88 time_resolution <- "1 sec"
89
90 # time zone applied to all data
91 time_zone <- "GMT"
92
93 # CRS
94 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
95
96 # Oregon North NAD83 HARN meters
97 epsg_2838 <- "+proj=lcc +lat_1=46 +lat_2=44.33333333333334 +lat_
98             0=43.666666666666666 +lon_0=-120.5 +x_0=2500000 +y_0=0 +ellps=GRS80
99             +units=m +no_defs "
100
101 # Oregon North NAD83 Meters UTM Zone 10
102 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
103             +no_defs "
104
105 # Function definition
106
107 # creating a custom not-in function
108 '%!in%' <- function(x,y){ '%in%'(x,y)}
109
110 # plot density in ggplot
111 get_density <- function(x, y, n = 100) {
112   dens <- MASS::kde2d(x = x, y = y, n = n)

```

```

109   ix <- findInterval(x, dens$x)
110   iy <- findInterval(y, dens$y)
111   ii <- cbind(ix, iy)
112   return(dens$z[ii])
113 }
114
115 set.seed(1)
116
117 # data processing


---


118 # start_date <- "2017-07-01"
119 # end_date <- "2018-09-30"
120 # inherit start/end date from init script in modeling project
121
122 # this should work once I update my pdx table
123 # pa <- st_read(dsn = con
124 #               #,geom_column = "geom" # depreceated!
125 #               #,EWKB = TRUE
126 #               #,query = paste0("SELECT DISTINCT * FROM pdx WHERE
127 #               created_at >= '
128 #               ,lubridate::ymd(start_date) + hours
129 #               (8)
130 #               ,"' AND created_at <= '
131 #               ,lubridate::ymd(end_date) + hours(8),
132 #               "';")
133 # )
134 # saveRDS(pa, "../data/frm/purpleAir5min.RDS")
135 # pa <- readRDS("../data/frm/purpleAir5min.RDS")
136
137 # hourly group by with sql


---


138 pa <- st_read(dsn = con
139               #,geom_column = "geom" # depreceated!
140               #,EWKB = TRUE
141               #,query = paste0("SELECT date(a.created_at), date_part('
142               hour', a.created_at) as hour, a.id, a.sensor, a.label, avg(a.pm2_5
143               _atm) pm2_5_atm, a.geom
144               FROM (SELECT DISTINCT * FROM pdx WHERE
145               created_at >= '
146               ,lubridate::ymd(start_date) + hours(8)
147               ,"' AND created_at <= '
148               ,lubridate::ymd(end_date) + hours(8), "
149               ' ) a
150               GROUP BY a.id, a.sensor, a.label, a.
151               geom, date(a.created_at), date_part('hour', a.created_at);")
152 )

```

```

146 pa$created_at <- paste(pa$date, pa$hour)
147 pa$created_at <- ymd_h(pa$created_at)
148 pa$created_at <- pa$created_at - hours(8)
149 pa %>% dplyr::select(created_at, everything(), -c(date, hour))
150 names(pa)[names(pa) == "created_at"] <- "datetime"
151
152 # 15 minute average PurpleAir


---


153 # hourly group by with sql
154 pa <- st_read(dsn = con
155               #,geom_column = "geom" # deprecated!
156               #,EWKB = TRUE
157               ,query = paste0("SELECT date_trunc('hour', a.created_at
158                               ) + date_part('minute', a.created_at)::int / 15 * interval '15 min
159                               ' AS created_at
160                               ,a.id, a.sensor, a.label, avg(a.pm2_5_
161                               atm) pm2_5_atm, a.geom
162                               FROM (SELECT DISTINCT * FROM pdx WHERE
163                               created_at >= '
164                               ,lubridate::ymd(start_date) + hours(8)
165                               ,"' AND created_at <= '
166                               ,lubridate::ymd(end_date) + hours(8), "
167                               ') a
168                               GROUP BY a.id, a.sensor, a.label, a.
169                               geom
170                               ,date_trunc('hour', a.created_at) +
171                               date_part('minute', a.created_at)::int / 15 * interval '15 min';")
172 )
173
174 ##### pa$created_at <- paste(pa$date, pa$hour, pa$fifteen)
175 pa$created_at <- ymd_hms(pa$created_at)
176 pa$created_at <- pa$created_at - hours(8)
177 pa %>% dplyr::select(created_at, everything())
178 # make sure the datetime columns match
179 names(pa)[names(pa) == "created_at"] <- "datetime"
180
181 # End 15-minute read PA


---


182
183 # lookup table for sensor geom
184 pa_points <- st_read(dsn = con
185                      #,geom_column = "geom"
186                      #,EWKB = TRUE
187                      #,query = "SELECT DISTINCT * FROM pdx_local_
188                      slope;"
189                      #,query = "SELECT DISTINCT * FROM pdx;"
190                      # compare PurpleAir to DEQ during regional PM
191                      event (wildfire)

```

```

183         ,query = "SELECT DISTINCT id , label , geom FROM
184         pdx GROUP BY id , label , geom;"
185     )
186     # define projection
187     st_crs(pa) <- epsg_26910
188     # st_crs(pa_hourly) <- epsg_26910
189     st_crs(pa_points) <- epsg_26910
190
191     # Relative standard deviation calc


---


192     # Reading in 5-minute neph data
193     # neph <- readRDS("./data/deq/neph5min.RDS")
194     frm <- readRDS("./data/deq/neph5min.RDS")
195     # frm <- readRDS("./data/deq/neph1hour.RDS")
196
197     rsd <- function(sd , mean) {
198         sd/mean
199     }
200
201     # 15-minute only 

---


202     # Group by 15-minute clean breaks!
203     frm$datetime <- floor_date(frm$datetime , "15minutes")
204
205     frm %>% dplyr::select(-date) %>% st_drop_geometry() %>%
206     group_by(datetime , site_id) %>% summarise(pm2_5_ref = mean(pm2_5_
207         ref))
208
209     # 15-minute only 

---


210     # aggregate by 15 minutes (or 1 hour)
211     frm_mean <- frm %>% group_by(datetime) %>% summarise(pm2_5_mean =
212         mean(pm2_5_ref)
213         ,n_mean = n()
214         ,pm2_5_rsd = rsd
215         (sd(pm2_5_ref) , mean(pm2_5_ref)))
216
217     # Reduce minimum sites to 4 (2017 data missing 1 site ?Cully)
218     rsd_threshold <- 0.10
219     # n_min <- 4 # 1-hour
220     n_min <- 5 # 15-min
221     time_res <- "15-min"
222
223     # For 1-hour data
224     # frm_mean %>% filter(pm2_5_rsd <= 0.10) %>% filter(n_mean >= n_min &
225         n_mean <= 6) %>% st_drop_geometry() %>% nrow()
226     # frm_mean %>% filter(pm2_5_rsd <= 0.05) %>% filter(n_mean >= n_min
227         & n_mean <= 6) %>% st_drop_geometry()

```

```

223
224 # For 15-minute data
225 frm_mean %>% filter(pm2_5_rsd <= rsd_threshold) %>% filter(n_mean >=
      n_min & n_mean <= 6) %>% st_drop_geometry() %>% nrow()
226 frm_mean %>% filter(pm2_5_rsd <= rsd_threshold) %>% filter(n_mean >=
      n_min & n_mean <= 6) %>% st_drop_geometry()
227
228
229 # Calc percent difference


---


230 # frm %>% inner_join(frm_mean)
231 # summary(frm)
232 #
233 # # DEQ 24-h datetime is introducing duplicates around midnight?
234 # frm$hour <- hour(frm$datetime)
235 # frm %>% filter(hour != 0)
236 # frm %>% filter(n_mean >=4 & n_mean <=6)
237 #
238 # # percent difference function
239 # pct_diff <- function(v1, v2) {
240 #   abs(v1-v2)/((v1+v2)/2)
241 # }
242 #
243 # # Find hours with low variation among 5-6 nephelometers
244 # frm$pct_diff <- pct_diff(frm$pm2_5_ref, frm$pm2_5_mean)
245 #
246 # frm_homo <- frm %>% filter(pct_diff <= 0.10) %>% arrange(datetime)
247 #
248 # # Join mean pct diff with mean pm by datetime
249 # frm_mean_homo <- frm_homo %>% group_by(datetime) %>%
250 #   summarise(pct_diff_mean = mean(pct_diff), n_pct = n()) %>% filter
      (n_pct >= 5) %>% left_join(frm_mean)
251 #
252 # # Join mean pct diff with mean pm by datetime and by site id!
253 # frm_site_homo <- frm_homo %>% group_by(datetime) %>%
254 #   summarise(pct_diff_mean = mean(pct_diff), n_pct = n()) %>% filter
      (n_pct >= 5) %>% left_join(frm)
255 #
256 # frm %>% st_as_sf(coords = c("lon","lat"), crs = wgs_84)
257 # frm <- frm_mean_homo # mean % difference of mean
258 frm <- frm_mean # RSD
259
260 # Join DEQ with PA


---


261 # matching the sel file with the 5stn id

```



```

262 # frm$site_id <- ifelse(frm$site_id == "PM2_5L_Est", "Portland SE
    Lafayette", frm$site_id)
263 str(frm)
264 str(pa)
265 # str(pa_hourly)
266
267 # check the time zone of pa data
268 attr(pa$datetime, "tzone")
269 # attr(pa_hourly$datetime, "tzone")
270 attr(frm$datetime, "tzone")
271
272 # Convert DEQ data to UTC!
273 # frm$datetime <- with_tz(frm$datetime, tzone = "UTC")
274 # attr(frm$datetime, "tzone")
275
276 # DEQ datetime isn't in US/Pacific, it's UTC-8 (they don't observe
    DST)
277 # Convert tz without changing datetime
278 # pa$datetime <- force_tz(pa$datetime, "US/Pacific")
279 # pa$datetime <- force_tz(pa$datetime, "GMT")
280 attr(pa$datetime, "tzone")
281
282 # pa_hourly$datetime <- force_tz(pa_hourly$datetime, "US/Pacific")
283 # attr(pa_hourly$datetime, "tzone")
284
285
286 # Join mean neph data with PA


---


287 df <- inner_join(pa, frm)
288 # df <- inner_join(pa_hourly, frm)
289 df$year <- lubridate::year(df$datetime)
290 df$month <- lubridate::month(df$datetime, label = TRUE)
291
292 # Exclude outliers in PurpleAir and Neph
293 df %>% filter(pm2_5_atm <= max_pm_range) # global variable stored in
    init.R
294 saveRDS(df, paste0("./data/homogenousPM/df_", time_res, ".RDS"))
295
296 # Loop through each sensor and run regression
297 sensors <- unique(df$id) # use id here instead of label b/c it has
    duplicates (e.g. Miller)
298 system("rm ./figures/pa_neph_cal/*/*.png")
299
300 r_squared_threshold <- 0.90
301 n_obs_threshold <- 50
302
303 lm_results <- Reduce(rbind, pblapply(sensors, function(n) {
304

```

```

305 # Select specific node
306 df_sensor <- filter(df, id %in% n)
307 label <- df_sensor$label[1] %>% gsub(pattern = "\\s|\\./|\\.\\.",
    replacement = "_") %>% tolower()
308
309 # Run models -----
310 mod <- lm(pm2_5_mean~pm2_5_atm, df_sensor)
311 summary_lm <- broom::glance(mod)
312 summary_lm$slope <- mod$coef[[2]]
313 summary_lm$intercept <- mod$coef[[1]]
314 # summary_lm$model_type <- "lm"
315 summary_lm$n_obs <- nrow(df_sensor)
316 summary_lm$id <- n
317
318 # Visualize CV -----
319 try({
320
321   if(summary_lm$r.squared >= r_squared_threshold & summary_lm$n_obs
    >= n_obs_threshold) {
322     nephRegression(df = df_sensor, y = "pm2_5_mean", x = "pm2_5_atm"
    ", outdir = "./figures/pa_neph_cal/pass/"
    ,clean_time = paste0("lm_", label), reduced = F)
323   } else {
324     nephRegression(df = df_sensor, y = "pm2_5_mean", x = "pm2_5_atm"
    ", outdir = "./figures/pa_neph_cal/fail/"
    ,clean_time = paste0("lm_", label), reduced = F)
325   }
326 }
327 })
328
329 return(summary_lm)
330 }
331 #,cl=detectCores()-1
332 )
333 )
334
335 saveRDS(lm_results, paste0("./data/homogenousPM/lm_results_", time_
    res, ".RDS"))
336 system(paste0("zip -r ./figures/lm_rsd10_", time_res, ".zip ./figures
    /pa_neph_cal"))
337
338 # see ./src/compareCF.R for 15-min vs. 1-hour comparison
339
340 lm_df <- lm_results %>% filter(r.squared >= r_squared_threshold) %>%
    filter(n_obs >= n_obs_threshold)
341
342 r2_violin <- ggplot(lm_results, aes(x = id, y = r.squared)) +
    geom_violin(fill = "cornflowerblue") +

```

```

346   geom_hline(yintercept = r_squared_threshold, color = "firebrick",
347             linetype = 2) +
348   ylab(expression(R^2))+
349   # ggtitle(paste0(expression(Distribution of R^2), " (Nephelometer~
350     PurpleAir)")) +
351   ggtitle(bquote('Distribution of '~R^2~'(Nephelometer~PurpleAir) '~.(
352     time_res))) +
353   theme_bw() +
354   theme(axis.title.x = element_blank(), axis.text.x = element_blank(),
355         , axis.ticks.x = element_blank())
356
357 r2_violin
358
359 png(filename = paste0("./figures/pa_neph_violins/r2_", time_res, ".
360   png")
361   ,width = 8
362   ,height = 6
363   ,units = "in"
364   ,res = 300
365   )
366 r2_violin
367 dev.off()
368
369 slope_violin <- ggplot(lm_df, aes(x = id, y = slope)) +
370   geom_violin(fill = "forestgreen") +
371   ylab(expression(beta)) +
372   ggtitle(paste0("Distribution of Slopes (Nephelometer~PurpleAir) ",
373     time_res)) +
374   theme_bw() +
375   theme(axis.title.x = element_blank(), axis.text.x = element_blank(),
376         , axis.ticks.x = element_blank())
377
378 slope_violin
379
380 png(filename = paste0("./figures/pa_neph_violins/slope_", time_res, ".
381   png")
382   ,width = 8
383   ,height = 6
384   ,units = "in"
385   ,res = 300
386   )
387 slope_violin
388 dev.off()
389
390 # I'm scrapping this idea for now. Might revisit 15-minute CF later
391   if needed...
392 # Salvage any "failed" sensors by hand
393 # id_pass <- c()

```

```

385
386 # Connect CF to each PurpleAir and upload to DB
387
388 # Checkpoint our homogenous PM results for our CF script
389 saveRDS(lm_df, "./data/cf/homogenous_pm_cf.RDS")
390
391 # Apply best method from EDA to pdx_cf
392 # Do this after storing data in DB (store even bad sensors CF for now
393   ...)
394 # pdx_cf %>%
395 #   group_by(id, label) %>%
396 #   slice(which.max(r.squared)) %>%
397 #   filter(r.squared >= 0.80) %>% arrange(label)
398
399 # Append geometry and convert to simplefeatures
400 pdx_cf <- inner_join(lm_df, pa_points) %>% st_as_sf()
401
402 # Prepare colnames for postgres (remove periods)
403 names(pdx_cf) <- gsub(x = names(pdx_cf), pattern = "\\.", "_") %>%
404   tolower()
405 # names(pdx_cf)[names(pdx_cf) == "id"] <- "label"
406
407 # HIMS Roof was returning Inf and NaN
408 pdx_cf %>% na.omit()
409
410 saveRDS(pdx_cf, "./data/cf/pdx_cf.RDS")
411
412 # open connection to our db
413 con <- dbConnect(drv = RPostgres::Postgres()
414   ,dbname = db
415   ,host = 'pgsql102.rc.pdx.edu' # not sure why object
416     host isn't working...
417   ,port = port
418   ,password = pw
419   ,user = user)
420
421 # Find a better way to do this... append = TRUE is not ideal, but
422   append = FALSE and overwrite = TRUE converts numeric to real
423   datatype!?!
424
425 # Write to db as lookup table
426
427 # clear table before writing new data
428 res <- dbSendQuery(con, statement = "delete from pdx_cf;")
429 dbClearResult(res)
430 res <- dbSendQuery(con, statement = "vacuum full pdx_cf;")
431 dbClearResult(res)
432

```

```

427 # Write the new CF data to the pdx_cf table in canopycontinuum
428 st_write(obj = pdx_cf
429         ,dsn = con
430         ,layer_options = "OVERWRITE=true"
431         ,drop_table = FALSE
432         ,try_drop = FALSE
433         ,debug = TRUE
434         ,append = TRUE
435         ,overwrite = FALSE
436         ,dataset_options = "GEOMETRY=AS_WKT"
437 )
438
439 # TODO create new pdx_cf table with appropriate attribute names!
440 # cf <- st_read(dsn = con
441 #             #,geom_column = "geom"
442 #             #,EWKB = TRUE
443 #             #,query = "SELECT DISTINCT * FROM pdx_local_slope;"
444 #             #,query = "SELECT DISTINCT * FROM pdx;"
445 #             # compare PurpleAir to DEQ during regional PM event (
446 #                 wildfire)
447 #             ,query = "SELECT * FROM pdx_cf;"
448 # )
449 # INSERT FLAG DATA SCRIPT HERE

```

```

450 # added to processPurpleAir in aod_modeling instead...
451 # pdx_flag <- st_read(dsn = con
452 #                   ,geom_column = "geom"
453 #                   ,query = "SELECT DISTINCT * FROM pdx_flag;")
454 #

```

Source/init.R

```

1 library(raster)
2 library(pbapply)
3 source("../src/functions.R")
4
5 # Global Variable definition

```

```

6 # Oregon North NAD83 Meters UTM Zone 10
7 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
8             +no_defs "
9 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
10 # Portland Study Area

```

```

11 study_area <- "./study_area/study_area.RDS"
12 bb <- "./study_area/bb.RDS"
13
14 # Study start and end date
15 start_date = "2017-09-01"
16 # end_date = "2018-09-30" # note, download/processGridMET must be re-
    ran if more recent end date is required!
17 # end_date = "2019-05-29"
18 end_date = "2019-03-31" # GridMet and PBL limited to ~April
19
20 crs = epsg_26910
21 study_area = "./study_area/study_area.RDS"
22 pm_df = "./data/purpleair/pm_df_24h.RDS"
23
24 # for testing functions
25 date <- "2017.10.10"
26
27 # Minimum Spatial Resolution for all variables
28 sp_res <- 50 # meters
29
30 # Max PM range (used for portlandCF.R, and processPurpleAir.R)
31 max_pm_range <- 250
32
33 # Use nephelometer data as a scaling factor for PurpleAir network?
34 scale_neph = F
35
36 # Set tmpdir for raster data
37 setRasterTempDir()
38
39 # Raster black white color palette
40 bw <- colorRampPalette(c('white', 'black'))(50)
41
42 # Print progressbar to CL
43 pbo = pboptions(type="timer")

```

Source/interpolateNDVI.R

```

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7 p_load(rgdal
8       , raster
9       , sp
10      , rgeos
11      , pbapply

```

```

12     #,rasterVis
13     ,zoo
14     ,magrittr
15     ,parallel
16     #,greenbrown # sourceforge repo
17 )
18
19
20 # library(raster); library(rasterVis); library(zoo)
21 # r1 = raster(matrix(c(NA, rep(1,8)), 3, 3))
22 # r2 = raster(matrix(c(NA, rep(2,8)), 3, 3))
23 # r3 = raster(matrix(c(NA, rep(3,8)), 3, 3))
24 # b1 = brick(list(r1,r2,r3))
25 # levelplot(b1)
26 #
27 # # fill in empty time steps
28 # b2 = brick(lapply(1:9, function(x) raster(matrix(NA, 3, 3))))
29 #
30 # old.layers = c(1,4,7)
31 # for (i in 1:nlayers(b1)) {
32 #   b2[[old.layers[i]]] = b1[[i]]
33 # }
34 # levelplot(b2, layout=c(9,1))
35 #
36 # for (cell in 1:ncell(b2)) {
37 #   if (all(is.na(as.vector(b2[cell])))) {
38 #     # na.spline wil fail if all are NA
39 #     new.values = as.numeric(rep(NA, dim(b2)[3]))
40 #   } else {
41 #     new.values = na.spline(as.vector(b2[cell]), na.rm = F)
42 #   }
43 #   b2[cell][] = new.values
44 # }
45 # levelplot(b2, layout=c(9,1))
46
47 ndvi <- stack(list.files(path = "./output/ndvi/", pattern = ".tif$",
48   full.names = T))
49 #levelplot(ndvi)
50
51 evi <- stack(list.files(path = "./output/evi/", pattern = ".tif$",
52   full.names = T))
53 #levelplot(evi)
54
55 # Graphically assess layers with cloud interference
56 # cloud_days <-
57   "2017.08.29|2017.11.01|2018.01.17|2018.02.18|2018.03.22"
58
59 # Filter out bad Landsat scenes

```

```

57 # ndvi <- subset(ndvi, grep(cloud_days, names(ndvi), value = T,
    invert=T))
58 # evi <- subset(evi, grep(cloud_days, names(evi), value = T, invert=T
    ))
59 # ndvi <- subset(ndvi, grep("2017.09.14|2017.09.30", names(ndvi),
    value = T, invert=F))
60
61 getDates <- function(stack) {
62   names <- names(stack)
63   dates <- gsub("^.*?\\.", "", names)
64   dates <- gsub("\\.", "-", dates) %>% as.Date()
65   return(dates)
66 }
67
68 getVars <- function(stack) {
69   names <- names(stack)
70   # extract variable name (characters before date)
71   vars <- gsub("\\..*$", "", names)
72   return(vars)
73 }
74
75 interpolateNDVI <- function(stack) {
76
77   # 16 day observations
78   bi_month <- getDates(stack)
79   vars <- getVars(stack)
80
81   # generate daily sequence
82   dates <- seq.Date(from = min(bi_month), to = max(bi_month), by = "
    day")
83   dates <- gsub("-", "\\.", dates)
84   daily_names <- paste0(vars, ".", dates)
85
86   # create empty rasters for missing days
87   daily_stack <- pblapply(dates, function(x) {
88     raster(
89       matrix(NA, nrow(stack), ncol(stack))
90       , crs = crs(stack)
91       #nrows = nrow(stack)
92       #ncols = ncol(stack)
93       #ext = extent(stack)
94       #values = 0
95       # ,xmin = xmin(stack)
96       # ,ymin = ymin(stack)
97       # ,xmax = xmax(stack)
98       # ,ymax = ymax(stack)
99     )
100     #values(r) <- NA

```



```

101   }
102   #,cl = detectCores()-1
103   )
104
105   s <- stack(daily_stack)
106   extent(s) <- extent(stack)
107   values(s) <- NA
108   names(s) <- daily_names
109
110   # fill in 16 day observations
111   daily_stack <- pblapply(names(s), function(x) {
112     if(x %in% names(stack) & x %in% names(s)) {
113       s[[x]] <- stack[[x]]
114     } else {
115       s[[x]]
116     }
117   })
118   #,cl = detectCores()-1
119   )
120
121   s <- stack(daily_stack)
122
123   # this works, but isn't parallel
124   # for (cell in 1:ncell(s)) {
125   #   if (all(is.na(as.vector(s[cell])))) {
126   #     new.values = as.numeric(rep(NA, dim(s)[3]))
127   #   } else {
128   #     new.values = na.spline(as.vector(s[cell]), na.rm = F)
129   #   }
130   #   s[cell][] = new.values
131   # }
132
133   # parallel version of above for loop (this takes 2 hours on hecate!
134   )
135   # daily_stack <- pblapply(1:ncell(s), function(cell) {
136   #   if (all(is.na(as.vector(s[cell])))) {
137   #     new_values <- as.numeric(rep(NA, dim(s)[3]))
138   #   } else {
139   #     new_values <- na.spline(as.vector(s[cell]), na.rm = F)
140   #   }
141   #   s[cell][] <- new_values
142   # }, cl = detectCores()-1)
143
144   # using raster calc is much faster but I don't understand what's
145   # happening at all!
146   # create empty vector for cell-wise raster processing
147   layers <- nlayers(s)
148   empty_layer <- rep(NA, layers)

```

```

147
148 # get the layer index of the 16-day observations
149 s_index <- names(s) %in% names(stack) %>% which()
150
151 # define our raster calc interpolation
152 rasterSpline <- function(x) {
153   # don't interpolate global NA cells
154   if(all(is.na(x))) {
155     empty_layer
156   }
157
158   # polynomial fitting daily raster cell to 16-day obs
159   else {
160     na.spline((empty_layer[c(s_index)] <- x), xout = 1:layers, na.rm = F)
161   }
162 }
163
164 # perform cell-level temporal interpolation on stack
165 # raster::beginCluster(n = detectCores() - 1)
166 s <- raster::calc(s, rasterSpline)
167 names(s) <- daily_names
168
169 # raster::endCluster()
170 writeRaster(s, file.path('./data', unique(vars), paste0(names(s), ".tif")))
171
172                                     ,overwrite=T
173                                     ,bylayer=T
174                                     ,format="GTiff")
175 }
176
177
178 interpolateNDVI(ndvi)
179 interpolateNDVI(evi)
180
181 ##
182
183 # ndvi2 <- stack(list.files("./data/ndvi", full.names = T))
184 # ndvi2 <- readRDS("./data/ndvi_daily_composite.RDS")
185 # names(ndvi2)
186 # plot(ndvi2)
187 # evi2 <- stack(list.files("./data/evi", full.names = T))
188 # evi2 <- readRDS("./data/evi_daily_composite.RDS")
189 # names(evi2)
190 # test <- evi2[[17:32]]
191 # plot(test)
192 #

```

```

193 # lapply(1:nlayers(ndvi), function(x) {
194 #   plot(ndvi[[x]], main = paste(names(ndvi)[[x]]))
195 #   Sys.sleep(0.3)
196 # })
197 #
198 # lapply(1:nlayers(ndvi2), function(x) {
199 #   plot(ndvi2[[x]], main = paste(names(ndvi2)[[x]]))
200 #   Sys.sleep(0.3)
201 # })
202 #
203 #
204 # lapply(1:nlayers(evi), function(x) {
205 #   plot(evi[[x]], main = paste(names(evi)[[x]]))
206 #   Sys.sleep(0.5)
207 # })
208 #
209 # lapply(1:nlayers(evi2), function(x) {
210 #   plot(evi2[[x]], main = paste(names(evi2)[[x]]))
211 #   Sys.sleep(0.5)
212 # })

```

Source/interpolateNeph.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-27
5 # IDW interpolation of DEQ nephelometer data
6
7 # load the necessary packages
8 if (!require(pacman)) {
9   install.packages("pacman")
10  library(pacman)
11 }
12
13 p_load(rgdal
14        ,plyr
15        ,dplyr
16        ,magrittr
17        ,gdalUtils
18        ,raster
19        ,rasterVis
20        ,sp
21        ,sf
22        ,rgeos
23        ,leaflet
24        ,lubridate
25        #,MODIS

```

```

26     #,bowerbird
27     ,gstat
28     ,parallel
29     ,snow
30     ,pbapply
31     ,ggplot2
32     ,rts
33     ,tidyr
34     ,RPostgres
35     ,ggmap
36     ,gridExtra
37     ,rlang)
38
39 source("./src/init.R")
40 source("./src/functions.R")
41
42 # set timezone to UTC/GMT to match postgres
43 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
44 #   PDT!
45 # DEQ only uses PST!
46 Sys.timezone()
47 Sys.setenv(TZ="GMT")
48 Sys.timezone()
49
50 # Read in data
51
52
53 # Create spatial interpolation functions
54
55 # call gstat on each PM variable
56 apply_gstat <- function(col_name, pm_data, study_area, day, outdir) {
57   pm_df <- dplyr::filter(pm_data, date >= day & date <= day) %>%
58     dplyr::select(date, col_name, geometry) %>% na.omit()
59   pm_df %>% as("Spatial")
60   pm_df %>% spTransform(CRSobj = crs(study_area))
61   gs <- gstat(formula = as.formula(paste(col_name, "~1")),
62               locations = pm_df)
63   r <- raster(study_area, crs = crs, res = sp_res, vals = 0)
64   idw <- raster::interpolate(r, gs)
65   idwr <- mask(idw, study_area)
66   layer_name <- paste0(col_name, ".", gsub("-", "\\.", day))
67   names(idwr) <- layer_name
68   #plot(idwr)

```

```

69   writeRaster(idwr, paste0(outdir, "/", layer_name, ".tif"), format =
    "GTiff", overwrite = T)
70
71 }
72
73
74 # Determine mean daily PM from the entire network (one value for all
    cells each day like PBL)
75 neph_mean <- function(col_name, pm_data, study_area, day, outdir) {
76   pm_df <- dplyr::filter(pm_data, date >= day & date <= day) %>%
77     dplyr::select(date, col_name, geometry) %>% na.omit() %>%
78     st_drop_geometry()
79   #pm_df %>% as("Spatial")
80   #pm_df %>% spTransform(CRSobj = crs(study_area))
81   daily_mean <- dplyr::summarise(pm_df, mean = mean(eval(parse(text =
    (col_name)))), na.rm = T))
82   r <- raster(study_area, crs = crs, res = sp_res, vals = daily_mean
    [[1]])
83   layer_name <- paste0(col_name, ".", gsub("-", "\\.", day))
84   names(r) <- layer_name
85   #plot(r)
86   writeRaster(r, paste0(outdir, "/", layer_name, ".tif"), format = "
    GTiff", overwrite = T)
87
88 }
89
90 # Call our ground-station nephelometer interpolation across each day
    (function wrapper)
91 interpolate_neph <- function(pm_data, day, vars, study_area, outdir)
    {
92
93   pblapply(vars, function(x) {
94
95     # IDW Interpolation
96     # apply_gstat(pm_data = pm_data
97     #             ,day = day
98     #             ,study_area = study_area
99     #             ,col_name = x
100    #             ,outdir = outdir)
101
102     # Daily Mean Nephelometer
103     neph_mean(pm_data = pm_data
104               ,day = day
105               ,study_area = study_area
106               ,col_name = x
107               ,outdir = outdir)
108     #,cl = detectCores()-1
109   })

```

```

110 }
111
112 # apply interpolation across each variable (fix start and end date
      later...)
113 # create date sequence
114 days <- seq.Date(as.Date(start_date), as.Date(end_date), by="days")
      %>% as.character()
115 # create list of variables (only one in this case.. but kept dynamci
      for future PM data?)
116 vars <- c("pm2.5.mean", "pm2.5.min", "pm2.5.max", "pm2.5.sd", "pm2.5.
      median")
117
118 # Running the interpolation function


---


119 pblapply(days, function(x) {
120   interpolate_neph(pm_data = neph
121                   ,day = x
122                   ,vars = vars
123                   ,outdir = "../data/neph"
124                   ,study_area = study_area)
125 }
126 ,cl = detectCores()-1
127 )
128
129 # Checking to see if it worked
130 # Create RDS stacks
131 r <- raster::stack(list.files("../data/neph/", "pm2.5.", full.names =
      T))
132
133 levelplot(r[[1:16]])
134 ugb <- readOGR("../shapefiles/ugb.shp") %>% spTransform(CRSobj = crs(r
      ))
135 plot(r[[1]])
136 plot(ugb, add = T)
137
138 # lapply(1:nlayers(r), function(x) {
139 #   plot(r[[x]], main = paste(names(r[[x]]))
140 #   ,breaks = c(5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70,
      80, 90)
141 #   ,col = terrain.colors(14))
142 #   plot(ugb, add = T)
143 #   Sys.sleep(0.5)
144 # })
145 #
146 # plot(r[["pm2.5.max.2018.07.04"]], col = terrain.colors(10), main =
      "2018-07-04 Max PM2.5")
147 # plot(ugb, add = T)

```

```

148 # plot(r[["pm2.5.mean.2018.07.04"]], col = terrain.colors(10), main =
    "2018-07-04 Mean PM2.5")
149 # plot(ugb, add = T)
150 # plot(r[["pm2.5.max.2018.01.16"]], col = terrain.colors(10))
151 # plot(ugb, add = T)

```

Source/purpleairQAQC.R

```

1 #!/usr/bin/env Rscript
2 args = commandArgs(trailingOnly=TRUE)
3
4 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
5 # Canopy Continuum Project, USFS
6 # PI Dr. Linda George
7 # 2019-01-10
8 # Identify outliers and flag faulty PurpleAir sensors
9
10
11 # set up environment


---


12
13 # test if there is at least one argument: if not, return an error
14 if (length(args)==0) {
15   purge_arg <- F
16   print("Setting db purge to F")
17 } else if (length(args)==1) {
18   purge_arg <- args[1]
19   print(paste0("Applying db purge argument: ", args[1]))
20 }
21
22 # load the necessary packages
23 if (!require(pacman)) {
24   install.packages("pacman")
25   library(pacman)
26 }
27
28 p_load(plyr
29        ,dplyr
30        ,ggplot2
31        ,stringr
32        ,magrittr
33        ,scales
34        ,lubridate
35        ,tidyr
36        ,sp
37        ,sf
38        ,rgdal
39        ,pbapply

```

```

40         ,parallel
41         ,RPostgres
42     )
43
44     # source("../aod_pm_modeling/src/init.R")
45     source("../src/functions.R")
46     source("../src/init.R")
47     # define global variables

```

```

48
49     # set timezone to UTC/GMT to match postgres
50     # otherwise, st_read() will convert timestamp to US/Pacific with PST/
51     #   PDT!
52     # DEQ only uses PST!
53     Sys.timezone()
54     Sys.setenv(TZ="GMT")
55     Sys.timezone()
56
57     ## connecting to local db
58     host <- 'pgsql120.rc.pdx.edu'
59     db <- 'canopycontinuum'
60     user <- 'porlando'
61     port <- 5433
62     pw <- scan("../batteries.pgpass", what = "") # in parent dir
63
64     # open connection to our db
65     con <- dbConnect(drv = RPostgres::Postgres()
66                     ,dbname = db
67                     ,host = 'pgsql102.rc.pdx.edu' # not sure why object
68                       host isn't working...
69                     ,port = port
70                     ,password = pw
71                     ,user = user)
72
73     # create unanimous time resolution for all data
74     time_resolution <- "1 sec"
75
76     # time zone applied to all data
77     time_zone <- "GMT"
78
79     # CRS
80     wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
81
82
83     # Albuquerque, NM, UTM 13N

```



```

84 utm_13N <- "+proj=utm +zone=13 +ellps=WGS84 +datum=WGS84 +units=m +no
    _defs "
85
86 # Sacramento, CA, UTM 10S, meters
87 epsg_26911 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
88
89 # Oregon North NAD83 HARN meters
90 epsg_2838 <- "+proj=lcc +lat_1=46 +lat_2=44.33333333333334 +lat_
    0=43.666666666666666 +lon_0=-120.5 +x_0=2500000 +y_0=0 +ellps=GRS80
    +units=m +no_defs "
91
92 # Oregon North NAD83 Meters UTM Zone 10
93 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
94
95 # Function definition
    

---


96
97 # creating a custom not-in function
98 '%!in%' <- function(x,y){ '%in%'(x,y)}
99
100 set.seed(1)
101
102 # remove geometry from sf object, convert to dataframe with only the
    elements/attributes
103 st_drop_geometry <- function(x) {
104   if(inherits(x, "sf")) {
105     x <- st_set_geometry(x, NULL)
106     class(x) <- 'data.frame'
107   }
108   return(x)
109 }
110
111
112 # data processing
    

---


113
114
115 # this should work once I update my pdx table
116 # pa <- st_read(dsn = con
117 #               ,geom_column = "geom"
118 #               ,EWKB = TRUE
119 #               ,query = "SELECT DISTINCT * FROM pdx_local_slope;"
120 #               ,query = "SELECT DISTINCT * FROM pdx;"
121 #               # compare PurpleAir to DEQ during regional PM event (
    wildfire)

```

```

122 #           ,query = paste0("SELECT DISTINCT * FROM pdx WHERE
      created_at >= '", start_date, "' AND created_at <= '", end_date,
      " '");
123 # )
124
125
126
127 # lookup table for sensor geom
128 pa_points <- st_read(dsn = con
129                      # ,geom_column = "geom"
130                      ,EWKB = TRUE
131                      # ,query = "SELECT DISTINCT * FROM pdx_local_
      slope;")
132                      # ,query = "SELECT DISTINCT * FROM pdx;"
133                      # compare PurpleAir to DEQ during regional PM
      event (wildfire)
134                      ,query = "SELECT DISTINCT id, label, geom FROM
      pdx GROUP BY id, label, geom;"
135 )
136
137 dbDisconnect(con)
138
139 # define projection
140 # st_crs(pa) <- epsg_26910
141 st_crs(pa_points) <- epsg_26910
142
143 # convert from UTC to UTC-8 or PST (same as DEQ)
144 # df$created_at <- lubridate::ymd_hms(df$created_at) - hours(8)
145
146 # make sure the datetime columns match
147 # names(pa)[names(pa) == "created_at"] <- "datetime"
148 # str(pa)
149
150 # check the time zone of pa data
151 # attr(df$datetime, "tzone")
152
153 # Flag data from faulty sensors


---


154 # pa_flag <- pa %>% dplyr::select(datetime, id, label, pm2_5_atm,
      geom)
155 # pa_flag$date <- as.Date(pa_flag$datetime)
156 # node_labels <- unique(gsub(" B$", "", pa_flag$label))
157 # head(pa_flag)
158 points <- unique(pa_points$geom)
159 # pa_df <- pa_flag
160 geom_id <- "POINT (512339.5 5042418)" # STAR LAB BEIHANY (no comma)
161 start_date <- "2017-07-01"
162 end_date <- as.character(Sys.Date() - 1) # in UTC timezone ...

```

```

163 # geoms <- unique(as.character(pa_flag$geom))
164 geoms <- unique(st_as_text(pa_points$geom))
165 # geoms <- rev(geoms)
166 # geom_id <- geoms[5]
167
168 flag_purpleair <- function(geom_id, day
169                             ,host = host
170                             ,db = db
171                             ,user = user
172                             ,port = port
173                             ,pw = pw) {
174
175   # connect to db
176   con <- dbConnect(drv = RPostgres::Postgres()
177                     ,dbname = db
178                     ,host = 'pgsql102.rc.pdx.edu'
179                     ,port = port
180                     ,password = pw
181                     ,user = user)
182
183   # check to see if flag exists for node/day
184   flag_check <- st_read(dsn = con
185                         # ,EWKB = T
186                         ,query = paste0("SELECT DISTINCT * FROM pdx_
187
188                                     ,lubridate::ymd(day)
189                                     ,"" AND geom = ST_SETSRID('"
190                                     geom_id , " '::geometry, ST_SRID(geom));"
191                                     ))
192
193   # skip node/day flag re-write to db
194   if(nrow(flag_check) == 0) {
195
196     # pull day's data for specific node
197     node <- st_read(dsn = con
198                     # ,EWKB = T
199                     ,query = paste0("SELECT DISTINCT * FROM pdx WHERE
200
201                                     ,lubridate::ymd(day) + hours(8) ,
202                                     "" AND created_at < '" # put dates in terms of local tz , instead
203                                     of UTC
204                                     ,lubridate::ymd(day) + hours(8) +
205                                     days(1)
206                                     #,"2018-09-01"
207                                     # ,""';"
208                                     ,"" AND geom = ST_SETSRID('"
209                                     geom_id , " '::geometry, ST_SRID(geom));"

```

```

204         ))
205
206
207
208     # make sure there's enough data for this day and sensor...
209     if(nrow(node) > 0) {
210
211         # Remove B from label name
212         node$node <- gsub(" B$", "", node$label)
213         node$created_at <- lubridate::ymd_hms(node$created_at) -
214         lubridate::hours(8)
215         node$date <- as.Date(node$created_at)
216
217         st_crs(node) <- epsg_26910
218         # Extract each day's observations from network
219         # df <- dplyr::filter(pa_df, date == as.Date(day)) %>% as.data.
220         frame()
221         # df$geom <- as.character(df$geom)
222
223         # Grab corresponding node_id
224         # node_geom <- dplyr::filter(df, st_as_text(geom) == geom_id)
225         %>%
226         # dplyr::select(node) %>% unique()
227         # node_id <- node_geom[[1]]
228
229         # Pull day's total network data
230         df <- st_read(dsn = con
231                       ,EWKB = T
232                       ,query = paste0("SELECT DISTINCT * FROM pdx WHERE
233                                     created_at >= '"
234                                     ,lubridate::ymd(day) + hours(8) ,
235                                     "' AND created_at < '" # put dates in terms of local tz, instead
236                                     of UTC
237                                     ,lubridate::ymd(day) + hours(8) +
238                                     days(1)
239                                     ,"'";
240                                     #,"'" AND geom = ST_SETSRID('" ,
241                                     geom_id ,"'::geometry, ST_SRID(geom));"
242                                     ))
243         df$created_at <- lubridate::ymd_hms(df$created_at) - lubridate
244         ::hours(8)
245         st_crs(df) <- epsg_26910
246         # exclude specific node data from the remaining network
247         network <- df %>%
248         filter(pm2_5_atm < 500) %>%
249         filter(id %!in% unique(node$id))
250         # network <- df %>% dplyr::filter(as.character(geom) != geom_id
251         & pm2_5_atm < 500)

```

```

242
243   # Compare A & B sensor of single node
244   node_wide <- node %>%
245     # as.data.frame() %>%
246     st_drop_geometry() %>%
247     dplyr::select(created_at, label, pm2_5_atm) %>%
248     group_by_at(vars(-pm2_5_atm)) %>%
249     dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
250     spread(key = label, value = pm2_5_atm) %>% dplyr::select(-row
_id)
251
252   mod <- lm(node_wide[[2]]~node_wide[[3]])
253
254   status_a <- data.frame(date = as.Date(day), label = names(node_
wide[2]))
255   status_b <- data.frame(date = as.Date(day), label = names(node_
wide[3]))
256
257   node_id <- unique(node$node)
258   status_a$id <- node %>% filter(node == node_id & sensor == "A")
%>% dplyr::select(id) %>%
259     unique() %>% st_drop_geometry() %>% as.character()
260
261   status_b$id <- node %>% filter(node == node_id & sensor == "B")
%>% dplyr::select(id) %>%
262     unique() %>% st_drop_geometry() %>% as.character()
263
264   status_a$r2 <- summary(mod)$adj.r.squared
265   status_b$r2 <- summary(mod)$adj.r.squared
266   status_a$m <- mod$coefficients[[2]]
267   status_b$m <- mod$coefficients[[2]]
268   status_a$b <- mod$coefficients[[1]]
269   status_b$b <- mod$coefficients[[1]]
270   status_a$median <- median(node_wide[[2]], na.rm = T)
271   status_b$median <- median(node_wide[[3]], na.rm = T)
272   status_a$median_log <- median(log(node_wide[[2]]+1), na.rm=T)
273   status_b$median_log <- median(log(node_wide[[3]]+1), na.rm=T)
274
275   median_network <- median(network$pm2_5_atm, na.rm = T)
276   median_log_network <- median(log(network$pm2_5_atm+1), na.rm =
T)
277   sd_network <- sd(network$pm2_5_atm)
278   sd_log_network <- sd(log(network$pm2_5_atm+1))
279
280   # compare sd with local neighbors instead of entire network?
281   status_a$diff <- abs((status_a$median-median_network)/sd_
network)

```

```

282     status_b$diff <- abs((status_b$median-median_network)/sd_
network)
283     status_a$diff_log <- abs((status_a$median_log-median_log_
network)/sd_log_network)
284     status_b$diff_log <- abs((status_b$median_log-median_log_
network)/sd_log_network)
285     z_crit <- 1.96
286     z_log_crit <- log(z_crit)
287     # z_log_crit <- log(z_crit+1) # which is correct?
288     status_a$diff_log > z_log_crit
289     status_b$diff_log > z_log_crit
290
291     # TODO add conditional for days with low n (negative R2!!!
with roof data?)
292
293     # compare sensors to surrounding network if correlation is weak
294     if(summary(mod)$adj.r.squared < 0.85) {
295
296         # FLAGGING
297         if(status_a$diff_log > z_log_crit) {
298             status_a$flag <- 1
299         } else {
300             status_a$flag <- 0
301         }
302         if(status_b$diff_log > z_log_crit) {
303             status_b$flag <- 1
304         } else {
305             status_b$flag <- 0
306         }
307
308     } else {
309         # do not flag any sensor (strong correlation between A & B)
310         status_a$flag <- 0
311         status_b$flag <- 0
312     }
313
314     #flag local extrema despite decent R2 between A & B
315     # FLAGGING
316     # if(status_a$diff_log > z_log_crit) {
317     #     status_a$flag <- 1
318     # } else {
319     #     status_a$flag <- 0
320     # }
321     # if(status_b$diff_log > z_log_crit) {
322     #     status_b$flag <- 1
323     # } else {
324     #     status_b$flag <- 0
325     # }

```

```

326
327   # add in remaining global parameters each row
328   status <- rbind(status_a, status_b)
329   status$median_network <- median_network
330   status$median_log_network <- median_log_network
331   status$sd_network <- sd_network
332   status$sd_log_network <- sd_log_network
333   status$z_crit <- z_crit
334   status$z_log_crit <- z_log_crit
335   pdx_flag <- status
336
337   # adding the actual sfc geom back
338   # asdf <- pa_df %>% filter(id == status_a$id) %>%
339   #   dplyr::select(id, label, geom)
340
341   # attaching geom to pdx_flag
342   pdx_flag$geom <- node$geom[1]
343   pdx_flag %>% st_as_sf()
344
345   # this is seriously ugly but it works and I don't want to redo
346   # how I'm lapplying over characters...
347   # Re-attaching the sfc class geom to add to status$geom for st_
348   write()
349   # node_char <- dplyr::filter(df, as.character(geom) == geom_id
350   ) %>% dplyr::select(-geom) %>%
351   #   head(1)
352   #
353   # node_geometry <- left_join(node_char, asdf
354   ,by = c("label", "id")) %>% st_as_
355   sf()
356   #
357   # node_geom <- unique(node_geometry$geom)
358   # something still broken with plot(pdx_flag), geom may be
359   affected...
360   # pdx_flag$geom <- st_as_sfc(node_geom)
361   # pdx_flag %>% st_as_sf()
362   # st_crs(pdx_flag) <- st_crs(pa_df)
363   # return(status)
364   # upload to db instead of storing in memory?
365   # open connection to our db
366   # con <- dbConnect(drv = RPostgres::Postgres()
367   ,dbname = db
368   ,host = 'pgsql102.rc.pdx.edu'
369   ,port = port
370   ,password = pw
371   ,user = user)
372
373   st_write(dsn = con

```

```

369         ,obj = pdx_flag
370         ,geom_name = "geom"
371         ,append = T)
372     # rm(pdx_flag, df, mod, network, node)
373     # print(head(pdx_flag, 2))
374     # this prints to console like a million times, but only the two
    distinct rows are actually uploaded!
375     print(paste0("Upload for ", node$node, " on ", day, " complete"
    ))
376     gc()
377   } else {
378     print(paste0("No data for ", geom_id, " on ", day, ""))
379   }
380
381   } else {
382     print(paste0("Flag already exists in db for ", geom_id, " on ",
    day, ""))
383   }
384   dbDisconnect(con)
385 }
386
387 # I need to loop through each sensor pair when flagging
388 flag_daily_purpleair <- function(geom_id, days
389                                ,host = host, db = db, user = user,
    port = port, pw = pw
390                                ) {
391
392   pblapply(days, function(x) {
393
394     # wrap in try block to avoid errors?
395     try({
396       flag_purpleair(day = x, geom_id = geom_id, host = host, db = db
    , user = user, port = port, pw = pw)
397     })
398   }
399   #,cl = detectCores()-1 #
400   #,cl = 3 # still craches session...
401   )
402   gc()
403 }
404
405
406 flag_network <- function(geoms, start_date, end_date
407                        ,host = 'pgsql120.rc.pdx.edu'
408                        ,db = 'canopycontinuum'
409                        ,user = 'porlando'
410                        ,port = 5433
411                        ,pw = scan("./batteries.pgpass", what = ""))

```



```

412         ,purge_db = F # set T when using new/
different outlier detection algo
413     ) {
414
415     if (purge_db) {
416
417         print("Begin Database Purge...")
418         con <- dbConnect(drv = RPostgres::Postgres()
419             ,dbname = db
420             ,host = 'pgsql102.rc.pdx.edu'
421             ,port = port
422             ,password = pw
423             ,user = user)
424
425         # clear table before writing new data
426         res <- dbSendQuery(con, statement = "delete from pdx_flag;")
427         dbClearResult(res)
428         res <- dbSendQuery(con, statement = "vacuum full pdx_flag;")
429         dbClearResult(res)
430         dbDisconnect(con)
431         print("Database purge complete!")
432     }
433
434     # loop through a given node each day
435     days <- seq.Date(as.Date(start_date)
436         ,as.Date(end_date)
437         ,by = "day")
438
439     pblapply(unique(geoms), function(x) {
440
441         flag_daily_purpleair(geom_id = x
442             ,days = days
443             ,host = host
444             ,db = db
445             ,user = user
446             ,port = port
447             ,pw = pw
448             )
449
450         # cat("")
451         # cat(paste0("Uploading geom ", x, " to pdx_flag complete!"))
452         gc()
453     }
454     #,cl = 3 # 8GB per core
455     ,cl = detectCores()-1
456     )
457 }
458

```

```

459 flag_network(geoms = geoms
460               ,start_date = start_date
461               ,end_date = end_date
462               ,purge_db = purge_arg)
463
464
465 #

```

```

466
467 # # investigate individual cases
468 # asdf <- pa_flag %>%
469 #   filter(date == "2018-07-27" & label == "STAR LAB BETHANY" | date
470 #         == "2018-07-27" & label == "STAR LAB BETHANY B") %>%
471 #   st_drop_geometry() %>%
472 #   as.data.frame() %>%
473 #   dplyr::select(pm2_5_atm, label) %>%
474 #   group_by_at(vars(-pm2_5_atm)) %>%
475 #   dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
476 #   spread(key = label, value = pm2_5_atm) %>% dplyr::select(-row_id)
477 #
478 #
479 # sub <- head(pa_flag, 1000)
480 # sub %>% st_drop_geometry()
481 # sub %>%
482 #   group_by_at(vars(-pm2_5_atm)) %>%
483 #   dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
484 #   spread(key = label, value = pm2_5_atm) %>% dplyr::select(-row_id)
485
486
487 #

```

Source/purpleAirCF.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-09-17
5 # determine correction factors for Portland PurpleAir network
6
7 # set up environment

```

```

8
9 # load the necessary packages
10 if (!require(pacman)) {

```

```
11   install.packages("pacman")
12   library(pacman)
13 }
14
15 p_load(readr
16        ,readxl
17        ,xlsx
18        ,ggplot2
19        ,plyr
20        ,dplyr
21        ,multidplyr
22        ,broom
23        ,reshape2
24        ,tidyr
25        ,stringr
26        ,magrittr
27        ,rlist
28        ,grid
29        ,gridExtra
30        ,tidyquant
31        ,scales
32        ,qdapRegex
33        ,sp
34        ,sf
35        ,mapview # ***** with specific leaflet install
36        ,devtools
37        ,RColorBrewer
38        ,classInt
39        ,htmltools
40        ,scales
41        ,htmlwidgets
42        ,httr
43        ,jsonlite
44        ,rgdal
45        ,pbapply
46        ,snow
47        ,parallel
48        ,data.table
49        ,RPostgres
50        ,tsoutliers
51        ,forecast
52        ,MASS
53        ,viridis
54        ,corrplot
55        ,ngeo
56 )
57
```

```

58 # define global variables
59
60 # set timezone to UTC/GMT to match postgres
61 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
    PDT!
62 # DEQ only uses PST!
63 Sys.timezone()
64 Sys.setenv(TZ="GMT")
65 Sys.timezone()
66
67 ## connecting to local db
68 host <- 'pgsql120.rc.pdx.edu'
69 db <- 'canopycontinuum'
70 user <- 'porlando'
71 port <- 5433
72 pw <- scan("./batteries.pgpass", what = "") # in parent dir
73
74
75 # open connection to our db
76 con <- dbConnect(drv = RPostgres::Postgres()
77                  ,dbname = db
78                  ,host = 'pgsql102.rc.pdx.edu' # not sure why object
    host isn't working...
79                  ,port = port
80                  ,password = pw
81                  ,user = user)
82
83
84 # create unanimous time resolution for all data
85 time_resolution <- "1 sec"
86
87 # time zone applied to all data
88 time_zone <- "GMT"
89
90 # CRS
91 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
92
93 # Oregon North NAD83 HARN meters
94 epsg_2838 <- "+proj=lcc +lat_1=46 +lat_2=44.33333333333334 +lat_
    0=43.666666666666666 +lon_0=-120.5 +x_0=2500000 +y_0=0 +ellps=GRS80
    +units=m +no_defs "
95
96 # Oregon North NAD83 Meters UTM Zone 10
97 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
98

```

```

99 # Function definition
100
101 # creating a custom not-in function
102 '%!in%' <- function(x,y){ '%in%'(x,y)}
103
104 # plot density in ggplot
105 get_density <- function(x, y, n = 100) {
106   dens <- MASS::kde2d(x = x, y = y, n = n)
107   ix <- findInterval(x, dens$x)
108   iy <- findInterval(y, dens$y)
109   ii <- cbind(ix, iy)
110   return(dens$z[ii])
111 }
112
113 set.seed(1)
114
115 # file_path <- "../data/frm/portland_5stn_20180101_to_20180719.csv"
116 # read function for the 5-min data that Meena sent over!
117 read_frm <- function(file_path) {
118
119   # read in the raw data
120   x <- read.csv(file_path, header = TRUE, skip = 2)
121
122   # delete sub headers
123   # x <- x[-c(1:2),]
124
125   # convert date from character to POSIXct
126   x$Date...Time <- mdy_hm(x$Date...Time, tz = time_zone)
127
128   x <- x %>% na.omit()
129
130   # convert to tidy format, gather on site id
131   long <- x %>%
132     gather(id, pm2_5_atm, -c(Date...Time))
133
134   # convert characters in pm2_5 data to NA
135   long$pm2_5_atm <- as.numeric(long$pm2_5_atm)
136
137
138   # exclude NAs (No Data, Zero, DL/Computer, etc. gets converted to
139   # NA)
140   long <- long %>% na.omit()
141
142   # alter column names
143   colnames(long) <- c("datetime"
144                       , "site_id"
145                       , "pm2_5_ref")

```

```

145
146 long$site_id <- gsub("^X[0-9]+\\.\\.", "", long$site_id)
147 long$site_id <- gsub("\\.", " ", long$site_id)
148
149 long$site_id <- ifelse(long$site_id == "Portland Near Rd", "
    Tualatin Bradbury Court", long$site_id)
150
151
152 long$lat[long$site_id == "Beaverton Highland Park"] <- 45.470183
153 long$lat[long$site_id == "Hillsboro Hare Field"] <- 45.528549
154 long$lat[long$site_id == "Portland SE Lafayette"] <- 45.496635
155 long$lat[long$site_id == "Portland Cully Helensview"] <- 45.562206
156 long$lat[long$site_id == "Sauvie Island"] <- 45.768528
157 long$lat[long$site_id == "Tualatin Bradbury Court"] <- 45.399189
158
159 long$lon[long$site_id == "Beaverton Highland Park"] <- -122.816418
160 long$lon[long$site_id == "Hillsboro Hare Field"] <- -122.972423
161 long$lon[long$site_id == "Portland SE Lafayette"] <- -122.602883
162 long$lon[long$site_id == "Portland Cully Helensview"] <-
    -122.575627
163 long$lon[long$site_id == "Sauvie Island"] <- -122.772305
164 long$lon[long$site_id == "Tualatin Bradbury Court"] <- -122.745538
165
166
167 long %>% dplyr::select(datetime, site_id, pm2_5_ref, lat, lon)
168 long %>% na.omit()
169
170 long$site_id <- gsub("\\ ", "_", long$site_id)
171 long$site_id <- tolower(long$site_id)
172 #long$site_id <- stringr::str_replace(long$site_id, ".", " ")
173
174 return(long)
175
176 }
177
178 # establish avg interval for xts() function
179 time_step <- 5
180
181 # for clean 5-min breaks
182 align.time.down = function(x,n) {
183   index(x) = index(x) - n
184   align.time(x,n)
185 }
186
187
188 # remove geometry from sf object, convert to dataframe with only the
    elements/attributes
189 st_drop_geometry <- function(x) {

```

```

190   if (inherits(x, "sf")) {
191     x <- st_set_geometry(x, NULL)
192     class(x) <- 'data.frame'
193   }
194   return(x)
195 }
196
197 # for clean 5-min breaks
198 align.time.down = function(x,n) {
199   index(x) = index(x) - n
200   align.time(x,n)
201 }
202
203 # data processing

```

```

204 # start_date <- "2017-07-01"
205 # end_date <- "2018-09-30"
206 # inherit start/end date from init script in modeling project
207 source("../src/init.R")
208
209 # this should work once I update my pdx table
210 pa <- st_read(dsn = con
211               #,geom_column = "geom" # depreceated!
212               #,EWKB = TRUE
213               ,query = paste0("SELECT DISTINCT *
214                               FROM pdx
215                               WHERE pm2_5_atm < ", max_pm_range, "
216
217                               AND
218                               created_at >= '
219                               ,lubridate::ymd(start_date) + hours(8)
220                               ,"' AND created_at <= '
221                               ,lubridate::ymd(end_date) + hours(8), "
222                               ';" )
223 )
224
225 # lookup table for sensor geom
226 pa_points <- st_read(dsn = con
227                      #,geom_column = "geom"
228                      #,EWKB = TRUE
229                      #,query = "SELECT DISTINCT * FROM pdx_local_
230                                slope;"
231
232                                #,query = "SELECT DISTINCT * FROM pdx;"
233                                # compare PurpleAir to DEQ during regional PM
234                                event (wildfire)
235                                ,query = "SELECT DISTINCT id , label , geom
236                                FROM pdx

```

```

232             GROUP BY id , label , geom;"
233   )
234
235   # define projection
236   st_crs(pa) <- epsg_26910
237   st_crs(pa_points) <- epsg_26910
238
239   # convert from UTC to UTC-8 or PST (same as DEQ)
240   pa$created_at <- lubridate::ymd_hms(pa$created_at) - hours(8)
241
242
243   # read in the frm data (not actually frm, but neph...) provided by
      Meena
244   # frm_files <- c("./data/frm/sel_pm25_5min_20170701_to_20180918.csv")
245   frm_files <- "./data/frm/bhp_hhf_tbc_sel_5min_pm25_20170701_to_
      20180918.csv"
246   frm <- ldply(frm_files , read_frm)
247
248   frm %>% st_as_sf(coords = c("lon","lat"), crs = wgs_84)
249
250   # matching the sel file with the 5stn id
251   # frm$site_id <- ifelse(frm$site_id == "PM2 5L_Est", "Portland SE
      Lafayette", frm$site_id)
252
253   # make sure the datetime columns match
254   names(pa)[names(pa) == "created_at"] <- "datetime"
255
256   str(frm)
257   str(pa)
258
259   # check the time zone of pa data
260   attr(pa$datetime , "tzone")
261   attr(frm$datetime , "tzone")
262
263   # TODO INSERT FLAG DATA SCRIPT HERE
      

---


264
265   # added to processPurpleAir in aod_modeling instead ...
266   # pdx_flag <- st_read(dsn = con
267   #                       ,geom_column = "geom"
268   #                       ,query = "SELECT DISTINCT * FROM pdx_flag;")
269
270   #
      

---


271
272   # run initial cor plot before creating individual regressions
273   # nearby_sensors <- c("byuki project")

```



```

274 #           , "byuki project B"
275 #           , "Haig St."
276 #           , "Haig St. B"
277 #           , "Marion Court Apartments"
278 #           , "Marion Court Apartments B"
279 #           , "STAR Lab Creston Kenilworth"
280 #           , "STAR Lab Creston Kenilworth B"
281 #           , "STAR Lab Powell-Hurst Gilbert"
282 #           , "STAR Lab Powell-Hurst Gilbert B")
283
284 # pull all of the Portland PurpleAir data
285 nearby_sensors <- unique(pa$label)
286
287 # I'm only comparing SEL to each PurpleAir!
288 sel <- frm %>% dplyr::filter(site_id == "Portland SE Lafayette" &
289   datetime >= start_date & datetime <= end_date) %>%
290   dplyr::select(datetime, id = site_id, pm2_5 = pm2_5_ref) %>%
291   dplyr::group_by_at(vars(-pm2_5)) %>%
292   dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
293   spread(key = id, value = pm2_5) %>% dplyr::select(-row_id) %>%
294   # remove outliers
295   filter('Portland SE Lafayette' < max_pm_range)
296
297 saveRDS(sel, "./data/frm/sel.RDS")
298
299 frm %>% dplyr::filter(datetime >= start_date & datetime <= end_date)
300   %>%
301   dplyr::select(datetime, id = site_id, pm2_5 = pm2_5_ref) %>%
302   dplyr::group_by_at(vars(-pm2_5)) %>%
303   dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
304   spread(key = id, value = pm2_5) %>% dplyr::select(-row_id) %>%
305   # remove outliers
306   filter('Portland SE Lafayette' < max_pm_range)
307
308 # Develop better filtering technique to exclude days when Plantower
309   reads above threshold
310 system.time({
311 purple <- pa %>% dplyr::filter(label %in% nearby_sensors & datetime
312   >= start_date & datetime <= end_date) %>%
313   # remove sticky geom
314   as.data.frame() %>%
315   dplyr::select(datetime, label = label, id, pm2_5 = pm2_5_atm) %>%
316   # remove outliers
317   # filter(pm2_5 < max_pm_range) %>%
318   dplyr::group_by_at(vars(-pm2_5)) %>%
319   dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
320   dplyr::select(-row_id)
321   # convert to wide df for corr matrix

```

```

318   # spread(key = site_id, value = pm2_5) %>%
319   })
320
321
322   # Exclude days when sensor exceeds threshold?
323   system.time({
324     outliers <- pa %>% dplyr::filter(label %in% nearby_sensors &
325       datetime >= start_date & datetime <= end_date) %>%
326       # remove stick geom
327       as.data.frame() %>%
328       dplyr::select(datetime, label = label, id, pm2_5 = pm2_5_atm) %>%
329       # remove outliers
330       #filter(pm2_5 < max_pm_range) %>%
331       filter(pm2_5 < 1000) %>%
332       dplyr::group_by_at(vars(-pm2_5)) %>%
333       dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
334       dplyr::select(-row_id)
335       # convert to wide df for corr matrix
336       # spread(key = site_id, value = pm2_5) %>%
337   })
338
339   # long df after changing purple pipes and site_id
340   # asdf <- inner_join(purple, sel)
341   asdf <- inner_join(purple, frm)
342   asdf$year <- lubridate::year(asdf$datetime)
343   asdf$month <- lubridate::month(asdf$datetime, label = TRUE)
344
345
346   # TODO loop through each ref/sensor pair!
347
348   lapply(unique(frm$site_id), function(x) {
349
350
351
352
353   })
354
355   r2_month <- asdf %>%
356     group_by(year, month, id, label) %>%
357     do(fitMonth = lm('Portland SE Lafayette '~pm2_5, data = .)) %>%
358     glance(fitMonth) %>%
359     arrange(desc(r.squared))
360
361   # need a better way to get the slope and intercept without losing the
362     std.error from each variable
363   slope_month <- asdf %>%
364     nest(-c(year, month, id, label)) %>%

```

```

364   mutate(
365     fit = map(data, ~lm('Portland SE Lafayette' ~ pm2_5, data = .)),
366     tidied = map(fit, tidy)
367   ) %>%
368   unnest(tidied) %>%
369   # dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
370   # dplyr::select(-c(std.error, statistic, p.value)) %>%
371   # spread(key = term, value = estimate) %>%
372   # dplyr::select(-c(row_id))
373   filter(term != "(Intercept)") %>%
374   filter(estimate < 5) %>%
375   filter(estimate > -5)
376
377 intercept_month <- asdf %>%
378   nest(-c(year, month, id, label)) %>%
379   mutate(
380     fit = map(data, ~lm('Portland SE Lafayette' ~ pm2_5, data = .)),
381     tidied = map(fit, tidy)
382   ) %>%
383   unnest(tidied) %>%
384   # dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
385   # dplyr::select(-c(std.error, statistic, p.value)) %>%
386   # spread(key = term, value = estimate) %>%
387   # dplyr::select(-c(row_id))
388   # filter(term != "'Portland SE Lafayette'") %>%
389   filter(term != "pm2_5") %>%
390   filter(estimate < 25) %>%
391   filter(estimate > -25)
392
393 # combine R2, slope, and intercept into single tidy dataframe
394
395 estimates_month <- inner_join(slope_month, intercept_month, by = c("
396   year", "month", "id", "label"), suffix = c(".m", ".b"))
397
398 names(r2_month)[names(r2_month) == 'p.value'] <- "p.value.r2"
399 names(r2_month)[names(r2_month) == 'statistic'] <- "statistic.r2"
400
401 lm_month <- inner_join(r2_month, estimates_month, by = c("year", "
402   month", "id", "label")) %>%
403   arrange(year, month, id)
404
405 # Add August 2018 CF to DataBase
406
407 pdx_cf <- lm_month %>%
408   # dplyr::select(-c(year.m, year.b)) %>%
409   # dplyr::filter(month == "Aug", year == "2018") %>%
410   arrange(desc(r.squared), id) %>%

```

```

407     dplyr::select(c(year, month, id, label, everything())) %>% unique()
408
409     pdx_cf$year <- as.character(pdx_cf$year)
410
411
412     # Apply best method from EDA to pdx_cf
413     # Do this after storing data in DB (store even bad sensors CF for now
414     ...)
415     # pdx_cf %>%
416     #   group_by(id, label) %>%
417     #   slice(which.max(r.squared)) %>%
418     #   filter(r.squared >= 0.80) %>% arrange(label)
419
420     # Append geometry and convert to simplefeatures
421     pdx_cf <- inner_join(pdx_cf, pa_points) %>% st_as_sf()
422
423     # Prepare colnames for postgres (remove periods)
424     names(pdx_cf) <- gsub(x = names(pdx_cf), pattern = "\\.", "_") %>%
425     tolower()
426     # names(pdx_cf)[names(pdx_cf) == "id"] <- "label"
427
428     # HIMS Roof was returning Inf and NaN
429     pdx_cf %>% na.omit()
430
431     # open connection to our db
432     con <- dbConnect(drv = RPostgres::Postgres()
433                      ,dbname = db
434                      ,host = 'pgsql102.rc.pdx.edu' # not sure why object
435                      host isn't working...
436                      ,port = port
437                      ,password = pw
438                      ,user = user)
439
440     # Find a better way to do this... append = TRUE is not ideal, but
441     # append = FALSE and overwrite = TRUE converts numeric to real
442     # datatype!?
443     # Write to db as lookup table
444
445     # clear table before writing new data
446     res <- dbSendQuery(con, statement = "delete from pdx_cf;")
447     dbClearResult(res)
448     res <- dbSendQuery(con, statement = "vacuum full pdx_cf;")
449     dbClearResult(res)
450
451     # Write the new CF data to the pdx_cf table in canopycontinuum
452     st_write(obj = pdx_cf
453             ,dsn = con

```

```

450         ,layer_options = "OVERWRITE=true"
451         ,drop_table = FALSE
452         ,try_drop = FALSE
453         ,debug = TRUE
454         ,append = TRUE
455         ,overwrite = FALSE
456         ,dataset_options = "GEOMETRY=AS_WKT"
457     )
458
459
460 # # define global graphics variables


---


461 # plot_width <- 14
462 # plot_height <- 10
463 # plot_dpi <- 600
464 #
465 # axis_text_size <- 1.2
466 # axis_title_size <- 16
467 #
468 # lower_limit <- 0
469 # upper_limit <- 1
470 #
471 #
472 # lm_month$yearmon <- as.yearmon(paste(lm_month$month, lm_month$year)
473   , format = "%b %Y")
474 #
475 # r2m <- ggplot(lm_month, aes(x = as.factor(yearmon), y = r.squared,
476   fill = month)) +
477 #   geom_boxplot() +
478 #   theme_bw() +
479 #   guides(fill = FALSE) +
480 #   xlab("") +
481 #   ylab(expression(R^2)) +
482 #   labs(title = "PurpleAir Correlation by Month") +
483 #   # facet_wrap(~id)
484 #   theme(plot.title = element_text(hjust = 0.5, size = 15, face = "
485     bold"),
486 #         plot.subtitle = element_text(hjust = 0.5, size=12, face = "
487     bold"),
488 #         axis.text = element_text(size=rel(axis_text_size), face = "
489     bold", colour = "black"),
490 #         axis.title = element_text(size=axis_title_size, face = "
491     bold"),
492 #         legend.title = element_text(size = 15, face = "bold"),
493 #         legend.text = element_text(size = 12, face = "bold"))
494 #
495 # r2m

```

```
490 #
491 #
492 # sm <- ggplot(lm_month, aes(x = as.factor(yearmon), y = estimate.m,
493 #   fill = month)) +
494 #   geom_boxplot() +
495 #   theme_bw() +
496 #   guides(fill = FALSE) +
497 #   xlab("") +
498 #   ylab("Slope") +
499 #   labs(title = "PurpleAir Calibration Slopes by Month") +
500 #   # facet_wrap(~id)
501 #   theme(plot.title = element_text(hjust = 0.5, size = 15, face = "
502 #     bold"),
503 #     plot.subtitle = element_text(hjust = 0.5, size=12, face = "
504 #       bold"),
505 #     axis.text = element_text(size=rel(axis_text_size), face = "
506 #       bold", colour = "black"),
507 #     axis.title = element_text(size=axis_title_size, face = "
508 #       bold"),
509 #     legend.title = element_text(size = 15, face = "bold"),
510 #     legend.text = element_text(size = 12, face = "bold"))
511 # sm
512 #
513 #
514 # im <- ggplot(lm_month, aes(x = as.factor(yearmon), y = estimate.b,
515 #   fill = month)) +
516 #   geom_boxplot() +
517 #   theme_bw() +
518 #   guides(fill = FALSE) +
519 #   xlab("") +
520 #   ylab("Intercept") +
521 #   labs(title = "PurpleAir Calibration Intercepts by Month") +
522 #   # facet_wrap(~id)
523 #   theme(plot.title = element_text(hjust = 0.5, size = 15, face = "
524 #     bold"),
525 #     plot.subtitle = element_text(hjust = 0.5, size=12, face = "
526 #       bold"),
527 #     axis.text = element_text(size=rel(axis_text_size), face = "
528 #       bold", colour = "black"),
529 #     axis.title = element_text(size=axis_title_size, face = "
530 #       bold"),
531 #     legend.title = element_text(size = 15, face = "bold"),
532 #     legend.text = element_text(size = 12, face = "bold"))
533 # im
534 #
```

```

528 #
529 # blank <- grid.rect(gp=gpar(col="white"))
530 #
531 # boxplots <- arrangeGrob(r2m, sm, im, nrow = 3, ncol = 1)
532 # boxplots
533 # grid.arrange(r2m, sm, im, nrow = 3, ncol = 1)
534 #
535 # ggsave(filename = paste0("./figures/summary/boxplots.png")
536 #       ,plot = boxplots
537 #       ,scale = 1
538 #       ,width = plot_width
539 #       ,height = plot_height
540 #       ,units = "in"
541 #       ,dpi = plot_dpi)
542 #
543 #
544 #
545 # # Matching Meena's sensor abbreviations

```

```

546 # long_sensor <- c("byuki project"
547 #                 , "byuki project B"
548 #                 , "Haig St."
549 #                 , "Haig St. B"
550 #                 , "Marion Court Apartments"
551 #                 , "Marion Court Apartments B"
552 #                 , "STAR Lab Creston Kenilworth"
553 #                 , "STAR Lab Creston Kenilworth B"
554 #                 , "STAR Lab Powell-Hurst Gilbert"
555 #                 , "STAR Lab Powell-Hurst Gilbert B"
556 #                 , "STAR Lab Aloha"
557 #                 , "STAR Lab Aloha B"
558 #                 , "Lower Boones Ferry Road"
559 #                 , "Lower Boones Ferry Road B"
560 #                 , "STAR Lab - Hillsdale"
561 #                 , "STAR Lab - Hillsdale B"
562 #                 , "Red Fox Hills"
563 #                 , "Red Fox Hills B"
564 #                 , "PSU STAR Lab Hayden Island"
565 #                 , "PSU STAR Lab Hayden Island B"
566 #                 , "PSU STAR Lab Roof North"
567 #                 , "PSU STAR Lab Roof North B"
568 #                 , "PSU STAR Lab Roof South"
569 #                 , "PSU STAR Lab Roof South B"
570 #                 , "PSU STAR Lab Rose City Park"
571 #                 , "PSU STAR Lab Rose City Park B")
572 #
573 # # matching Meena's abbrev. for the sensors she focused on
574 # short_sensor <- c("byu1"

```

```

575 #           , "byu2"
576 #           , "hag1"
577 #           , "hag2"
578 #           , "mca1"
579 #           , "mca2"
580 #           , "crk1"
581 #           , "crk2"
582 #           , "phg1"
583 #           , "phg2"
584 #           , "alo1"
585 #           , "alo2"
586 #           , "lbf1"
587 #           , "lbf2"
588 #           , "hil1"
589 #           , "hil2"
590 #           , "rfh1"
591 #           , "rfh2"
592 #           , "hay1"
593 #           , "hay2"
594 #           , "sln1"
595 #           , "sln2"
596 #           , "sls1"
597 #           , "sls2"
598 #           , "rcp1"
599 #           , "rcp2"
600 # )
601 #
602 # asdf$id <- mapvalues(asdf$id, from = long_sensor, to = short_sensor
603 # )
604 # asdf %>% filter(id %in% short_sensor)
605 #
606 #
607 # # compare total slope, r2, intercept with Meena's results
608 # -----
609 # r2_total <- asdf %>%
610 #   group_by(id) %>%
611 #   do(fitTotal = lm(pm2_5 ~ 'Portland SE Lafayette', data = .)) %>%
612 #   glance(fitTotal) %>%
613 #   arrange(desc(r.squared))
614 #
615 # # need a better way to get the slope and intercept without losing
616 # # the std.error from each variable
617 # slope_total <- asdf %>%
618 #   nest(-c(id)) %>%
619 #   mutate(
620 #     fit = map(data, ~lm(pm2_5 ~ 'Portland SE Lafayette', data = .)),
621 #     tidied = map(fit, tidy)
622 #   )

```



```

620 # ) %>%
621 # unnest(tidied) %>%
622 # # dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
623 # # dplyr::select(-c(std.error, statistic, p.value)) %>%
624 # # spread(key = term, value = estimate) %>%
625 # # dplyr::select(-c(row_id))
626 # filter(term != "(Intercept)") %>%
627 # filter(estimate < 5) %>%
628 # filter(estimate > -5)
629 #
630 #
631 # intercept_total <- asdf %>%
632 # nest(-c(id)) %>%
633 # mutate(
634 #   fit = map(data, ~lm(pm2_5~'Portland SE Lafayette', data = .)),
635 #   tidied = map(fit, tidy)
636 # ) %>%
637 # unnest(tidied) %>%
638 # # dplyr::mutate(row_id=1:n()) %>% ungroup() %>%
639 # # dplyr::select(-c(std.error, statistic, p.value)) %>%
640 # # spread(key = term, value = estimate) %>%
641 # # dplyr::select(-c(row_id))
642 # filter(term != "'Portland SE Lafayette'") %>%
643 # filter(estimate < 25) %>%
644 # filter(estimate > -25)
645 #
646 # # combine R2, slope, and intercept into single tidy dataframe
647 # -----
648 # estimates_total <- inner_join(slope_total, intercept_total, by = c(
649 #   "id"), suffix = c(".m", ".b"))
650 #
651 # names(r2_total)[names(r2_total) == 'p.value'] <- "p.value.r2"
652 # names(r2_total)[names(r2_total) == 'statistic'] <- "statistic.r2"
653 #
654 # lm_total <- inner_join(r2_total, estimates_total, by = c("id")) %>%
655 #   arrange(id)
656 #
657 # lm_summary <- lm_total %>%
658 #   dplyr::select(c(id, r.squared, estimate.m, estimate.b))
659 # write.csv(lm_summary, row.names = FALSE, "./reports/lm_total_
660 #   results.csv")
661 #
662 # # running lm on Vivek's sensors during August by hand!
663 # -----
664 # # find the best sensors from above manipulation
665 # top10 <- lm_month %>% arrange(desc(r.squared)) %>% head(10)

```

```

662 # a <- asdf %>% filter(id == "STAR Lab Creston Kenilworth" & month
    == "Aug")
663 # moda <- lm(a$pm2_5~a$'Portland SE Lafayette')
664 # summary(moda)
665 #
666 # b <- asdf %>% filter(id == "STAR Lab Creston Kenilworth B" & month
    == "Aug")
667 # modb <- lm(b$pm2_5~b$'Portland SE Lafayette')
668 # summary(modb)
669 #
670 # BEGIN CF EDA

```

```

671
672 # # the slopes vary for a given sensor, despite having strong
    correlations...
673 # gg <- pdx_cf %>%
674 #   filter(r.squared >= 0.85) %>%
675 #   dplyr::select(year, month, id, label, r.squared, estimate.m,
    estimate.b) %>%
676 #   arrange(label)
677 # unique(gg$label)
678 #
679 # # temporary fix is to just use the CF with the strongest
    correlation, or take the average?
680 # max_r2 <- pdx_cf %>%
681 #   group_by(id, label) %>%
682 #   slice(which.max(r.squared)) %>%
683 #   dplyr::select(id, label, r.squared, estimate.m, estimate.b) %>%
684 #   filter(r.squared >= 0.85) %>% arrange(label)
685 #
686 # bad_r2 <- pdx_cf %>%
687 #   group_by(id, label) %>%
688 #   slice(which.max(r.squared)) %>% arrange(r.squared) %>%
689 #   dplyr::select(id, label, r.squared, estimate.m, estimate.b) %>%
690 #   filter(r.squared < 0.85) %>% arrange(label)
691 #
692 # mean_r2 <- pdx_cf %>%
693 #   group_by(id, label) %>%
694 #   filter(r.squared >= 0.85) %>%
695 #   dplyr::select(year = year, month, id, label, r.squared, estimate.
    m, estimate.b) %>%
696 #   summarise_if(is.numeric, .funs=mean) %>%
697 #   arrange(label)
698 #
699 # diff <- inner_join(mean_r2, max_r2, by = c("id", "label"), suffix =
    c(".mean", ".max")) %>%

```

```

700 #   dplyr::select(id, label, r.squared.mean, r.squared.max, estimate.
      m.mean, estimate.m.max, estimate.b.mean, estimate.b.max)
701 #
702 # diff$r2_diff <- abs(diff$r.squared.max-diff$r.squared.mean)
703 # diff$slope_diff <- abs(diff$estimate.m.max-diff$estimate.m.mean)
704 # diff$int_diff <- abs(diff$estimate.b.max-diff$estimate.b.mean)
705 #
706 # diff %>% arrange(desc(slope_diff))
707
708 # END CF EDA

```

Source/unionStreets.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-19
5 # combine RLIS and WA streets data into single shapefile
6
7 # needed for nvim-R
8 if (basename(getwd()) == "src") {
9   setwd("../")
10  getwd()
11 }
12
13
14 # load the necessary packages
15 if (!require(pacman)) {
16   install.packages("pacman")
17   library(pacman)
18 }
19
20 p_load(plyr
21        ,dplyr
22        ,magrittr
23        ,tools
24        ,rgdal
25        ,raster
26        ,sp
27        ,sf
28        ,rgeos
29        ,stringr
30        ,RColorBrewer
31        ,pbapply
32        ,parallel)
33

```

```

34 # Oregon North NAD83 Meters UTM Zone 10
35 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
36
37 # Portland Study Area
38 study_area <- readRDS("./study_area/study_area.RDS")
39
40 # Portland Streets (not from the rlis dir, we write there insteads)
41 pdx <- readOGR("./data/pdx_streets/streets.shp") %>% spTransform(
    CRSobj = epsg_26910)
42
43 # Vancouver Streets
44 vnc <- readOGR("./data/wsdot/WSDOT__Local_Agency_Public_Road_Lines.
    shp")
45 vnc %>% spTransform(CRSobj = epsg_26910)
46 vnc %>% gIntersection(study_area) # does this only return lines that
    intersect the border of our study area, or also lines that are
    contained by it?
47
48 # Combine them together
49 x <- raster::union(pdx, vnc) # faster but it might be different...
50 writeOGR(x, dsn = "./data/rlis", layer = "streets", driver = "ESRI
    Shapefile", overwrite = T)
51
52
53
54 #*-----Graveyard
    -----*#
55 # using rgeos gUnion
56 # x <- gUnion(pdx, vnc) # very slow!
57 ## sample data: line lengths
58 # df <- data.frame(len = sapply(1:length(x), function(i) gLength(x[i,
    ])))
59 # rownames(df) <- sapply(1:length(x), function(i) x@lines[[i]]@ID)
60 # ## SpatialLines to SpatialLinesDataFrame
61 # y <- SpatialLinesDataFrame(x, data = df)
62 # writeOGR(y, dsn = "./data/rlis/", layer = "streets", driver = "ESRI
    Shapefile", overwrite = T)
63 # ran into a bunch of issues with the gdb with rgdal and sf...
64 # gdb file
65 # fgdb <- "./data/wsdot/LAPR.gdb"
66 # List all feature classes in a file geodatabase
67 # subset(ogrDrivers(), grepl("GDB", name))
68 # fc_list <- ogrListLayers(fgdb)
69 # print(fc_list)
70 # Read the feature class
71 # van <- readOGR(dsn=fgdb, layer="LAPR_Lines")

```

```

72 # van <- readOGR("./data/wsdot/LAPR.gdb") %>% spTransform(CRSobj =
    epsg_26910)
73 # van <- readOGR("./data/wsdot/LAPR.gdb", layer = "LAPR_Lines")
74 # sf <- st_read(fgdb, layer="LAPR_Lines") %>% st_transform(crs=epsg_
    26910)
75 # van %>% filter(FederalFunctionalClassDesc %in% c("Rural Minor
    Collector", "Urban Minor Collector", ))
76 # study_sf <- st_as_sf(study_area)
77 # sf <- st_intersection(sf, study_sf)
78 #*

```

```
*#
```

Source/processNDVI.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-10-18
5 # process raw hdf MODIS NDVI data, convert to GeoTiff, perform weekly
    , monthly averages
6
7 # load the necessary packages
8 if (!require(pacman)) {
9   install.packages("pacman")
10  library(pacman)
11 }
12
13 p_load(rgdal
14        ,dplyr
15        ,magrittr
16        ,gdalUtils
17        ,raster
18        ,sp
19        ,sf
20        ,rgeos
21        ,MODIS
22        ,parallel
23        ,ggplot2
24        ,pbapply
25        #,greenbrown # sourceforge repo
26        )
27 source("./src/init.R")
28 source("./src/functions.R")
29
30 study_area <- readRDS(study_area)
31
32

```

```

33 #
34 # determine bounding box for portland
35
36 # ndvi_path <- "./MODIS/MOD13A2.006" # 1 km
37 ndvi_path <- "./MODIS/MOD13Q1.006" # 250 m
38
39 ndvi_files <- list.files(path = ndvi_path, pattern = "\\\\.hdf$"
40                          ,all.files = FALSE, full.names = TRUE
41                          ,recursive = TRUE # grab files from all
42                          ,ignore.case = FALSE)
43
44 percentNA <- function(r) {
45   sum(values(is.na(r)))/ncell(r)
46 }
47
48 # Reproject, crop, and resample to match study area
49 processNDVI <- function(file_path, study_area = study_area, proj =
50   epsg_26910) {
51   cat("\n")
52
53   # extract date from file path
54   date <- stringr::str_extract(file_path, '
55     [0-9][0-9][0-9][0-9].[0-9][0-9].[0-9][0-9]')
56   date_clean <- stringr::str_replace_all(date, "\\.", "-")
57
58   # coerce 16 day average to daily composite?
59   dates <- seq.Date(from = as.Date(date_clean)
60                     ,to = as.Date(date_clean) + lubridate::days(15)
61                     ,to = as.Date(date_clean)
62                     ,by = "1 day")
63
64   sds <- get_subdatasets(file_path)
65
66   # ndvi <- sds[grepl("16DAY_1km_VI:1 km 16 days NDVI", sds)] %>%
67     readGDAL %>% raster
68   # evi <- sds[grepl("16DAY_1km_VI:1 km 16 days EVI", sds)] %>%
69     readGDAL %>% raster
70
71   ndvi <- sds[grepl("16DAY_250m_500m_VI:250m 16 days NDVI", sds)] %>%
72     readGDAL %>% raster
73   evi <- sds[grepl("16DAY_250m_500m_VI:250m 16 days EVI", sds)] %>%
74     readGDAL %>% raster
75

```

```

72 # Not sure how to make use of this layer yet... Only applies to
    Pixel Reliability == 1
73 # vi_quality <- sds[grepl("16DAY_250m_500m_VI:250m 16 days VI
    Quality", sds)] %>% readGDAL %>% raster
74 # 10 other variables (QA, cloud mask, water, climatology, aerosols
    ?)
75
76 # Exclude Low Quality Pixels from NDVI & EVI layers
77 pix_rel <- sds[grepl("16DAY_250m_500m_VI:250m 16 days pixel
    reliability", sds)] %>% readGDAL %>% raster
78 values(pix_rel)[values(pix_rel) == -1] <- NA # Fill/No Data: Not
    Processed
79 # values(pix_rel)[values(pix_rel) == 1] <- NA # Marginal data:
    Useful, but look at other QA information
80 values(pix_rel)[values(pix_rel) == 2] <- NA # Snow/Ice: Target
    covered with snow/ice
81 values(pix_rel)[values(pix_rel) == 3] <- NA # Cloudy: Target not
    visible, covered with cloud
82 values(pix_rel)[values(pix_rel) == 0] <- 1 # Good Data: Use with
    Confidence
83
84 ndvi <- ndvi*pix_rel
85 evi <- evi*pix_rel
86
87 print(percentNA(ndvi))
88 print(percentNA(evi))
89
90 # Not useful for annual median values, but might be useful for
    daily interpolation...
91 na_threshold <- 1.00 # decimal percent
92
93 if (percentNA(ndvi) < na_threshold && percentNA(evi) < na_threshold
    ) {
94
95     # combine NDVI and EVI into a single stack
96     r <- stack(ndvi, evi)
97     names(r) <- c(paste0("ndvi.", date), paste0("evi.", date))
98
99     r <- raster::projectRaster(from = r, method = 'bilinear', crs =
    proj)
100     study_area <- spTransform(study_area, CRSobj = proj)
101
102     if(identical(crs(study_area), crs(r))) {
103
104         m <- mask(r, study_area)
105         cr <- crop(m, study_area)
106
107         pblapply(dates, function(x) {

```

```

108     pblapply(1:nlayers(cr), function(y) {
109         layer_name <- names(cr[[y]])
110         var <- gsub("\\\\.*$", "", layer_name)
111         date <- gsub("-", "\\.", x)
112         writeRaster(cr[[y]]
113             ,filename = paste0("./output/", var, "/", var,
114                 ".", date, ".tif")
115             ,format = "GTiff"
116             ,overwrite = TRUE)
117     },cl = detectCores()-1
118 )
119 }
120 #,cl = detectCores()-1
121 )
122 }
123
124 }
125 }
126
127 # Call our processing function
128 pblapply(ndvi_files, function(x) {
129     processNDVI(file_path = x
130                 ,study_area = study_area
131                 )
132 }
133 ,cl = detectCores()-1
134 #,cl = 8
135 )
136
137 # test our output
138 ndvi <- stack(list.files(path = "./output/ndvi/", pattern = ".tif$",
139     full.names = T))
140 plot(ndvi)
141
142 evi <- stack(list.files(path = "./output/evi/", pattern = ".tif$",
143     full.names = T))
144 plot(evi)
145
146 # Convert 16-day composites to annual median layers
147 # Florian's temporal composite example (doesn't work for what I need)
148 # import 16 day NDVI
149 # tfs <- readRDS("./data/ndvi_tfs.RDS")
150 # ndvi <- sapply(tfs[[1]], "[", 1)
151 # cday <- sapply(tfs[[1]], "[", 2)
152 #
153 # ndvi_day <- temporalComposite(ndvi, cday, interval = "day", fun =
154     mean)

```



```

152 # saveRDS(ndvi_day, "../data/ndvi_day_composite.RDS")
153 # ndvi_day <- readRDS("../data/ndvi_day_composite.RDS")

```

Source/processGridMET.R

```

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7 p_load(rgdal
8        ,rgeos
9        ,sp
10       ,raster
11       ,dplyr
12       ,magrittr
13       ,pbapply
14       ,parallel
15       ,ncdf4
16       ,snow)
17
18 # needed for nvim-R
19 if (basename(getwd()) == "src") {
20   setwd("../")
21   getwd()
22 }
23
24
25 source("../src/init.R")
26
27
28 # converts gridMet # of days from 1900-01-01 to date (%Y-%m-%d)
29 formatDateLayer <- function(layer, var) {
30   layer %>% stringr::str_replace_all("X", "") %>%
31     as.numeric() %>%
32     as.Date(origin = "1900-01-01") %>%
33     as.character()
34   layer <- paste0(var, ".", layer)
35   return(layer)
36 }
37
38 # processes gridMet stack for one variable for one year, saves to RDS
39   (preserves layer names)
40 processGridMet <- function(file_name
41                            ,study_area # RDS path
42                            ,crs # output crs
43                            ,out_dir # output (rds)

```

```

43         ) {
44     # extract variable name and year
45     var_year <- basename(file_name) %>%
46       gsub(pattern = "\\..nc", replacement = "")
47     var <- gsub("_[0-9][0-9][0-9][0-9]", "", var_year)
48     cat("\n")
49     print(paste0("Processing ", var_year))
50     r <- raster::stack(file_name)
51     #r %>% projectRaster(crs = crs(epsg_26910))
52     names(r) <- lapply(names(r), function(x) {
53       formatDateLayer(layer = x
54         , var = var)})
55     # universal study area boundary box
56     x <- readRDS(study_area) %>% spTransform(CRSobj = crs)
57     # create larger buffer before masking/cropping
58     y <- rgeos::gBuffer(x, width = 1000)
59     y %>% spTransform(CRSobj = crs(r))
60     m <- mask(r, y, getCover = T) # masking on x excludes a few cells!
61     cr <- crop(m, extent(y))
62
63     # project using ngb for wind direction, bilinear interpolation for
64     # everything else
65     if(var == "th") {
66       # project to epsg_26910 @ 1 km resolution
67       cr %>% projectRaster(crs = crs, method = "ngb", res = sp_res)
68       %>%
69       mask(x, getCover = T) %>%
70       crop(extent(x))
71     } else {
72       # project to epsg_26910 @ 1 km resolution
73       cr %>% projectRaster(crs = crs, method = "bilinear", res = sp_
74         res) %>%
75       mask(x, getCover = T) %>%
76       crop(extent(x))
77     }
78
79     # Create sub-directory if necessary
80     sub_dir <- paste0(out_dir, "/", var)
81     if(!dir.exists(sub_dir)) {
82       print(paste0("Creating sub-directory: ", sub_dir))
83       dir.create(sub_dir)
84     }
85
86     writeRaster(cr, file.path(paste0(out_dir, "/", var, "/", names(cr),
87       ".tif"))
88       , format = "GTiff"
89       , overwrite = TRUE
90       , bylayer = T

```

```

87     )
88     rm(r, m, cr, x, y)
89     gc()
90
91 }
92
93 # testing our function on a single file
94 # processGridMet( file_name = "gridMET/nc/pr_2017.nc"
95 #                 ,study_area = "./study_area/study_area.RDS"
96 #                 ,crs = crs
97 #                 ,out_dir = "./gridMET/"
98 #                 #)
99
100
101 gridMetFiles <- list.files(path = "./gridMET/nc", pattern = ".nc",
102                             full.names = T)
103
104 pblapply(gridMetFiles, function(x) {
105     processGridMet(file_name = x
106                   ,study_area = "./study_area/study_area.RDS"
107                   ,crs = crs
108                   ,out_dir = "./data")
109     ,cl = detectCores()-1 # Memory allocation error in parallel!
110 })

```

Source/processNLCD.R

```

1 # Created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # 2019-01-30
3 # Transform NLCD into binary raster for each UHI campaign
4
5 # Load Dependencies
6
7 # Conditionally install pacman library if we can't already load it
8 if(!suppressPackageStartupMessages(require(pacman))) {
9     install.packages('pacman')
10    library(pacman)
11 }
12
13 # Use the pacman::p_load() to handle package installation/loading
14 p_load(raster # For working with raster data
15       ,sp # Spatial Library
16       ,sf # Simple Features Library
17       ,rasterVis # Plot nice looking rasters
18       ,rgdal # Geodata abstraction library for reading/writing
19       spatial data

```

```

19     ,rgeos # Geometry engine open source for performing spatial
      transformation
20     ,dplyr # Grammar of data manipulation
21     ,magrittr # Provides the pipe operator (%>%)
22     ,parallel # used for detectCores()
23     ,pbapply # Multithreading with progress bar
24     #,gdalUtils # Extra GDAL utilities
25     ,snow # Another library for parallel computing
26     #,geojsonio # Working with geojson
27 )
28
29 # Globa Variable Definition


---


30 source("./src/init.R")
31 source("./src/functions.R")
32
33 # Set tmpdir for raster data
34 setRasterTempDir()
35
36 study_area <- readRDS("./study_area/study_area.RDS")
37
38 # Reading in our NLCD Layer


---


39 nlcd <- raster(list.files("./data/nlcd_2011_landcover_2011_edition_
      2014_10_10"
40                        ,pattern = "\\img$"
41                        ,full.names = T
42 ))
43
44 # Function Definition


---


45 processNLCD <- function(nlcd, study_area, outdir) {
46   # Grab the CRS of the ambient temperature raster
47   study_crs <- proj4string(study_area)
48
49   # Let's convert our raster into a bounding box vector of its extent
50   # This will speed up our NLCD cropping
51   bb <- as(extent(study_area), "SpatialPolygons")
52   proj4string(bb) <- proj4string(study_area)
53
54   # Buffer study region to accommodate distortion/edge effects from
55   # reprojecting later
56   bb_buf <- gBuffer(bb, width = 10^5)
57

```

```

58 # Reproject ambient temperature to match NLCD
59 bb_nlcd <- spTransform(bb_buf, CRSobj = proj4string(nlcd))
60
61 # Make sure the projections are the same before cropping
62 if (identical(crs(bb_nlcd), crs(nlcd))) {
63   cr <- crop(nlcd, bb_nlcd)
64   # plot(cr)
65   m <- mask(cr, bb_nlcd)
66   # plot(m)
67 } else {
68   stop("NLCD and BB CRS are not identical!")
69 }
70
71 beginCluster()
72 r <- projectRaster(m, crs = study_crs, res = sp_res, method = 'ngb'
73 )
74 r %>% crop(bb) %>% mask(bb)
75 endCluster()
76
77 # Add the attribute table back (it is lost during projection)
78 r@data@attributes <- m@data@attributes
79
80 # Retrieve color legend from NLCD data (it is also lost during
81 # projection)
82 r@legend@colortable <- m@legend@colortable
83 # plot(r10m)
84
85 # Convert to stack of binary landcover layers
86 s <- binaryLandCover(r)
87
88 # # Visually inspect the transformation
89 # levelplot(s, colorkey = F)
90
91 # Create an output directory if it doesn't already exist
92 if(!dir.exists(outdir)) {
93   dir.create(outdir)
94 }
95
96 # Save our transformed NLCD stack as a GeoTiff
97 writeRaster(s, file.path('./data', "nlcd", paste0(names(s), ".tif"))
98             ,overwrite=T
99             ,bylayer=T
100             ,format="GTiff")
101
102 # # Save our transformed NLCD stack as an RDS to preserve the layer
103 # names!
104 # saveRDS(s
105 #         ,paste0(outdir, "nlcd_", study_region, "_", trav, ".RDS")

```

```

103   # )
104
105   # clean up
106   gc()
107
108 }
109
110
111 # Retrieves attribute names from NLCD
112 getAttributes <- function(nlcd) {
113
114   # Let's create a lookup table for our landcover attributes
115   metadata <- data.frame(id = nlcd@data@attributes[[1]]$ID
116                          , attribute = as.character(
117                                nlcd@data@attributes[[1]]$NLCD.2011.Land.Cover.Class))
118
119   # There are a lot of missing values that we should clean up
120   metadata %>% droplevels(exclude = "") %>% na.omit()
121
122   # Let's clean up the attribute names while we're at it
123
124   # First let's convert everything to lower case
125   metadata$attribute <- tolower(metadata$attribute)
126
127   # Next, let's replace any spaces and forward slashes with
128   # underscores
129   metadata$attribute <- gsub(" |\\/","_", metadata$attribute)
130
131   # Finally, let's delete any commas!
132   metadata$attribute <- gsub(","," ", metadata$attribute)
133
134   return(metadata)
135 }
136
137 # Define one-hot encoding function for NLCD raster
138 binaryLandCover <- function(nlcd) {
139
140   # Retrieve number of unique landcover values
141   id <- unique(getValues(nlcd)) %>% sort()
142
143   # Retrieve landcover attributes metadata
144   metadata <- getAttributes(nlcd)
145
146   # Join the landcover attribute names to the observed landcover id
147   # values
148   attributes <- merge(as.data.frame(id), metadata)

```

```

148 # Loop through each landcover and create presence/absence layer
    then name it by LC code
149 s <- pblapply(id, function(x) {
150
151     # Create a new raster layer for each landcover class
152     # r <- assign(paste0("r", x), nlcd)
153     r <- nlcd
154
155     # Assign 1 if cell value matches landcover code, 0 otherwise
156     r[] <- ifelse(r[] == x, 1, 0)
157
158     # attach landcover code to layer name
159     names(r) <- paste0(attributes[id == x,][2])
160
161     return(r)
162 }
163 # run our loop on multiple cores
164 ,cl = detectCores()-1
165 ) %>%
166     # combine each presence/absence raster into a stack
167     stack()
168
169 }
170
171 # Create NLCD for Jackson's Lab5
172 # processTraverse(nlcd = nlcd, study_region = "lab5", trav = "am",
    outdir = "../data/example/")
173
174 # # Main processing function
175 # processNLCD <- function(nlcd, study_regions, travs, outdir) {
176 #
177 #     # loop through each study region
178 #     pblapply(study_regions, function(x) {
179 #
180 #         # loop through each traverse for each study region
181 #         pblapply(travs, function(y) {
182 #
183 #             # run our main processing function!
184 #             try(processTraverse(nlcd = nlcd, study_region = x, trav = y,
    outdir = outdir))
185 #         })
186 #     })
187 #
188 # }
189
190 # Calling our functions

```

```

191 processNLCD(nlcd = nlcd
192             ,study_area = study_area
193             ,outdir = "./data/nlcd/"
194 )
195
196
197 # # Visually inspect the transformed data


---


198 # lapply(study_regions, function(x) {
199 #   lapply(travs, function(y) {
200 #     try({
201 #       s <- readRDS(list.files("./data/nlcd", pattern = paste0(x, "_",
202 #         y), full.names = T))
203 #       levelplot(s, colorkey = F)
204 #     })
205 #   })
206 # })

```

Source/processRoads.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-16
5 # convert road network vector to raster road density
6
7 # needed for nvim-R
8 if (basename(getwd()) == "src") {
9   setwd("../")
10  getwd()
11 }
12
13
14 # load the necessary packages
15 if (!require(pacman)) {
16   install.packages("pacman")
17   library(pacman)
18 }
19
20 p_load(plyr
21       ,dplyr
22       ,magrittr
23       ,tools
24       ,rgdal
25       ,raster
26       ,sp
27       ,sf
28       ,rgeos

```



```

29     ,stringr
30     ,fasterize
31     ,spatstat
32     #,spex
33     ,RColorBrewer
34     ,leaflet
35     ,pbapply
36     ,parallel)
37
38
39 source("./src/init.R")
40
41 # Oregon North NAD83 Meters UTM Zone 10
42 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
43
44 # Rasterize RLIS road data


---


45 # list of shape files in rlis
46 layers <- list.files("./data/rlis", pattern = "\\\\.shp$", full.names =
    T)
47 # rs <- readRDS("./study_area/study_area.RDS") %>% raster(res = 50,
    crs = crs)
48 # values(rs) <- 1
49 # layer <- layers[1]
50
51 processRoads <- function(layer = NULL # shapefile name w/ extension
52                           ,outdir = "./data/" # output directory
53                           ,crs = epsg_26910 # spatial reference system
54                           in meters
55                           ,res = sp_res # raster resolution in meters
56                           ,study_area = "./study_area/study_area.RDS"
57                           ) {
58   var <- file_path_sans_ext(basename(layer))
59   outfile <- paste0(outdir, var, "/", var, ".tif")
60   subdir <- dirname(outfile)
61
62   if(!dir.exists(subdir)) {
63     print(paste0("Creating ", subdir, " subdirectory"))
64     dir.create(subdir)
65   }
66
67   if(!file.exists(outfile)) {
68     print(paste0(outfile, " is being processed."))
69
70

```

```

71   # read in shapefile and reproject
72   vec <- readOGR(layer) %>% spTransform(CRSobj = crs)
73   rs <- readRDS(study_area) %>% raster(res = sp_res, crs =
projection(vec))
74   rs[] <- 1:ncell(rs)
75   print("rasterToPolygons")
76   rsp <- rasterToPolygons(rs)
77   # print("spex::polygonize")
78   # rsf <- spex::polygonize()
79   # rp <- intersect(vec, rsp) # I think this is causing memory
error?
80   print("st_intersection")
81   rp <- st_intersection(st_as_sf(vec), st_as_sf(rsp))
82   print("as Spatial")
83   rp <- as(rp, "Spatial")
84
85   # Memory expensive!
86   print("rgeos density")
87   if ("SpatialLinesDataFrame" %in% class(vec)) {
88     rp$density <- gLength(rp, byid=T)
89   } else if ("SpatialPolygonsDataFrame" %in% class(vec)) {
90     rp$density <- gArea(rp, byid=T)
91   } else if ("SpatialPointsDataFrame" %in% class(vec)) {
92     print("fix this to work with point layers later!")
93     # girp$density <- gIntersection(rsp, vec, byid=T) %>% length()
%>% as.integer()
94     rp$density <- sp::over(vec, rsp)
95     # rp$density <- gContains(rp, byid=T)
96   }
97
98   print("tapply")
99   z <- tapply(rp$density, rp$layer, sum)
100  r <- raster(rs)
101  r[as.integer(names(z))] <- z
102
103  a <- r
104  values(a)[values(a)<=0] <- NA
105  # values(a)[values(a)>0] <- 100
106  # values(a)[values(a)<=0] <- 100
107
108  pal <- colorNumeric(c("#0C2C84", "#41B6C4", "#FFFFCC"), values(a),
,
109                      na.color = "transparent")
110
111  leaflet() %>% addProviderTiles(providers$Stamen.TonerLite) %>%
addRasterImage(a, colors=pal) %>%
112    addLegend(pal = pal, values = values(a),
113              title = "Road Density")

```

```

114
115     # write out
116     writeRaster(r
117                 ,filename = outfile
118                 ,format = "GTiff"
119                 ,overwrite = T
120     )
121 }
122 }
123
124 # Calling our function
125 print('begin tapply loop')
126 pblapply(layers , function(x) processRoads(layer = x)
127          #,cl = detectCores()-1 # only run in parallel on Hecate
128          )
129
130 #

```

```

131
132 # # refactor
133 # vectorToRaster <- function(layer = NULL # shapefile name w/
134 #                             extension
135 #                             ,indir = "./data/rlis/" # directory
136 #                             ,outdir = "./data/" # output directory
137 #                             ,crs = epsg_26910 # spatial reference
138 #                             system in meters
139 #                             ,res = 50 # raster resolution in meters
140 #                             ,study_area = "./study_area/study_area.
141 #                             RDS"
142 # ) {
143 #
144 #     var <- file_path_sans_ext(layer)
145 #     outfile <- paste0(outdir, var, "/", var, ".tif")
146 #
147 #     if(!file.exists(outfile)) {
148 #
149 #         print(paste0(outfile, " is being processed. "))
150 #
151 #         # read in shapefile and reproject
152 #         vector <- readOGR(dsn = indir, layer = var)
153 #         study_area <- readRDS(study_area) %>% spTransform(CRS(crs))
154 #
155 #         # check that we have a polylines feature class
156 #         if("SpatialLinesDataFrame" %in% class(vector)) {
157 #
158 #             # reproject vector

```

```

156 #       lines_utm <- spTransform(vector, CRS(crs))
157 #       # plot(study_area)
158 #       # plot(lines_utm, add = T)
159 #       # create empty raster
160 #       lines_utm_rst <- raster(extent(study_area), crs = crs(study_
area), res = res)
161 #
162 #       # determine the length of lines in each cell
163 #       lengths <- pbsapply(1:ncell(lines_utm_rst), function(x) {
164 #       # create placeholder raster
165 #       tmp_rst <- lines_utm_rst
166 #       # fill in placeholder value
167 #       tmp_rst[x] <- 1
168 #       # convert to vector
169 #       tmp_vec <- rasterToPolygons(tmp_rst)
170 #       # print(x)
171 #       # calculate the length of lines within each cell
172 #       if (gIntersects(lines_utm, tmp_vec)) {
173 #       lines_utm_crp <- crop(lines_utm, tmp_vec)
174 #       lines_utm_crp_len <- gLength(lines_utm_crp)
175 #       return(lines_utm_crp_len)
176 #       } else {
177 #       return(0)
178 #       }
179 #       }, cl = detectCores()-1
180 #       )
181 #
182 #       # set the cell value to the road density
183 #       lines_utm_rst[] <- lengths / 1000 # convert to km
184 #
185 #       # write out
186 #       writeRaster(lines_utm_rst
187 #       ,filename = outfile
188 #       ,format = "GTiff"
189 #       ,overwrite = T
190 #       )
191 #       # spplot(lines_utm_rst, scales = list(draw = TRUE), xlab = "x
", ylab = "y",
192 #       #       col.regions = colorRampPalette(brewer.pal(9, "YlOrRd
")),
193 #       #       sp.layout = list("sp.lines", lines_utm))
194 #       } else {
195 #
196 #       if ("SpatialPolygonsDataFrame" %in% class(vector)) {
197 #
198 #       poly_utm <- spTransform(vector, CRS(crs))
199 #
200 #       # create empty raster

```

```

201 #       poly_utm_rst <- raster(extent(study_area), crs = projection
      (study_area), res = res)
202 #
203 #       # determine the length of poly in each cell
204 #       areas <- pbsapply(1:ncell(poly_utm_rst), function(x) {
205 #         # create placeholder raster
206 #         tmp_rst <- poly_utm_rst
207 #         # fill in placeholder value
208 #         tmp_rst[x] <- 1
209 #         # convert to vector
210 #         tmp_vec <- rasterToPolygons(tmp_rst)
211 #         # print(x)
212 #         # calculate the area of poly within each cell
213 #         if (gIntersects(poly_utm, tmp_vec)) {
214 #           poly_utm_crp <- crop(poly_utm, tmp_vec)
215 #           poly_utm_crp_area <- gArea(poly_utm_crp)
216 #           return(poly_utm_crp_area)
217 #         } else {
218 #           return(0)
219 #         }
220 #       }, cl = detectCores()-1
221 #     )
222 #
223 #       # set the cell value to the road density
224 #       poly_utm_rst[] <- areas
225 #
226 #       # write out
227 #       writeRaster(poly_utm_rst
228 #         ,filename = outfile
229 #         ,format = "GTiff"
230 #         ,overwrite = T
231 #       )
232 #
233 #       spplot(poly_utm_rst, scales = list(draw = TRUE), xlab = "x
      ", ylab = "y",
234 #         col.regions = colorRampPalette(brewer.pal(9, "YlOrRd
      ")),
235 #         sp.layout = list("sp.lines", poly_utm))
236 #
237 #       } else {
238 #         next
239 #       }
240 #     }
241 #
242 #   } else {
243 #     print(paste0(outfile, " already exists!"))
244 #   }
245 #

```

```

246 # }
247
248 # # Very coarse, not going to work...
249 # pop_r <- rasterize(x = acs_sp, y = template_r, field = "B00001_001E",
250   " ", fun=mean, mask=F, na.rm=T)
251
252 # leaflet() %>% addProviderTiles(providers$Stamen.TonerLite) %>%
253   addRasterImage(r, colors=pal) %>%
254   addLegend(pal = pal, values = values(r),
255     title = "Road Density")
256
257 # # SpatialLinesLengths method
258 # rrst.poly <- rasterToPolygons(rs)
259 # rp <- gIntersection(vec, rrst.poly, byid = T)
260 # rp <- SpatialLinesDataFrame(rp, data.frame(row.names=sapply(slot(rp),
261   "lines")),
262   function(y) slot(y, "ID")), ID=1:length(rp),
263   length=
264   SpatialLinesLengths(rp)/1000))
265
266 # rd.rst <- rasterize(rp, rs, field="length", fun="sum")
267
268 # The slow way

```

```

265 # layers <- list.files("./data/rlis", pattern = "\\\\.shp$")
266 #
267 # # call our processing function
268 # pblapply(layers, function(x) {
269 #   vectorToRaster(x)
270 # })
271
272
273 # # visually inspecting our newly cropped rasters
274 # streets <- raster("./data/streets/streets.tif")
275 # spplot(streets)
276 # extent(streets)
277 #
278 # fwy <- raster("./data/fwy/fwy.tif")
279 # spplot(fwy)
280 # extent(fwy)
281 #
282 # arterial <- raster("./data/arterial/arterial.tif")
283 # spplot(arterial)
284 # extent(arterial)
285 #
286 # maj_art <- raster("./data/maj_art/maj_art.tif")

```

```
287 # spplot(maj_art)
288 # extent(maj_art)
289 #
290 # railroad <- raster("./data/railroad/railroad.tif")
291 # spplot(railroad)
292 # extent(railroad)
293 #
294 # railyards <- raster("./data/railyards/railyards.tif")
295 # spplot(railyards)
296 # extent(railyards)
297 #
298 # s <- stack(fwy, arterial, maj_art, streets, railroad, railyards)
299 # plot(s)
300
301 # Deprepeated!
302 # # list rasters that need to be cropped
303 # r_names <- list.files("./data/rllis", pattern = "\\\\.tif$", full.
    names=T)
304 # r_names
305 #
306 # file_path <- r_names[1]
307 # study_area <- ". /study_area/study_area.RDS"
308 # crs <- epsg_26910
309 #
310 #
311 #
312 # # function that crops/masks raster layer by study area
313 # cropRaster <- function(file_path, study_area, crs) {
314 #   r <- raster(file_path)
315 #   x <- readRDS(study_area) %>% spTransform(CRSobj = crs(crs))
316 #   extent(r)
317 #   m <- mask(r, x, getCover = T)
318 #   extent(m)
319 #   # m <- r
320 #   extent(x)
321 #   cr <- crop(m, extent(x), snap="near")
322 #   extent(cr)
323 #   writeRaster(cr
324 #     ,filename = file_path
325 #     ,format="GTiff"
326 #     ,overwrite=T
327 #   )
328 # }
329
330 # calling our function
331 # pblapply(r_names, function(x) {
332 #   cropRaster(file_path = x
333 #     ,study_area = ". /study_area/study_area.RDS"
```

```
334 #           ,crs = epsg_26910
335 #           )}}
```

Source/processPopDensity.R

```
1 # created by Philip Orlando
2 # Sustainable Atmospheres Research Lab
3
4 # load the necessary packages
5 if (!require(pacman)) {
6   install.packages("pacman")
7   library(pacman)
8 }
9
10 p_load(readr
11         ,rlang
12         ,ggplot2
13         ,plyr
14         ,dplyr
15         ,tidyr
16         ,stringr
17         ,magrittr
18         ,rgeos
19         ,rgdal
20         ,sp
21         ,leaflet
22         ,sf
23         ,raster
24         ,mapview
25         ,tidycensus
26         #,tidyverse
27         ,RPostgres
28         ,RColorBrewer
29         ,classInt
30         ,htmltools
31         ,scales
32         ,htmlwidgets
33         ,rPython
34         ,devtools
35         ,pbapply
36         ,parallel
37         ,rasterVis
38 )
39
40 source("../src/init.R")
41 source("../src/functions.R")
42
43 study_area <- readRDS("../study_area/study_area.RDS")
```



```

44
45
46 # GPW v4 data

47 gpw <- raster("./data/pop/gpw_v4_population_density_adjusted_to_2015_
    unwpp_country_totals_rev11_2015_30_sec.tif")
48 f <- paste0(tempdir(), "/", names(gpw), ".tif")
49 writeRaster(gpw, f, format = "GTiff", overwrite=T)
50 e <- bbox(extent(study_area))
51 tr <- rep(sp_res, 2)
52 # tr <- rep(1000, 2)
53 gdalUtils::gdalwarp(f, s_srs=proj4string(gpw), t_srs=proj4string(
    study_area), sub('\.tif', '_clipped.tif', f), tr=tr,
54                   r='near', te=c(e), multi = TRUE, overwrite = TRUE
    )
55 cr <- raster(list.files(tempdir(), "_near.*\\.tif$", full.names=T))
56 print("Renaming clipped/projected layers")
57 names(cr) <- sub('_clipped$', '', names(cr))
58 levelplot(cr, margin=F)
59
60 lapply(c("near", "cubicspline", "bilinear", "cubic", "lanczos", "
    average"), function(i) {
61   if(i == "near") {
62     tr <- rep(1000, 2)
63   } else {
64     tr <- rep(50, 2)
65   }
66   cr <- gdalUtils::gdalwarp(f, s_srs=proj4string(gpw), t_srs=
    proj4string(study_area), sub('\.tif', paste0('_', i, '_clipped.
    tif'), f), tr=tr,
67                   r=i, te=c(e), multi = TRUE, overwrite =
    TRUE)
68   cr <- raster(list.files(tempdir(), paste0("_", i, "_clipped\\.tif$"),
    full.names=T))
69   names(cr) <- paste0("gpw_", i, "_", unique(tr), "m")
70   writeRaster(cr, filename = paste0("./data/pop/", names(cr), ".tif"),
    format = "GTiff", overwrite=T)
71   if(i == "bilinear") {
72     writeRaster(cr, filename = "./data/pop/pop_dens.tif", format = "
    GTiff", overwrite=T)
73   }
74   rasterVis::levelplot(cr, main = names(cr), margin=F)
75   print(paste0("Processing ", names(cr)))
76 })
77 r <- raster("./data/pop/gpw_near_1000m.tif")
78 s <- stack(list.files("./data/pop", "50m\\.tif$", full.names = T))
79 plot(gpw, margin=F)

```

```

80 levelplot(r, margin=F)
81 levelplot(s)
82
83 # get acs data
84 # # grab our census key in the root directory
85 # KEY <- scan("census_key.pgpss", what = "")
86 # census_api_key(KEY, install = TRUE, overwrite = TRUE)
87 # readRenviroon("~/Renviroon")
88
89 # # reading in census data
90 # acs_or <- get_decennial(year = 2010 # unquote on linux
91 #                          ,geography = "block"
92 #                          ,variables = "B00001_001E" # unweighted total
93 #                          ,state = "OR"
94 #                          ,county = c("Multnomah"
95 #                                       , "Washington"
96 #                                       , "Clackamas"
97 #                                       , "Yamhill"
98 #                                       , "Columbia"
99 #                                       , "Marion"
100 #                                       , "Linn"
101 #                                       , "Hood River"
102 #                                       , "Wasco"
103 #                                       , "Benton"
104 #                                       , "Polk"
105 #                                       , "Tillamook"
106 #                                       , "Clatsop"
107 #                                       , "Lincoln"
108 #                                       ) # counties taken from wiki sacra metro
109 #                          ,key = KEY
110 #                          ,output = "wide"
111 #                          ,geometry = TRUE
112 #                          ,cb = F
113 #                          ,tigris_use_cache = TRUE
114 #                          ) %>% na.omit()
115 #
116 # acs_wa <- get_acs(year = 2017 # unquote on linux
117 #                   ,geography = "block group"
118 #                   ,variables = "B00001_001E" # unweighted total
119 #                   ,state = "WA"
120 #                   ,county = c("Clark"
121 #                                , "Cowlitz"
122 #                                , "Skamania"

```

```

123 #                                     ,"Wahkiakum"
124 #                                     ,"Pacific"
125 #                                     ,"Lewis"
126 #                                     ,"Klickitat"
127 #                                     )
128 #                                     ,key = KEY
129 #                                     ,output = "wide"
130 #                                     ,geometry = TRUE
131 #                                     #,cb = F
132 #                                     #,tigris_use_cache = TRUE
133 #                                     ) %>% na.omit()
134 #
135 # acs <- rbind(acs_or, acs_wa)
136 #
137 #
138 # # # Checkpoint get_acs for hecate
139 # # saveRDS(acs, "../output/acs.RDS")
140 #
141 # acs <- readRDS("../output/acs.RDS")
142 #
143 # # reproject into meters
144 # acs <- st_transform(acs, epsg_26910)
145 #
146 # # Now we're creating a logical vector of geometries whose areas are
147 # # /aren't greater than zero
148 # isAboveZero <- as.vector(sf::st_area(acs)) > 0
149 # # Let's inspect the number of zero area geometries in Travis County
150 # # , TX
151 # table(isAboveZero)
152 # # Now let's convert our sf object into a SpatialPolygonsDataFrame,
153 # # excluding any zero area polygons!
154 # acs_sp <- as(acs[isAboveZero,], "Spatial")
155 #
156 #
157 #
158 # # Trying out the rasterize function

```

```

159 # template_r <- raster("../data/ndvi/ndvi.2017.01.01.tif") #
160 # # placeholder raster
161 # pop_r <- rasterize(x = acs_sp, y = template_r, field = "B00001_001E",
162 # # fun=mean, mask=F, na.rm=T)
163 # # spplot(acs_sp["B00001_001E"])
164 #
165 # rasterVis::levelplot(pop_r, margin=F)

```

```

164 # # Read in fwy data for reference
165 # fwy <- readOGR("../data/rllis/fwy.shp") %>% spTransform(CRSobj = crs(
    pop_r)) %>% crop(pop_r) %>% fortify()
166 # df_r <- as.data.frame(pop_r, xy = T)
167 # df_r$pop_dens <- as.numeric(df_r$layer)
168 # ggplot() +
169 #   geom_raster(data = df_r
170 #               ,aes(x = x, y = y, fill = pop_dens)) +
171 #   scale_fill_viridis_c(option = "A") +
172 #   geom_path(data = fwy, aes(x = long, y = lat, group = group),
    color = "grey60") +
173 #   theme_minimal()
174
175 # Using custom density raster function

```

```

176
177 # acsToRaster <- function(vector = NULL, study_area = study_area, buf
    _res = sp_res, res = sp_res, crs = epsg_26910) {
178 #
179 #   # create an empty raster
180 #   template_rst <- raster(extent(gBuffer(study_area, width = buf_res
    ))
181 #                           ,crs = projection(study_area), res = sp_
    res)
182 #
183 #   # determine the density of a feature in each cell
184 #   density <- pbsapply(1:ncell(template_rst), function(x) {
185 #
186 #     # create placeholder raster
187 #     tmp_rst <- template_rst
188 #
189 #     # add placeholder value
190 #     tmp_rst[x] <- 1
191 #
192 #     # convert single cell extent to vector
193 #     tmp_vec <- rasterToPolygons(tmp_rst)
194 #
195 #     pbapply(X = vector, MARGIN = 1, FUN = function(y) {
196 #
197 #       # Check to see if the feature is within the raster cell
198 #       if (gIntersects(vector[y,], tmp_vec)) {
199 #
200 #         # Crop feature by the extent of a single raster cell
201 #         vector_crp <- crop(vector, tmp_vec)
202 #
203 #         # Perform different calculation for Points, Lines, and
    Polygons

```

```

204 #         if ("SpatialLinesDataFrame" %in% class(vector)) {
205 #             cell_value <- gLength(vector_crp)
206 #         } else if ("SpatialPolygonsDataFrame" %in% class(vector)){
207 #             cell_value <- gArea(vector_crp)
208 #         } else if ("SpatialPointsDataFrame" %in% class(vector)) {
209 #             cell_value <- gIntersection(vector_crp, tmp_vec) %>%
length() %>% as.integer()
210 #         } else {
211 #             print("Object not of class Spatial*DataFrame!")
212 #             next
213 #         }
214 #         return(cell_value)
215 #     } else {
216 #         # If the feature does not intersect with the cell, assign 0
217 #         return(0)
218 #     }
219 # }
220 # ,cl = detectCores()-1
221 # )
222 #
223 #     # set the cell value to the kernel density
224 #     template_rst[] <- density
225 #
226 #
227 #
228 # })
229 #
230 #
231 #     # write to file
232 #     writeRaster(template_rst
233 #                 ,filename = outfile
234 #                 ,format = "GTiff"
235 #                 ,overwrite = T)
236 #
237 # }
238
239 # # list of shape files in rlis
240 # layers <- list.files("./data/rlis", pattern = "\\\\.shp$")
241 #
242 # # call our processing function
243 # pblapply(layers, function(x) {
244 #     vectorToRaster(x)
245 # })
246
247
248 #

```

```
249
250 # # determine the bounding box of the city boundary
251 # bb <- bbox(study_area)
252 #
253 # # specify the desired cell size
254 # cs <- c(sp_res, sp_res) # 2km x 2km
255 #
256 # # cell offset and starting point (bottom right corner?)
257 # cc <- bb[, 1] + (cs/2) # cell offset, centering bottom right corner
    at the halfway point
258 #
259 # # number of cells per direction
260 # cd <- ceiling(diff(t(bb))/cs)
261 #
262 # # convert to GridTopology
263 # grd <- GridTopology(cellcentre.offset = cc, cellsize = cs, cells.
    dim = cd)
264 # grd
265 #
266 # # convert to spatial grid dataframe
267 # sp_grd <- SpatialGridDataFrame(grd, data = data.frame(id=1:prod(cd)
    ),
268 #                               proj4string = CRS(proj4string(study_
    area)))
269 #
270 #
271 # # convert from SpatialGridDataFrame to polygons for gIntersection()
    with city boundary
272 # print("convert to grid sp")
273 # grid_poly <- as(sp_grd, "SpatialPolygonsDataFrame")
274 #
275 # # # clipping grid by the city boundary
276 # # grid <- grid_poly[sacra, ]
277 # # grid <- grid_poly
278 #
279 # # convert to sf object
280 # print("convert to grid sf")
281 # grid <- st_as_sf(grid_poly)
282 #
283 # # iterate through each grid cell to get the area-weighted
    population from the block group data
284 # print("begin pblapply!")
285 # df <- Reduce(rbind, pblapply(1:nrow(grid), function(i) {
286 #
287 #   # capture each row of our grid dataframe
288 #   cell <- grid[i, ]
289 #
290 #   # store cell id variable
```

```

291 #   cell_id <- cell$id
292 #
293 #   # determine the grid cell area (4 km^2)
294 #   cell_area <- as.numeric(st_area(cell$geometry))
295 #
296 #   row_cell <- Reduce(rbind, lapply(1:nrow(acs), function(j) {
297 #
298 #       # capture each row of our block group data
299 #       bg <- acs[j, ]
300 #
301 #       # determine if a block group intersects with a grid cell
302 #       overlap <- st_intersects(cell$geometry, bg$geometry)[[1]]
303 #
304 #       # calculate relative
305 #       if(!is_empty(overlap)) {
306 #
307 #           bg_area <- as.numeric(st_area(bg$geometry))
308 #           relative_area <- as.numeric(st_area(st_intersection(cell$
309 # geometry, bg$geometry)))
310 #           bg_pop <- bg$B00001_001E
311 #           weighted_pop <- bg_pop*(relative_area/bg_area)
312 #           bg_name <- bg$NAME
313 #
314 #           # print each row to console
315 #           print(paste(cell_id, bg_name, weighted_pop, bg_pop))
316 #
317 #           row_bg <- data.frame(grid_cell_id = cell_id
318 #                                ,bg_name = bg_name
319 #                                ,bg_pop = bg_pop
320 #                                ,relative_area = relative_area
321 #                                ,bg_area = bg_area
322 #                                ,cell_area = cell_area
323 #                                )
324 #
325 #           # store each row in our output dataframe
326 #           # output_df = rbind(output_df
327 #                                ,data.frame(grid_cell_id = cell_id
328 #                                              ,bg_name = bg_name
329 #                                              ,weighted_pop = weighted_pop
330 #                                              ,bg_pop = bg_pop
331 #                                              ,relative_area = relative_
332 # area
333 #                                              ,bg_area = bg_area
334 #                                              ,cell_area = cell_area
335 #                                              )
336 #                                ,stringsAsFactors=FALSE)
337 #           # return(output_df)

```

```
337 #   }
338 #   }
339 # ))
340 # return(row_cell)
341 #   }
342 #   ,cl = detectCores()-1
343 #   ))
344 # saveRDS(df, "./output/pop_dens.RDS")
345 # stop("Hecate Processing complete")
346
347 # # create any empty dataframe
348 # output_names <- c("grid_cell_id"
349 #                   , "bg_name"
350 #                   , "weighted_pop"
351 #                   , "bg_pop"
352 #                   , "relative_area"
353 #                   , "bg_area"
354 #                   , "cell_area"
355 # )
356 #
357 # output_df <- data.frame(matrix(ncol = length(output_names)
358 #                                ,nrow = 0))
359 #
360 # colnames(output_df) <- output_names
361 # print("Begin for loop :/")
362 # for(i in 1:nrow(grid)) {
363 #
364 #   # capture each row of our grid dataframe
365 #   cell <- grid[i, ]
366 #
367 #   # store cell id variable
368 #   cell_id <- cell$id
369 #
370 #   # determine the grid cell area (4 km^2)
371 #   cell_area <- as.numeric(st_area(cell$geometry))
372 #
373 #   # iterate through each block group
374 #   for(j in 1:nrow(acs)) {
375 #
376 #     # capture each row of our block group data
377 #     bg <- acs[j, ]
378 #
379 #     # determine if a block group intersects with a grid cell
380 #     overlap <- st_intersects(cell$geometry, bg$geometry)[[1]]
381 #
382 #     # calculate relative
383 #     if(!is_empty(overlap)) {
384 #
```



```

385 #         bg_area <- as.numeric(st_area(bg$geometry))
386 #         relative_area <- as.numeric(st_area(st_intersection(cell$
geometry, bg$geometry)))
387 #         bg_pop <- bg$B00001_001E
388 #         weighted_pop <- bg_pop*(relative_area/bg_area)
389 #         bg_name <- bg$NAME
390 #
391 #         # print each row to console
392 #         print(paste(cell_id, bg_name, weighted_pop, bg_pop))
393 #
394 #         # store each row in our output dataframe
395 #         output_df = rbind(output_df
396 #                             ,data.frame(grid_cell_id = cell_id
397 #                                           ,bg_name = bg_name
398 #                                           ,weighted_pop = weighted_pop
399 #                                           ,bg_pop = bg_pop
400 #                                           ,relative_area = relative_area
401 #                                           ,bg_area = bg_area
402 #                                           ,cell_area = cell_area
403 #                                           )
404 #                             ,stringsAsFactors=FALSE)
405 #
406 #     }
407 #
408 #
409 # }
410 #
411 # }
412 #
413 # # sum each grid cell's weighted pop for each intersecting bg
414 # grid_pop <- output_df %>%
415 #   group_by(grid_cell_id) %>%
416 #   summarise(population = sum(weighted_pop))
417 #
418 # saveRDS(grid_pop, "./output/pop_dens/pop_dens.RDS")
419 #
420 # # append pop data back to the original grid data
421 # grid <- left_join(grid, grid_pop, by = c("id" = "grid_cell_id"))
422 #
423 # # convert to sp class for leaflet?
424 # grid_sp <- as(grid, "Spatial")
425 # projection(grid_sp)
426 # grid_sp <- spTransform(grid_sp, CRSobj = CRS(wgs_84))
427 # projection(grid_sp)
428 #
429 # # Convert to raster?
430 # saveRDS(grid_sp, "./output/pop_dens/grid_sp.RDS")

```

Source/processPBL.R

```

1 # load the necessary packages
2 if (!require(pacman)) {
3   install.packages("pacman")
4   library(pacman)
5 }
6
7 p_load(rgdal
8       ,rgeos
9       ,sp
10      ,ncdf4
11      ,raster
12      ,rasterVis
13      ,dplyr
14      ,magrittr
15      ,pbapply
16      ,parallel
17      ,gdalUtils
18      ,tools
19      ,pryr
20      ,snow)
21
22 # Read in global variables
23 source("../src/init.R")
24
25 # CRS
26 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
27 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
28             +no_defs "
29
30 formatLayerName <- function(layer) {
31   # layer %>% stringr::str_replace_all("X", "") %>%
32   #   as.POSIXct(format = "%Y.%m.%d.%H.%M.%S")
33   layer %>% stringr::str_replace_all("X", "")
34   layer <- paste0("pbl.", layer)
35   return(layer)
36 }
37
38 # GDAL WARP
39 warpStack <- function(stack, study_region) {
40   print(paste0("Writing GeoTiffs for gdalwarp to ", tempdir()))
41   ff <- paste0(tempdir(), "/", names(stack), ".tif")
42   pblapply(ff, function(f) {
43     layer <- stack[[basename(file_path_sans_ext(f))]]
44     writeRaster(layer, f, format = "GTiff", overwrite=T)
45   }, cl = detectCores()-1)

```

```

46 e <- bbox(extent(study_region))
47 tr <- c(sp_res, sp_res)
48 print("Begin gdalwarp")
49 pblapply(ff, function(f) {
50   gdalUtils::gdalwarp(f, s_srs=proj4string(stack), t_srs=
     proj4string(study_region), sub('\.tif', '_clipped.tif', f), tr=tr
     ,
51     r='bilinear', te=c(e), multi = TRUE,
     overwrite = TRUE)
52 }
53 ,cl = detectCores()-1
54 )
55 rm(stack, e, tr, ff, study_region)
56 gc()
57 print(paste0("Reading in clipped/projected stack from ", tempdir())
     )
58 cr <- stack(list.files(tempdir(), "_clipped\\.tif$", full.names=T))
59 print("Renaming clipped/projected layers")
60 names(cr) <- sub('_clipped$', '', names(cr))
61 return(cr)
62 }
63
64 # assigns mean value of entire layer to each cell
65 meanLayer <- function(stack) {
66
67   # Average our buffer to get the best approximation of regional PBL
68   print("Calculate meanLayer")
69   pblapply(1:nlayers(stack), function(x) {
70
71     r <- stack[[x]]
72     r[] <- raster::cellStats(r, stat='mean', na.rm=T) %>% as.numeric
       ()
73     writeRaster(r, paste0(tempdir(), "/", names(r), "_mean.tif"),
       overwrite=T, format="GTiff")
74     rm(r)
75     gc()
76   },cl = detectCores()-1 # mem limit!
77 )
78
79 print(paste0("Reading in meanLayer stack from ", tempdir()))
80 s <- stack(list.files(tempdir(), "_mean\\.tif$", full.names=T))
81 print("Renaming meanLayer stack")
82 names(s) <- sub('_mean$', '', names(s))
83
84 return(s)
85
86 }
87

```

```

88 # Extract min/max PBL each date
89 pblMinMax <- function(pbl_stack) {
90
91     print("Calculate pblMinMax")
92
93     # Extract timestamps from layer names
94     timestamps <- names(pbl_stack) %>% gsub(pattern = "^pbl.",
95         replacement = "") %>% lubridate::ymd_hms()
96
97     # Convert to vector of unique dates
98     dates <- as.Date(timestamps) %>% gsub(pattern = "\\-", replacement
99         = ".") %>% unique()
100
101     # Loop through each date to find the min/max PBL layers
102     pblapply(dates, function(x) {
103
104         # Find the row indices for a given date
105         date_index <- grepl(paste0("pbl\\.", x, ".*"), names(pbl_stack))
106
107         # Extract these layers from the stack
108         date_stack <- pbl_stack[[which(date_index)]]
109
110         # Find the min and max layers for this date
111         max_pbl <- max(date_stack)
112         min_pbl <- min(date_stack)
113
114         # Stack the results
115         min_max <- stack(min_pbl, max_pbl)
116         rm(min_pbl, max_pbl)
117         gc()
118
119         # Assign new names
120         names(min_max) <- c(paste0("pbl.min.", x), paste0("pbl.max.", x))
121
122         # Write to file
123         print(paste0("Writing ", names(min_max), " to tmp file in ",
124             tempdir()))
125         writeRaster(min_max, paste0(tempdir(), "/", names(min_max), "_
126             minmax.tif"),
127             ,overwrite=T
128             ,format="GTiff"
129             ,bylayer=T)
130
131         # Garbage collection
132         rm(date_stack, date_index, min_max)
133         gc()
134     }, cl = detectCores() - 1)

```

```

132
133   print(paste0("Reading in min/max PBL stack from ", tempdir()))
134   s <- stack(list.files(tempdir(), "_minmax\\.tif$", full.names=T))
135   print("Renaming min/max PBL stack")
136   names(s) <- sub('_minmax$', '', names(s))
137
138   # Garbage collection
139   rm(timestamps, dates)
140   gc()
141
142   return(s)
143
144 }
145
146 processPBL <- function(file_name
147                        ,study_area
148                        ,crs
149                        ,out_dir) {
150   # Read in data
151   r <- raster::stack(file_name)
152
153   # Format layer names
154   names(r) <- lapply(names(r), function(i) {
155     formatLayerName(layer = i)
156   })
157
158   # Read in study area
159   x <- readRDS(study_area) %>% spTransform(CRSobj = crs(crs))
160
161   # GDAL WARP
162   cr <- warpStack(stack = r, study_region = x)
163
164   # Compute mean PBL for each 3-hour observation
165   s <- meanLayer(cr)
166
167   # Extract min/max PBL layers for each day
168   s <- pblMinMax(pbl_stack = s)
169   rm(cr, x)
170   gc()
171
172   # Split the min/max layers apart to save in separate directories
173   print("Subset min/max from stack")
174   s_min <- subset(s, grep('^pbl.min.*', names(s), value = T))
175   s_max <- subset(s, grep('^pbl.max.*', names(s), value = T))
176
177   # Write each stack type to file
178   print("Writing min stack to file")
179   pblapply(1:nlayers(s_min), function(i) {

```

```

180     writeRaster(s_min[[i]], file.path(paste0(out_dir, "min/", names(s
      _min[[i]]), ".tif"))
181         ,format = "GTiff"
182         ,overwrite = TRUE
183         ,bayer = T
184     )
185 }, cl = detectCores()-1
186 )
187
188 print("Writing max stack to file")
189 pblapply(1:nlayers(s_max), function(i) {
190     writeRaster(s_max[[i]], file.path(paste0(out_dir, "max/"), paste0
      (names(s_max[[i]]), ".tif"))
191         ,format = "GTiff"
192         ,overwrite = TRUE
193         ,bayer = T
194     )
195 }, cl = detectCores()-1
196 )
197
198 # Clean up
199 print("Garbage collection")
200 rm(s_min, s_max, s)
201 gc()
202 }
203
204
205 # Create a list of raw PBL nc data
206 PBLFiles <- list.files(path = "./data/PBL/nc", pattern = "\\\\.nc$",
      full.names = T)
207
208 # For testing our function
209 # file_name <- PBLFiles[2]
210
211 # Apply our data transformation function to each file
212 pblapply(PBLFiles, function(x) {
213     processPBL(file_name = x
214         ,study_area = study_area
215         ,crs = epsg_26910
216         ,out_dir = "./data/PBL/")
217     # Clean up
218     gc()
219     #,cl = detectCores()-1
220     )
221
222 # f <- list.files(path = "./data/PBL/tif/", full.names = T)
223 # r <- stack(f)
224 # a <- subset(r, 1:16)

```

```

225 # plot(a)
226 # spplot(a)

```

Source/processElevation.R

```

1  # load the necessary packages
2  if (!require(pacman)) {
3    install.packages("pacman")
4    library(pacman)
5  }
6
7  p_load(rgdal
8         ,rgeos
9         ,sp
10        ,raster
11        ,dplyr
12        ,magrittr
13        ,pbapply
14        ,parallel
15        ,snow)
16
17  source("../src/init.R")
18
19  processElev <- function(file_name
20                          ,study_area = "../study_area/study_area.RDS"
21                          ,crs = crs
22                          ,outdir = "../data/elev") {
23    r <- raster(file_name)
24    x <- readRDS(study_area) %>% spTransform(CRSobj = crs(crs))
25    # create larger buffer before masking/cropping
26    y <- rgeos::gBuffer(x, width = 10000)
27    y %>% spTransform(CRSobj = crs(r))
28    # x %>% spTransform(CRSobj = crs(r))
29    m <- mask(r, y, getCover = T) # masking on x excludes a few cells!
30    cr <- crop(m, extent(y))
31    # project to epsg_26910 @ 50 m resolution
32    cr %>% projectRaster(crs = crs, method = "bilinear", res = sp_res)
33    cr %>% mask(x) %>% crop(extent(x))
34    # out_file <- gsub(basename(file_name), pattern = "\\\\.nc",
35                      replacement = ".tif")
36    outfile <- "elev.tif"
37    raster::writeRaster(cr
38                       ,filename = paste0(outdir, "/", outfile)
39                       ,format = "GTiff"
40                       ,overwrite = TRUE
41                       )
42  }

```

```
43
44 # I'm using the single elevation layer for each day. It's not going
    to change that much each
45 processElev( file_name = "./data/elev/aster_dem_pdx.tif"
46              ,crs = crs
47              ,outdir = "./data/elev")
```

Source/processNeph.R

```
1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-13
5 # process DEQ automatic data, convert to tidy format, save as RDS
6
7 # load the necessary packages
8 if (!require(pacman)) {
9   install.packages("pacman")
10  library(pacman)
11 }
12
13 p_load(rgdal
14        ,plyr
15        ,dplyr
16        ,magrittr
17        ,gdalUtils
18        ,raster
19        ,sp
20        ,sf
21        ,rgeos
22        ,leaflet
23        ,lubridate
24        #,MODIS
25        #,bowerbird
26        #,gstat
27        ,parallel
28        ,snow
29        ,pbapply
30        ,ggplot2
31        ,rts
32        ,tidyr
33        ,RPostgres
34        ,ggmap
35        ,gridExtra
36        ,readxl)
37
38
39 # Load in global variables
```



```
40 source("./src/init.R")
41
42 # Load in misc function
43 source("./src/functions.R")
44
45 # set timezone to UTC/GMT to match postgres
46 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
  PDT!
47 # DEQ only uses PST!
48 Sys.timezone()
49 Sys.setenv(TZ="GMT")
50 Sys.timezone()
51 # time zone applied to all data
52 time_zone <- "GMT"
53
54
55 # Read in PM data
  

---


56
57 # Read in 1-hour Automatic Data from Excel
58 read_frm <- function(file_path) {
59
60   # read in the raw data
61   x <- read_excel(file_path)
62
63   sites <- x[3,]
64   sites <- sites[which(!is.na(sites))]
65   sites <- sites[1,-1] %>% as.character() %>% gsub(pattern = "\\s",
     replacement = "_") %>% tolower()
66   header <- x[4,]
67
68   body <- x[-c(1:4),]
69
70   # Hardcode column names for now...
71   colnames(body) <- header[1, ]
72   colnames(body)[2] <- sites[1]
73   colnames(body)[5] <- sites[2]
74   colnames(body)[8] <- sites[3]
75   colnames(body)[11] <- sites[4]
76   colnames(body)[14] <- sites[5]
77   colnames(body)[17] <- sites[6]
78
79   x <- body[,c(1:2,5,8,11,14,17)]
80
81   # convert date from character to POSIXct
82   x$Date <- mdy_hm(x$Date, tz = time_zone)
83
```

```

84   # This drops a lot of days!
85   # x <- x %>% na.omit()
86
87   # convert to tidy format, gather on site id
88   long <- x %>%
89     gather(id, pm2_5_atm, -c(Date))
90
91   # convert characters in pm2_5 data to NA
92   long$pm2_5_atm <- as.numeric(long$pm2_5_atm)
93
94
95   # exclude NAs (No Data, Zero, DL/Computer, etc. gets converted to
96   # NA)
97   long <- long %>% na.omit()
98   long %>% unique()
99
100  # alter column names
101  colnames(long) <- c("datetime"
102                      , "site_id"
103                      , "pm2_5_ref")
104
105  long$lat[long$site_id == "beaverton_highland_park"] <- 45.470183
106  long$lat[long$site_id == "hillsboro_hare_field"] <- 45.528549
107  long$lat[long$site_id == "portland_se_lafayette"] <- 45.496635
108  long$lat[long$site_id == "portland_cully_helensview"] <- 45.562206
109  long$lat[long$site_id == "sauvie_island"] <- 45.768528
110  long$lat[long$site_id == "tualatin_bradbury_court"] <- 45.399189
111
112  long$lon[long$site_id == "beaverton_highland_park"] <- -122.816418
113  long$lon[long$site_id == "hillsboro_hare_field"] <- -122.972423
114  long$lon[long$site_id == "portland_se_lafayette"] <- -122.602883
115  long$lon[long$site_id == "portland_cully_helensview"] <-
116    -122.575627
117  long$lon[long$site_id == "sauvie_island"] <- -122.772305
118  long$lon[long$site_id == "tualatin_bradbury_court"] <- -122.745538
119  long %>% dplyr::select(datetime, site_id, pm2_5_ref, lat, lon)
120  long %>% na.omit()
121  return(long)
122  }
123
124  # establish avg interval for xts() function
125  time_step <- 5
126
127  # for clean 5-min breaks
128  align.time.down = function(x,n) {
129    index(x) = index(x) - n

```

```

130   align.time(x,n)
131 }
132
133
134 # remove geometry from sf object, convert to dataframe with only the
    elements/attributes
135 st_drop_geometry <- function(x) {
136   if (inherits(x, "sf")) {
137     x <- st_set_geometry(x, NULL)
138     class(x) <- 'data.frame'
139   }
140   return(x)
141 }
142
143
144
145
146 # read functions for neph data that Meena provided
147 read_2017_neph <- function(file_path) {
148
149   x <- read.csv(file_path)
150   names(x)[names(x) == "Datetime.Local"] <- "datetime"
151   x$datetime <- as.POSIXct(x$datetime, "%Y-%m-%d %H:%M:%S")
152   names(x)[names(x) == "stn_id"] <- "site_id"
153   names(x)[names(x) == "Sample.Measurement"] <- "pm2_5_ref"
154
155   x$site_id[x$site_id == 410670111] <- "Beaverton Highland Park"
156   x$site_id[x$site_id == 410670004] <- "Hillsboro Hare Field"
157   x$site_id[x$site_id == 410510080] <- "Portland SE Lafayette"
158   x$site_id[x$site_id == 410090004] <- "Sauvie Island"
159   x$site_id[x$site_id == 410670005] <- "Tualatin Bradbury Court"
160
161   x$lat[x$site_id == "Beaverton Highland Park"] <- 45.470183
162   x$lat[x$site_id == "Hillsboro Hare Field"] <- 45.528549
163   x$lat[x$site_id == "Portland SE Lafayette"] <- 45.496635
164   x$lat[x$site_id == "Portland Cully Helensview"] <- 45.562206
165   x$lat[x$site_id == "Sauvie Island"] <- 45.768528
166   x$lat[x$site_id == "Tualatin Bradbury Court"] <- 45.399189
167
168   x$lon[x$site_id == "Beaverton Highland Park"] <- -122.816418
169   x$lon[x$site_id == "Hillsboro Hare Field"] <- -122.972423
170   x$lon[x$site_id == "Portland SE Lafayette"] <- -122.602883
171   x$lon[x$site_id == "Portland Cully Helensview"] <- -122.575627
172   x$lon[x$site_id == "Sauvie Island"] <- -122.772305
173   x$lon[x$site_id == "Tualatin Bradbury Court"] <- -122.745538
174
175   x %>% dplyr::select(datetime, site_id, pm2_5_ref, lat, lon)
176   x %>% na.omit()

```

```

177   return(x)
178
179 }
180
181 read_2017_5min <- function(file_path) {
182
183   # read in the raw data
184   x <- read.csv(file_path, header = TRUE, skip = 2)
185
186   # delete sub headers
187   # x <- x[-c(1:2),]
188
189   # convert date from character to POSIXct
190   x$Date...Time <- mdy_hm(x$Date...Time, tz = time_zone)
191
192   x <- x %>% na.omit()
193
194   # convert to tidy format, gather on site id
195   long <- x %>%
196     gather(id, pm2_5_atm, -c(Date...Time))
197
198   # convert characters in pm2_5 data to NA
199   long$pm2_5_atm <- as.numeric(long$pm2_5_atm)
200
201
202   # exclude NAs (No Data, Zero, DL/Computer, etc. gets converted to
203   # NA)
204   long <- long %>% na.omit()
205
206   # alter column names
207   colnames(long) <- c("datetime"
208                       , "site_id"
209                       , "pm2_5_ref")
210
211   long$site_id <- gsub("^X[0-9]+\\.\\.", "", long$site_id)
212   long$site_id <- gsub("\\\\.", " ", long$site_id)
213
214   long$site_id <- ifelse(long$site_id == "Portland Near Rd", "
215     Tualatin Bradbury Court", long$site_id)
216
217   long$lat[long$site_id == "Beaverton Highland Park"] <- 45.470183
218   long$lat[long$site_id == "Hillsboro Hare Field"] <- 45.528549
219   long$lat[long$site_id == "Portland SE Lafayette"] <- 45.496635
220   long$lat[long$site_id == "Portland Cully Helensview"] <- 45.562206
221   long$lat[long$site_id == "Sauvie Island"] <- 45.768528
222   long$lat[long$site_id == "Tualatin Bradbury Court"] <- 45.399189
223
224   long$lon[long$site_id == "Beaverton Highland Park"] <- -122.816418

```

```

223   long$lon[long$site_id == "Hillsboro Hare Field"] <- -122.972423
224   long$lon[long$site_id == "Portland SE Lafayette"] <- -122.602883
225   long$lon[long$site_id == "Portland Cully Helensview"] <-
      -122.575627
226   long$lon[long$site_id == "Sauvie Island"] <- -122.772305
227   long$lon[long$site_id == "Tualatin Bradbury Court"] <- -122.745538
228
229
230   long %>% dplyr::select(datetime, site_id, pm2_5_ref, lat, lon)
231   long %>% na.omit()
232
233   long$site_id <- gsub("\\ ", "_", long$site_id)
234   long$site_id <- tolower(long$site_id)
235   #long$site_id <- stringr::str_replace(long$site_id, ".", " ")
236
237   return(long)
238
239 }
240
241
242 read_2018_5min <- function(file_path) {
243
244   # read in the raw data
245   x <- read_excel(file_path)
246
247   # delete sub headers
248   x <- x[-c(1:2),]
249   x <- x[,2:ncol(x)]
250   names(x)[names(x) == "Date & Time - start of obs period"] <- "Date"
251   # convert date from character to POSIXct
252   x$Date <- ymd_hms(x$Date, tz = time_zone)
253   x <- x %>% na.omit()
254
255   # convert to tidy format, gather on site id
256   long <- x %>%
257     gather(id, pm2_5_atm, -c(Date))
258
259   # convert characters in pm2_5 data to NA
260   long$pm2_5_atm <- as.numeric(long$pm2_5_atm)
261
262
263   # exclude NAs (No Data, Zero, DL/Computer, etc. gets converted to
      NA)
264   long <- long %>% na.omit()
265
266   # alter column names
267   colnames(long) <- c("datetime"
268                       , "site_id"

```

```

269         , "pm2_5_ref")
270
271 # long$site_id <- gsub("^X[0-9]+\\.\\.", "", long$site_id)
272 #long$site_id <- gsub("\\\\.", " ", long$site_id)
273
274 long$site_id <- ifelse(long$site_id == "Portland Near Rd", "
    Tualatin Bradbury Court", long$site_id)
275
276 long$lat[long$site_id == "Beaverton Highland Park"] <- 45.470183
277 long$lat[long$site_id == "Hillsboro Hare Field"] <- 45.528549
278 long$lat[long$site_id == "Portland SE Lafayette"] <- 45.496635
279 long$lat[long$site_id == "Portland Cully Helensview"] <- 45.562206
280 long$lat[long$site_id == "Sauvie Island"] <- 45.768528
281 long$lat[long$site_id == "Tualatin Bradbury Court"] <- 45.399189
282
283 long$lon[long$site_id == "Beaverton Highland Park"] <- -122.816418
284 long$lon[long$site_id == "Hillsboro Hare Field"] <- -122.972423
285 long$lon[long$site_id == "Portland SE Lafayette"] <- -122.602883
286 long$lon[long$site_id == "Portland Cully Helensview"] <-
    -122.575627
287 long$lon[long$site_id == "Sauvie Island"] <- -122.772305
288 long$lon[long$site_id == "Tualatin Bradbury Court"] <- -122.745538
289
290
291 long %>% dplyr::select(datetime, site_id, pm2_5_ref, lat, lon)
292 long %>% na.omit()
293
294 long$site_id <- gsub("\\ ", "_", long$site_id)
295 long$site_id <- tolower(long$site_id)
296 #long$site_id <- stringr::str_replace(long$site_id, ".", " ")
297
298 return(long)
299
300 }
301
302 read_2018_neph <- function(file_path) {
303
304 # extract header
305 header <- read.csv(file_path, nrow = 1, skip = 2, header = FALSE,
    stringsAsFactors = FALSE) %>%
306   select_if(~ !any(is.na(.)))
307
308 # extract body
309 x <- read.csv(file_path, header = TRUE, skip = 4, stringsAsFactors
    = FALSE)
310
311 colnames(header) <- unlist(header[1,])
312 colnames(x) <- colnames(header)

```

```

313
314   names(x)[names(x) == "Date & Time"] <- "datetime"
315   x$datetime <- as.POSIXct(x$datetime, format = "%m/%d/%Y %H:%M")
316   x <- x %>%
317     gather(key = site_id, value = pm2_5_ref, -datetime)
318   x$pm2_5_ref <- as.numeric(x$pm2_5_ref)
319   x <- x %>% na.omit()
320   x$lat[x$site_id == "Beaverton Highland Park"] <- 45.470183
321   x$lat[x$site_id == "Hillsboro Hare Field"] <- 45.528549
322   x$lat[x$site_id == "Portland SE Lafayette"] <- 45.496635
323   x$lat[x$site_id == "Portland Cully Helensview"] <- 45.562206
324   x$lat[x$site_id == "Sauvie Island"] <- 45.768528
325   x$lat[x$site_id == "Tualatin Bradbury Court"] <- 45.399189
326
327   x$lon[x$site_id == "Beaverton Highland Park"] <- -122.816418
328   x$lon[x$site_id == "Hillsboro Hare Field"] <- -122.972423
329   x$lon[x$site_id == "Portland SE Lafayette"] <- -122.602883
330   x$lon[x$site_id == "Portland Cully Helensview"] <- -122.575627
331   x$lon[x$site_id == "Sauvie Island"] <- -122.772305
332   x$lon[x$site_id == "Tualatin Bradbury Court"] <- -122.745538
333
334   return(x)
335
336 }
337
338 neph2017 <- read_2017_5min("./data/frm/bhp_hhf_tbc_sel_5min_pm25_
339   20170701_to_20180918.csv")
340
341 neph2018 <- read_2018_5min("./data/frm/pm25_5min_bhp_hhf_pch_sel_sis_
342   tbc_sep18_to_may19.xlsx")
343
344 # TODO Sauvie Island is missing from 2017 data!
345
346 # converting from hourly to daily, computing min, max, mean, sd
347 neph <- rbind(neph2017, neph2018)
348
349 # remove any duplicates (e.g. September 2018)
350 neph %>% unique()
351
352 neph$date <- lubridate::date(neph$datetime)
353
354 neph_daily <- neph %>% dplyr::select(-datetime) %>% group_by(date,
355   site_id, lat, lon) %>%
356   summarize_if(is.numeric
357     , funs(pm2.5.mean = mean
358       , pm2.5.min = min
359       , pm2.5.max = max
360       , pm2.5.sd = sd
361       , pm2.5.median = median))

```

```

358         ,na.rm = T)
359
360 neph %>% st_as_sf(coords = c("lon","lat"), crs = wgs_84)
361 neph_daily %>% st_as_sf(coords = c("lon","lat"), crs = wgs_84)
362 # Inspect the data and clean up outliers
363 summary(neph)
364 summary(neph_daily)
365
366 # Yikes there are definitely some issues with the mean/max values
367 plot(neph_daily$date, neph_daily$pm2.5.mean)
368
369 # Let's filter by our max pm range init variable (250)
370 neph_daily %>% filter(pm2.5.mean <= max_pm_range)
371 summary(neph_daily)
372
373 neph %>% filter(pm2_5_ref <= max_pm_range)
374 summary(neph)
375
376 # Looks a lot better now
377 plot(neph_daily$date, neph_daily$pm2.5.mean)
378
379 # TODO Create neph 15-minute averages?
380
381 # Write our clean neph data to file
382 saveRDS(neph_daily, "../data/deq/neph1day.RDS")
383 saveRDS(neph, "../data/deq/neph5min.RDS")
384
385 neph <- read_frm("../data/frm/AutomaticData5_29_2019.xlsx")
386 neph %>% st_as_sf(coords = c("lon","lat"), crs = wgs_84)
387 neph %>% filter(pm2_5_ref <= max_pm_range)
388 saveRDS(neph, "../data/deq/neph1hour.RDS")

```

Source/processPurpleAir.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-28
5 # pull PurpleAir data from database and create daily averages
6
7 # load the necessary packages
8 if (!require(pacman)) {
9   install.packages("pacman")
10  library(pacman)
11 }
12
13 p_load(rgdal
14        ,plyr

```



```
15     ,dplyr
16     ,magrittr
17     ,gdalUtils
18     ,raster
19     ,sp
20     ,sf
21     ,rgeos
22     ,parallel
23     ,lubridate
24     ,ggplot2
25     ,rts
26     ,RPostgres
27     ,ggmap
28     ,gridExtra)
29
30 source("../src/functions.R")
31 source("../src/init.R")
32
33 # set timezone


---


34
35 # set timezone to UTC/GMT to match postgres
36 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
37   PDT!
38 # DEQ only uses PST!
39 Sys.timezone()
40 Sys.setenv(TZ="GMT")
41 Sys.timezone()
42 # Connect to Database


---


43
44 ## connecting to local db
45 host <- 'pgsql120.rc.pdx.edu'
46 db <- 'canopycontinuum'
47 user <- 'porlando'
48 port <- 5433
49 pw <- scan("../batteries.pgpass", what = "") # in parent dir
50
51
52 # open connection to our db
53 con <- dbConnect(drv = RPostgres::Postgres()
54                   ,dbname = db
55                   ,host = 'pgsql102.rc.pdx.edu' # not sure why object
56                   host isn't working...
57                   ,port = port
```



```

92                                     ,lubridate::ymd(end_date) + hours(8), "
93                                     ';" )
94 )
95 # convert from UTC to UTC-8 or PST (same as DEQ)
96 pa$created_at <- lubridate::ymd_hms(pa$created_at) - lubridate::hours
97   (8)
98 # rename the datetime column
99 names(pa)[names(pa) == "created_at"] <- "datetime"
100
101 # check the time zone of pa data
102 attr(pa$datetime, "tzone")
103
104 # set SRID
105 st_crs(pa) <- epsg_26910
106 pa$date <- lubridate::date(pa$datetime)
107 head(pa)
108
109 # Apply Individual Correction Factors each sensor (Aug 2018)
110 pa_cf <- st_read(dsn = con
111                  # ,geom_column = "geom"
112                  # ,EWKB = TRUE
113                  ,query = "SELECT DISTINCT * FROM pdx_cf ;")
114
115
116 # remove geom for now...
117 pa %>% st_drop_geometry()
118 pa_cf %>% st_drop_geometry()
119 # pa_cf$year %>% as.integer()
120 pa$id %>% as.integer()
121
122 # # Find the CF with the maximum R2 for each sensor, excluding
123   anything below 0.8
124 # pa_cf %>%
125 #   group_by(id, label) %>%
126 #   # use the month with highest correlation (includes August 2017
127   for some sensors)
128 #   filter(year == 2018 & month == "Aug") %>%
129 #   slice(which.max(r_squared)) %>%
130 #   filter(r_squared > 0.85) %>%
131 #   na.omit()
132
133 # join CF and PA data
134 pa %>% inner_join(pa_cf %>% dplyr::select(c(id, label, r_squared,
135   slope, intercept))) %>%
136   dplyr::select(c(datetime, id, label, everything()))

```

```

134
135 # apply correction factor
136 pa$pm2_5_cf_x <- (pa$pm2_5_atm*pa$slope)+pa$intercept
137
138 # inspect the new data (compare with lm figures)
139 pa %>% dplyr::select(c(datetime, label, id, slope, pm2_5_atm, pm2_5_
    cf_x, r_squared)) %>%
140   filter(datetime == as.Date("2018-08-01")) %>%
141   arrange(label)
142
143 # inspect raw data and cleaned data
144 pa %>% dplyr::filter(r_squared > 0.85) %>% ggplot(aes(x = label, y =
    pm2_5_cf_x)) +
145   geom_boxplot() +
146   theme(axis.text.x = element_text(angle = 45, hjust = 1))
147
148 pa %>% filter(pm2_5_cf_x < max_pm_range & r_squared > 0.85 & slope >=
    0.4 & slope <= 1.6) %>%
149   na.omit() %>%
150   dplyr::filter(r_squared > 0.8) %>% ggplot(aes(x = label, y = pm2_5_
    cf_x)) +
151   geom_boxplot() +
152   theme(axis.text.x = element_text(angle = 45, hjust = 1))
153
154 pa %>% filter(pm2_5_cf_x < max_pm_range & r_squared > 0.85 & slope >=
    0.4 & slope <= 1.6) %>%
155   na.omit() %>%
156   dplyr::filter(r_squared > 0.8) %>% ggplot(aes(x = as.factor(id), y
    = slope)) +
157   geom_boxplot() +
158   theme(axis.text.x = element_text(angle = 45, hjust = 1))
159
160 pa_cf %>% ggplot(aes(x = 1, y = slope, fill = as.factor(1))) + geom_
    violin() + xlab("") +
161   theme_minimal() + ggtitle("PurpleAir Calibration Factors") +
162   theme(legend.title = element_blank(), legend.position = "none",
    axis.text.x = element_blank())
163
164 pa_cf %>% ggplot(aes(x = 1, y = r_squared, fill = as.factor(1))) +
    geom_violin() + xlab("") +
165   theme_minimal() + ggtitle("PurpleAir Calibration Factors") +
166   theme(legend.title = element_blank(), legend.position = "none",
    axis.text.x = element_blank())
167
168
169 # Remove faulty sensors

```

```

170 pa_flag <- st_read(dsn = con
171                     # ,geom_column = "geom"
172                     # ,EWKB = T
173                     ,query = "SELECT DISTINCT * FROM pdx_flag;")
174
175
176 # examine quality of flagging on suspect sensors
177 top_flag <- pa_flag %>% filter(flag == 1) %>%
178   dplyr::select(label, id) %>%
179   group_by(label, id) %>%
180   mutate(n = n()) %>%
181   summarise_if(is.numeric, mean) %>%
182   arrange(desc(n))
183
184 # ensure id column type matches pa
185 pa$id <- as.character(pa$id)
186
187 # With pdx_flag == 0
188
189 # TODO confirm outlier detection algo is not worthwhile with new CF
190 # methods...
191 # cleaning data by slope between 0.5 and 1.5 helps reduce additional
192 # outliers
193 # pa_clean <- pa %>% inner_join(pa_flag, by = c("date", "id", "label
194 #   ")) %>%
195 #   # exclude faulty sensor data, and trim extremes
196 #   filter(flag == 0 & pm2_5_cf_x <= max_pm_range & r_squared >= 0.9)
197
198 # Not using the pdx_flag algo
199
200 pa_clean <- pa %>% inner_join(pa_flag, by = c("date", "id", "label")
201   ) %>%
202   filter(pm2_5_cf_x <= max_pm_range & r_squared >= 0.9)
203
204 # pa_dirty <- pa %>% left_join(pa_flag, by = c("date", "id", "label
205 #   "))
206
207 # pa_filter <- pa %>% left_join(pa_flag, by = c("date", "id", "label
208 #   ")) %>%
209 #   # exclude faulty sensor data, and trim extremes
210 #   filter(pm2_5_cf_x <= max_pm_range & r_squared >= 0.85 & slope >=
211 #     0.5 & slope <= 1.5)
212
213 nrow(pa_clean)/nrow(pa)
214
215 pa_clean %>% ggplot(aes(x = label, y = pm2_5_cf_x)) +
216   geom_violin() +
217   theme(axis.text.x = element_text(angle = 45, hjust = 1))

```

```

209
210 # pa_clean <- pa %>%
211 #   filter(pm2_5_cf_x < max_pm_range & r_squared > 0.85 & slope >=
212 #     0.4 & slope <= 1.6) %>%
213 #   na.omit()
214 pa_5m <- pa_clean %>%
215   dplyr::select(-c(date, geom))
216
217 pa_summary <- pa_clean %>%
218   dplyr::select(-datetime) %>%
219   group_by(date, id, sensor, label) %>%
220   summarise_at("pm2_5_cf_x", funs(mean, median, min, max))
221
222 pa_summary$diff <- abs(pa_summary$mean - pa_summary$median)
223
224 pa_summary %>%
225   group_by(id, sensor, label) %>%
226   summarise_at("diff", funs(mean, median, max, min)) %>%
227   arrange(desc(max))
228
229 pa_24h <- pa_clean %>%
230   dplyr::select(-c(datetime, geom)) %>%
231   group_by(date, id, sensor, label) %>%
232   summarise_if(is.numeric, funs(mean), na.rm = T)
233
234 pa_24h_all <- pa_dirty %>%
235   dplyr::select(-c(datetime, geom)) %>%
236   group_by(date, id, sensor, label) %>%
237   summarise_if(is.numeric, funs(mean), na.rm = T)
238
239 pa_24h_filter <- pa_filter %>%
240   dplyr::select(-c(datetime, geom)) %>%
241   group_by(date, id, sensor, label) %>%
242   summarise_if(is.numeric, funs(mean), na.rm = T)
243
244 pa_24h %>% ggplot(aes(x = label, y = pm2_5_cf_x)) +
245   geom_boxplot() +
246   theme(axis.text.x = element_text(angle = 45, hjust = 1))
247
248 pa_24h %>% ggplot(aes(x = date, y = pm2_5_cf_x, col = flag)) +
249   geom_point() +
250   theme_bw()
251
252 pa_24h_all %>% filter(pm2_5_cf_x <= max_pm_range & label %in% top_
253   flag$label) %>% na.omit() %>%
254   ggplot(aes(x = date, y = pm2_5_cf_x, col = as.factor(flag))) +
255   geom_point(alpha = 0.6) +

```

```

255   theme_bw() +
256   scale_color_manual(values = c("#000000", "#ba2525")) +
257   labs(y = "PM2.5 (ug/m3)", x = "", color = "Outlier Flag", title = "
      Modified Z-Score Outlier Detection") +
258   theme(legend.position="bottom")
259
260   pa_24h_all %>% filter(date >= "2018-01-01" & date <= "2018-03-01")
      %>%
261   filter(pm2_5_cf_x <= max_pm_range & label %in% top_flag$label) %>%
      na.omit() %>%
262   ggplot(aes(x = date, y = pm2_5_cf_x, col = as.factor(flag))) +
263   geom_point(alpha = 0.6) +
264   theme_bw() +
265   scale_color_manual(values = c("#000000", "#ba2525")) +
266   labs(y = "PM2.5 (ug/m3)", x = "", color = "Outlier Flag", title = "
      Modified Z-Score Outlier Detection") +
267   theme(legend.position="bottom")
268
269   ggsave(last_plot(),
270         ,filename = paste0("./figures/outlier_detection/", print_clean
      _time(), "-Jan-Mar-z-score-outlier-ts.png")
271   )
272
273
274   pa_24h_all %>% filter(date >= "2018-07-01" & date <= "2018-09-01")
      %>%
275   filter(pm2_5_cf_x <= max_pm_range & label %in% top_flag$label) %>%
      na.omit() %>%
276   ggplot(aes(x = date, y = pm2_5_cf_x, col = as.factor(flag))) +
277   geom_point(alpha = 0.6) +
278   theme_bw() +
279   scale_color_manual(values = c("#000000", "#ba2525")) +
280   labs(y = "PM2.5 (ug/m3)", x = "", color = "Outlier Flag", title = "
      Modified Z-Score Outlier Detection") +
281   theme(legend.position="bottom")
282
283   ggsave(last_plot(),
284         ,filename = paste0("./figures/outlier_detection/", print_clean
      _time(), "-Jul-Sep-z-score-outlier-ts.png")
285   )
286
287   pa_24h_filter %>% na.omit() %>% ggplot(aes(x = date, y = pm2_5_cf_x,
      col = as.factor(flag))) +
288   geom_point(alpha = 0.25) +
289   theme_bw() +
290   scale_color_manual(values = c("#000000", "#ba2525")) +
291   labs(y = "PM2.5 (ug/m3)", x = "", color = "Outlier Flag", title = "
      Modified Z-Score Outlier Detection") +

```

```

292   theme(legend.position="bottom")
293
294   ggsave(last_plot()
295         ,filename = paste0("./figures/outlier_detection/", print_clean
296           _time(), "-z-score-outlier-ts.png")
297         )
298   # Reattach geometry

```

```

299   # PurpleAir geometry
300   # lookup table for sensor geom
301   pa_points <- st_read(dsn = con
302                       ,geom_column = "geom"
303                       ,EWKB = TRUE
304                       ,query = "SELECT DISTINCT id , label , geom FROM
305                                 pdx;"
306                       )
307   # set SRID
308   st_crs(pa_points) <- epsg_26910
309
310   # # Average pm per node
311   # pa_5m$node <- gsub(" B$", "", pa_5m$label)
312
313
314   # This takes forever and isn't being used...
315   # # pa_5m$id <- as.integer(pa_5m$id)
316   # pa_5m %>% inner_join(pa_points) %>% st_as_sf()
317   # st_crs(pa_5m) <- epsg_26910
318   #
319   # # convert geom to text for grouping
320   # pa_5m$geom_text <- st_as_text(pa_5m$geom)
321   #
322   # # average node value by node, date, geom_text
323   # pa_5m_node <- pa_5m %>% ungroup() %>%
324   #   dplyr::select(-c(id, sensor, label)) %>%
325   #   group_by(datetime, node, geom_text) %>%
326   #   summarise_if(is.numeric, funs(mean)) %>% ungroup() %>%
327   #   dplyr::select(date, node, pm2_5_cf_x, geom_text)
328   #
329   # # convert back to sf
330   # pa_5m_node$geom <- st_as_sfc(pa_5m_node$geom_text)
331   # pa_5m_node %>% st_as_sf()
332   # st_crs(pa_5m_node) <- epsg_26910
333   # str(pa_5m_node)
334   #
335   # pa_5m_node %>% as("Spatial")

```



```

336
337 # Average pm per node
338 pa_24h$node <- gsub(" B$", "", pa_24h$label)
339
340 # attach geometry
341 pa_points$id <- as.character(pa_points$id)
342 pa_24h %>% inner_join(pa_points) %>% st_as_sf() # crs is lost!
343 # st_crs(pa_24h) <- epsg_26910
344
345 # convert geom to text for grouping
346 pa_24h$geom_text <- st_as_text(pa_24h$geom)
347
348 # average node value by node, date, geom_text
349 pa_24h_node <- pa_24h %>% ungroup() %>%
350   dplyr::select(-c(id, sensor, label)) %>%
351   group_by(date, node, geom_text) %>%
352   summarise_if(is.numeric, funs(mean)) %>% ungroup() %>%
353   dplyr::select(c(date, node, pm2_5_cf_x, geom_text))
354
355 head(pa_24h_node)
356
357 # convert back to sf
358 # pa_24h_node$geom <- st_as_sfc(pa_24h_node$geom_text)
359 # pa_24h_node %>% st_as_sf()
360 # st_crs(pa_24h_node) <- epsg_26910
361 str(pa_24h_node)
362 # head(pa_24h_node)
363
364 # make sure it preserved geometries when node names are the same...
365 miller <- pa_24h_node %>% filter(node == "Miller")
366
367 # exclude bad Miller sensor in NE Portland
368 pa_24h_node %>%
369   filter(geom_text != miller[1,]$geom_text)
370
371 # drop geom_text column
372 pa_24h_node %>% dplyr::select(-geom_text)
373
374 # finally, convert back to sp
375 pa_24h_node %>% as("Spatial")
376
377 # Write to file

```

```

378 # saveRDS(pa_5m_node, "../data/purpleair/pm_df_5m.RDS")
379 saveRDS(pa_24h_node, "../data/purpleair/pm_df_24h.RDS")
380 # writeOGR(pa, "../data/purpleair/", layer = "pm_df_5m", driver = "
    ESRI Shapefile", overwrite = T)

```

```

381 # writeOGR(pa_24h, "../data/purpleair/", layer = "pm_df_24h", driver =
      "ESRI Shapefile", overwrite = T)

```

Source/buffer.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-19
5 # create daily stacks of GIS predictors, buffer and extract them
6
7 # needed for nvim-R
8 if (basename(getwd()) == "src") {
9   setwd("../")
10  getwd()
11 }
12
13 # load the necessary packages


---


14 if (!require(pacman)) {
15   install.packages("pacman")
16   library(pacman)
17 }
18
19 p_load(plyr
20        ,dplyr
21        ,magrittr
22        ,tools
23        ,rlang
24        ,rgdal
25        ,raster
26        ,rasterVis
27        ,corrplot
28        ,sp
29        ,rgeos
30        ,ggplot2
31        ,stringr
32        ,RColorBrewer
33        ,pbapply
34        ,parallel
35        ,randomForest
36        ,ranger
37        ,tibble
38        ,broom
39        ,lubridate
40        #,mlr # one of these conflicts with raster somewhere...
41        #,tuneRanger
42        ,breakDown # visualize ranger model

```

```
43 )
44
45 # Load in global variables
46 source("../src/init.R")
47
48 # Load in misc function
49 source("../src/functions.R")
50
51 # create a list of daily predictor variables (abbreviations)
52 vars <- c(
53   "pbl.min"
54   , "pbl.max"
55   , "pr"
56   , "vs"
57   , "th"
58   , "tmmn"
59   , "tmmx"
60   , "rmin"
61   , "rmax"
62   #, "sph"
63   , "ndvi" # annual median (not daily resolution anymore...)
64   , "evi" # annual median (not daily resolution anymore...)
65   #, "pm2.5.mean"
66   #, "pm2.5.max"
67   #, "pm2.5.min"
68   #, "pm2.5.sd"
69   , "pm2.5.median"
70 )
71
72 #list of static predictors
73 static <- c(
74   "fwy"
75   , "streets"
76   , "maj_art"
77   , "arterial"
78   , "railroad"
79   , "railyards"
80   , "elev"
81   , "pop_dens" # GPW v4 Interpolated Population Density Data
82   , "barren_land"
83   , "cultivated_crops"
84   , "deciduous_forest"
85   , "developed_high_intensity"
86   , "developed_low_intensity"
87   , "developed_medium_intensity"
88   , "developed_open_space"
89   , "emergent_herbaceous_wetlands"
90   , "evergreen_forest"
```

```

91   , "hay_pasture"
92   , "herbaceous"
93   , "mixed_forest"
94   , "open_water"
95   , "shrub_scrub"
96   , "woody_wetlands"
97   #, "evi" # Treat these as static for now?
98   #, "ndvi" # Treat these as static for now?
99   #, "point"
100  #, "nonpoint"
101  #, "onroad"
102  #, "nonroad"
103 )
104
105 # Define global model start-time to compare RDS objects and figures
    later _____
106 clean_time <- print_clean_time()
107 saveRDS(clean_time, "./models/clean_time/clean_time.RDS")
108 saveRDS(clean_time, paste0("./models/clean_time/", clean_time, "_
    clean_time.RDS"))
109
110 # Define read functions for static and dynamic variables
    _____
111 # read functions for daily and static predictors
112 readVar <- function(var, date = NULL, study_area) {
113   if(is_null(date)) {
114     # print(var)
115     f <- list.files("./data", pattern = paste0("^", var, "\\\\.tif$"),
116       full.names = T, recursive = T)
117   } else {
118     f <- list.files("./data", pattern = paste0("^", var, "\\.", date,
119       "\\\\.tif$"), full.names = T, recursive = T)
120   }
121   # Exclude buffered rasters from list.files!
122   f <- f[!grepl("buf_vars|buf_static", f)]
123   if(length(f) == 1) {
124     r <- raster(f) %>% resample(study_area, method = 'ngb')
125   } else print(paste0("More than one file selected for raster layer
126     : '", var, "'!"))
127   return(r)
128 }
129
130 # Focal Buffer functions
    _____
131
132 # focal buffer functions credited to Jackson Voelkel @ SUPR
133 # Buffer sequence
134 buffers <- c(0, 50, 100, 300, 500, 1000) # ESCAPE Project Buffers

```

```

131 # buffers <- c(0, 25, 100) # for testing
132 # buffers <- c(sp_res, seq(0, 1200, 50)) # Meena's Buffers
133 # buffers <- c(0) # No Buffers (still need to run the script though)
134
135 # Checkpoint with clean_time
136 saveRDS(buffers, paste0("./data/buffers/", clean_time, "_buffers.RDS"
137 ))
138
139 # Run a single moving window
140 focalBufferRaster <- function(rast, bufferDist) {
141   # skip wind direction and PBL during buffering
142   if (!grepl(paste0('^th|pbl.*|pm2\\.5\\.\\.\\.|^barren_land\\.\\.\\.|^
143     cultivated_crops\\.\\.\\.|^deciduous_forest\\.\\.\\.|^
144     _intensity\\.\\.\\.|^barren_land\\.\\.\\.|^
145     space\\.\\.\\.|^
146     forest\\.\\.\\.|^
147     ^hay_pasture.*|^herbaceous\\.\\.\\.|^mixed_forest
148     ^open_water\\.\\.\\.|^shrub_scrub\\.\\.\\.|^woody_
149     wetlands\\.\\.\\.')
150     ,names(rast))) {
151     buf <- focal(rast
152       ,focalWeight(rast, bufferDist, type="circle")
153       # necessary for road layers
154       ,na.rm = T)
155     buf[is.na(buf)] <- 0
156     names(buf) <- paste0(names(rast), ".", bufferDist, "m")
157     return(buf)
158   } else if (grepl(paste0('^barren_land\\.\\.\\.|^cultivated_crops\\.\\.\\.|^
159     deciduous_forest\\.\\.\\.|^
160     ^developed_high_intensity\\.\\.\\.|^developed_
161     medium_intensity\\.\\.\\.|^
162     ^developed_low_intensity\\.\\.\\.|^developed_
163     open_space\\.\\.\\.|^
164     ^emergent_herbaceous_wetlands\\.\\.\\.|^
165     evergreen_forest\\.\\.\\.|^
166     ^hay_pasture.*|^herbaceous\\.\\.\\.|^mixed_
167     forest\\.\\.\\.|^barren_land\\.\\.\\.|^
168     ^open_water\\.\\.\\.|^shrub_scrub\\.\\.\\.|^woody_
169     wetlands\\.\\.\\.')
170     ,names(rast))) {
171     buf <- focal(x = rast, fun = sum, w = focalWeight(rast,
172       bufferDist, type = "rectangle"), na.rm = T)
173     buf[is.na(buf)] <- 0
174     names(buf) <- paste0(names(rast), ".", bufferDist, "m")

```

```

165     return(buf)
166   }
167
168 }
169
170
171 # Wind Vector Averaging Function
172 focalBufferWind <- function(stack, bufferDist) {
173   # grab the wind direction and speed layers from stack
174   wd <- raster::subset(stack, grep('^th\\.*', names(stack), value = T
175   ))
176   ws <- raster::subset(stack, grep('^vs\\.*', names(stack), value = T
177   ))
178   # determine u & v components
179   u <- ws * sin(2*pi*wd/360)*(-1)
180   v <- ws * cos(2*pi*wd/360)*(-1)
181
182   # fun focal on each component
183   mean_u <- focal(u, focalWeight(u, bufferDist, type = "circle"), na.
184   rm=T)
185   mean_v <- focal(v, focalWeight(v, bufferDist, type = "circle"), na.
186   rm=T)
187
188   # convert back to degrees
189   mean_wd <- (atan2(mean_u, mean_v) * 360/2/pi) + 180
190
191   # assign wd buffer name to output
192   names(mean_wd) <- paste0(names(wd), ".", bufferDist, "m")
193
194   return(mean_wd)
195 }
196
197 focalBufferOneHot <- function(stack, buffers, cl) {
198   lc <- raster::subset(stack, grep(paste0('^barren_land\\.*|^
199   cultivated_crops\\.*|^deciduous_forest\\.*|^
200   \\.*|^developed_high_intensity\\.*|^
201   \\.*|^developed_medium_intensity\\.*|^
202   \\.*|^developed_low_intensity\\.*|^
203   wetlands\\.*|^evergreen_forest\\.*|^
204   herbaceous\\.*|^mixed_forest\\.*|^barren_land\\.*|^

```

```

202                                     , '^open_water\\.*|^shrub_
      scrub\\.*|^woody_wetlands\\.*')
203                                     , names(stack), value = T))
204
205 lc_buf <- pblapply(buffers, function(bufferDist) {
206   lc_s <- lapply(1:nlayers(lc), function(i) {
207     # Focal weight with sum normalizes between 0-1???
208     lc_prop <- focal(x = lc[[i]], fun = sum, w = focalWeight(lc[[i
209     ]], bufferDist, type = "rectangle"), na.rm = T)
210     names(lc_prop) <- paste0(names(lc[[i]]), '.', bufferDist, 'm')
211     return(lc_prop)
212   }) %>% stack()
213   return(lc_s)
214 }
215 , cl = cl
216 ) %>% stack()
217 return(lc_buf)
218 }
219 # apply focalBufferRaster to entire stack

```

```

220 focalBufferStack <- function(stack, bufferDist) {
221
222   s_list <- lapply(1:nlayers(stack), function(x) {
223     focalBufferRaster(rast = stack[[x]], bufferDist)
224   })
225
226   # Ignored layer names return NULL and must be filtered out
227   s <- s_list[!vapply(s_list, is.null, logical(1))] %>% stack()
228
229   # wind direction buffering (requires wd and ws)
230   if (any(grepl('^th\\.*', names(stack))) & any(grepl('^vs\\.*',
231   names(stack)))) {
232     wd <- focalBufferWind(stack, bufferDist)
233     s %>% stack(wd)
234     rm(wd)
235     gc()
236   }
237   # Replace NAs with 0
238   # s[is.na(s)] <- 0 # This renames the stack to layer.1 etc.!!!!
239   return(s)
240 }
241 # Run all of the focal buffers at once!

```

```

242 createBuffers <- function(stack, buffers, cl = NULL) {
243   if(!rlang::is_null(cl)) {

```

```

244     s_list <- pblapply(buffers, function(x) focalBufferStack(stack,
245       bufferDist = x), cl = cl)
246   } else {
247     s_list <- lapply(buffers, function(x) focalBufferStack(stack,
248       bufferDist = x))
249   }
250   s <- s_list[!vapply(s_list, is.null, logical(1))] %>% stack()
251   return(s)
252 }
253
254 # function resamples and combines all GIS predictors into single
255 # raster stack
256 stackPredictors <- function(date=NULL, crs, study_area, vars) {
257   if (rlang::is_null(date)) {
258     s <- lapply(vars, function(x) readVar(var = x, study_area = study
259       _area)) %>%
260     stack()
261   } else {
262     s <- lapply(vars, function(x) readVar(var = x, date = date, study
263       _area = study_area)) %>%
264     stack()
265   }
266   return(s)
267 }
268
269 # stackPredictors <- function(date, crs, study_area, static, vars) {
270 #   # Study Area Extent Raster used for resampling...
271 #   # a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>%
272 #   raster(res = sp_res, vals = 0)
273 #   # a <- study_area
274 #   # read daily predictors
275 #   r <- lapply(vars, function(x) readVar(var = x, date = date, study
276 #     _area = study_area)) %>% stack()
277 #   # read static predictors
278 #   y <- lapply(static, function(x) readStatic(var = x, study_area =
279 #     study_area)) %>% raster::stack()
280 #   # combine them
281 #   s <- raster::stack(r, y)
282 #   rm(r, y)
283 #   gc()
284 #   return(s)
285 # }

```



```

284 # }
285
286 # Raster processing functions

```

```

287 # Combine all predictors for a given day
288 bufferPredictors <- function(date, crs, study_area, bb, vars) {
289
290   # Study Area Extent Raster used for resampling...
291   a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>% raster(
     res = sp_res, vals = 0)
292
293   # Final bounding box
294   b <- readRDS(bb) %>% spTransform(CRSobj = crs) %>% raster(res = sp_
     res, vals = 0)
295
296   # Create Raster Stack
297   s <- stackPredictors(date = date
298                       , crs = crs
299                       , study_area = a
300                       , vars = vars)
301
302   # Buffering

```

```

303   s_buf <- createBuffers(s, buffers = buffers)
304
305   # Add PBL and Neph data (not buffered)
306   pbl <- raster::subset(s, grep('^pbl\\.\\.*', names(s), value = T))
307   # neph <- raster::subset(s, grep('^pm2\\.\\.5\\.\\.*', names(s), value =
     T))
308   neph <- raster::subset(s, grep('^pm2\\.\\.5\\.\\.median*', names(s),
     value = T))
309   s_buf %>% raster::stack(pbl, neph)
310
311   # strip date from daily predictor layer names
312   names(s_buf) <- gsub(x = names(s_buf), pattern = paste0("\\\\.\\.", date
     ), replacement = "")
313
314   # Rename 0m buffer to match non-buffered layers
315   names(s_buf) <- gsub(x = names(s_buf), pattern = paste0("\\\\.0m$"),
     replacement = "")
316
317   # Crop extent to original bounding box (10 times smaller than
     buffer boundary)
318   s_buf %>% raster::crop(b, snap = 'near') %>% resample(b, method =
     'ngb')
319   s_buf %>% raster::mask(b)
320

```

```

321
322 # Write s_buf to file


---


323 # return a cropped raster (using the largest buffer distance to cut
324   from)
325 writeRaster(s_buf
326             ,filename = paste0("./data/buf_vars/", date, ".", names
327   (s_buf), ".tif")
328             ,bylayer=T
329             ,format="GTiff"
330             ,overwrite=T)
331
332 # lapply(1:nlayers(s_buf), function(n) {
333 #   writeRaster(s_buf[[n]]
334 #             ,filename = paste0("./data/buf/", date, ".", names(
335   s_buf[[n]]), ".tif")
336 #             ,format="GTiff"
337 #             ,overwrite=T
338 #             )
339 # })
340
341 rm(neph, pbl, s, a, b, s_buf)
342 gc()
343 }
344
345 # Apply focal buffers to static variables


---


346 bufferStatic <- function(crs, study_area, bb, static) {
347
348   # Study Area Extent Raster used for resampling...
349   a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>% raster(
350     res = sp_res, vals = 0)
351
352   # Final bounding box
353   b <- readRDS(bb) %>% spTransform(CRSobj = crs) %>% raster(res = sp_
354     res, vals = 0)
355
356   # Create Raster Stack
357   s <- stackPredictors(crs = crs
358     ,study_area = a
359     ,vars = static)
360
361   # Buffering


---


362
363   s_buf <- createBuffers(s, buffers = buffers
364     ,cl = detectCores()-1

```

```

359         )
360
361     # Larger Buffers for population density? Henderson paper?
362     pop_buf <- createBuffers(s[[ 'pop_dens' ]]
363                             , buffers = c(750, 1250, 1500, 2000, 2500)
364                             , cl = detectCores() - 1)
365
366     s_buf <- stack(s_buf, pop_buf)
367
368     # # Loops through buffers for NLCD data
369     # lc_buf <- focalBufferOneHot(s, buffers = buffers
370     #                             , cl = detectCores() - 1
371     #                             )
372     # s_buf <- stack(s_buf, lc_buf)
373
374     # Rename 0m buffer to match non-buffered layers
375     names(s_buf) <- gsub(x = names(s_buf), pattern = paste0("\\.0m$"),
376                         replacement = "")
377
378     # Crop extent to original bounding box (10 times smaller than
379     #   buffer boundary)
380     s_buf %>% raster::crop(b, snap = 'near') %>% resample(b, method =
381     'ngb')
382     s_buf %>% raster::mask(b)
383
384     # Write s_buf to file
385
386
387
388
389
390
391 }
392
393
394
395 # wrap our stacking function into a date sequence generator
396
397
398 bufferDailyPredictors <- function(start_date
399                                   , end_date
400                                   , crs

```

```

399                                     ,study_area
400                                     ,bb
401                                     ,vars # list of vars
402                                     ,static # list of static vars
403 ) {
404
405   # Purge any remnant buffer files before loop
406   f_vars <- list.files("./data/buf_vars", full.names = T)
407   if(!rlang::is_empty(f_vars)) {
408     print("Purging ./data/buf_vars...")
409     pblapply(f_vars, file.remove, cl = detectCores()-1)
410   }
411
412   f_static <- list.files("./data/buf_static", full.names = T)
413   if(!rlang::is_empty(f_static)) {
414     print("Purging ./data/buf_static...")
415     pblapply(f_static, file.remove, cl = detectCores()-1)
416   }
417
418   # Create static buffers only once -----
419   print("Creating new static buffers")
420   bufferStatic(crs = crs, bb = bb, study_area = study_area, static =
     static)
421
422   dates <- sequenceDates(start_date, end_date)
423   print("Creating new daily buffers...")
424   # Reduce and rbind are necessary for parallel processing (avoid
     date.layer.buf.tif generation)!
425   # Do not refactor this!!! Leave it alone!!! Still doing it on
     hecate?
426   # df <- Reduce(rbind, pblapply(dates, function(x) {
427     #   bufferPredictors(date = x
428     #                       ,study_area = study_area
429     #                       ,bb = bb
430     #                       ,crs = crs
431     #                       ,vars = vars
432     #                       ,static = static
433     #   })
434   #   ,cl = detectCores()-1
435   #   ))
436   # return(df)
437
438   pblapply(dates, function(x) {
439     bufferPredictors(date = x
440                       ,study_area = study_area
441                       ,bb = bb
442                       ,crs = crs
443                       ,vars = vars

```

```

444         )
445     }
446     ,cl = detectCores()-1
447     #,cl = 6
448     )
449     gc()
450 }
451
452
453 # Running our function on multiple days


---


454 buffer_time <- system.time(bufferDailyPredictors(start_date = start_
455     date
456     "2018-09-01"
457     "2018-09-08" # for quick profiling
458     area
459     ,crs = epsg_26910
460     ,study_area = study_
461     ,bb = bb
462     ,vars = vars
463     ,static = static
464     ))
465 saveRDS(buffer_time, paste0("./models/buffer_time/", clean_time, "_
466     buffer_time.RDS"))
467 # system(paste0("tar -czvf ", clean_time, "_buffer_backup.tar.gz ./
468     data/buf"))

```

Source/extract.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-11-19
5 # create daily stacks of GIS predictors, buffer and extract them
6
7 # needed for nvim-R
8 if (basename(getwd()) == "src") {
9     setwd("../")
10    getwd()
11 }
12
13 # load the necessary packages


---


14 if (!require(pacman)) {

```

```
15   install.packages("pacman")
16   library(pacman)
17 }
18
19 p_load(plyr
20       ,dplyr
21       ,magrittr
22       ,tools
23       ,rgdal
24       ,raster
25       ,rasterVis
26       ,corrplot
27       ,sp
28       ,rgeos
29       ,ggplot2
30       ,stringr
31       ,RColorBrewer
32       ,pbapply
33       ,parallel
34       ,randomForest
35       ,ranger
36       ,tibble
37       ,broom
38       ,lubridate
39       #,mlr # one of these conflicts with raster somewhere...
40       #,tuneRanger
41       ,breakDown # visualize ranger model
42 )
43
44 # Load in global variables
45 source("../src/init.R")
46
47 # Load in misc function
48 source("../src/functions.R")
49
50 # Load in our most recent dataset by timestamp
51 # clean_time <- readRDS("../models/clean_time/clean_time.RDS")
52 # clean_time <- print_clean_time()
53 clean_time <- "2019-06-19_04_31_39"
54 # clean_time <- "2019-04-12_09_43_08"
55 # clean_time <- "2019-04-15_22_56_59"
56 # clean_time <- "2019-04-22_20_43_46"
57 # clean_time <- "2019-04-26_15_20_16"
58
59 # Raster processing functions
60
61 # Combine all predictors for a given day
```

```

61 extractPredictors <- function(date, crs, study_area, bb, pm_df,
    static, scale_neph = scale_neph) {
62
63   # Study Area Extent Raster used for resampling...
64   a <- readRDS(study_area) %>% spTransform(CRSobj = crs) %>% raster(
    res = sp_res, vals = 0)
65
66   # read PurpleAir data
67   pa <- readRDS(pm_df) %>% spTransform(CRSobj = crs)
68
69   # Final bounding box
70   b <- readRDS(bb) %>% spTransform(CRSobj = crs) %>% raster(res = sp_
    res, vals = 0)
71
72   # Read in our variable buffers
73   s_buf_vars <- raster::stack(list.files("./data/buf_vars", pattern =
    paste0(date, ".*\\.tif$"), full.names = T))
74
75   # strip date from daily predictor layer names
76   names(s_buf_vars) <- gsub(x = names(s_buf_vars), pattern = paste0("
    ^X", date, "\\."), replacement = "")
77
78   # # Read in our static buffers
79   s_buf_static <- raster::stack(list.files("./data/buf_static",
    pattern = ".*\\.tif$", full.names = T))
80
81   # Combine static and variable buffer stack
82   s_buf <- stack(s_buf_vars, static)
83
84   # # Reclassify NA that buffer script missed
85   s_buf[is.na(s_buf)] <- 0
86
87   # # Add x and y values as predictors to raster layer
88   # lat <- lon <- subset(s_buf, grep("pm2.5.median", names(s_buf),
    value = T))
89   # xy <- coordinates(s_buf)
90   # lon[] <- xy[,1]
91   # lat[] <- xy[,2]
92   # names(lon) <- "x"
93   # names(lat) <- "y"
94   # plot(stack(lon, lat))
95   # s_buf %>% stack(lon, lat)
96
97   # # Compare differences between s_buf layers and df attributes
98   # colnames(df[,which(colnames(df) %!in% names(s_buf))])
99

```

```

100   # Extract PurpleAir data


---


101   pa <- pa[which(pa$date == gsub("\\.", "\\-", date)),]
102
103   # Simple extract grabs only the intersecting cell value
104   # s_extract_simple <- raster::extract(s_buf, pa, method = 'simple',
105     sp = T, na.rm = T)
106   s_extract <- raster::extract(s_buf, pa, method = 'bilinear', sp = T
107     , na.rm = T)
108
109   # Convert to data.frame
110   df <- raster::as.data.frame(s_extract) %>% na.omit()
111
112   # Rename lat and lon to re-convert to raster later ...
113   names(df)[names(df) == "coords.x1"] <- "lon"
114   names(df)[names(df) == "coords.x2"] <- "lat"
115
116   # Attach temporal variables


---


117
118   # These are categorical variables that get converted into integers
119   # during modeling
120
121   # Add DayOfWeek variable
122   df$weekday <- lubridate::wday(df$date) %>% factor(levels = c(1:7))
123
124   # Add Season variable
125   df$season <- getSeason(df$date) %>% factor(levels = c(1:4))
126
127   # # Add Month Variable? Captures phenological differences in PM
128   # from vegetation?
129   df$month <- lubridate::month(df$date) %>% factor(levels = c(1:12))
130
131   # Weekend/Weekday Captures differences in on-road mobile emissions?
132   df$weekend <- ifelse(lubridate::wday(df$date) %in% c(6,7), 1, 0)
133     %>% factor(levels = c(0:1))
134
135   # strip date from daily predictor layer names
136   # names(df) <- gsub(x = names(df), pattern = paste0("\\.", date),
137     replacement = "")
138
139   # Convert back to sp (used later)
140   # xy <- df[,c("x", "y")]
141   # sp <- SpatialPointsDataFrame(coords = xy, data = df)
142   # proj4string(sp) <- proj4string(s_extract)

```



```

138   # Convert Absolute PM to Neph-scaled PM
139
140   # Explicitly define response variable as "Y"
141   # df <- cbind(Y=pa@data$pm2_5_cf_x, df)
142   df$Y <- df$pm2_5_cf_x
143
144   # if(scale_neph) {
145   #
146   #   # Determine relative PM concentration
147   #   df$Y <- df$Y - df$pm2.5.median
148   #
149   # }
150
151   df$Y_scaled <- (df$Y - df$pm2.5.median)
152
153   # # add these extra variables as raster layers?
154   # df_sp <- df
155   # coordinates(df_sp) <- ~x+y
156   # gridded(df_sp) <- T
157   # dfr <- rasterFromXYZ(df_sp)
158   # These will be added within predictRasters instead?
159
160   return(df)
161   gc()
162 }
163
164
165 # wrap our stacking function into a date sequence generator
166
167 extractDailyPredictors <- function(start_date
168                                   ,end_date
169                                   ,crs
170                                   ,study_area
171                                   ,bb
172                                   ,pm_df
173                                   ,scale_neph
174 ) {
175   dates <- sequenceDates(start_date, end_date)
176
177   # Read in the static data once
178   static <- raster::stack(list.files("./data/buf_static", pattern = "
179   .*\\.tif$", full.names = T))
180
181   df <- Reduce(rbind, pblapply(dates, function(x) {
182     extractPredictors(date = x
183                       ,study_area = study_area

```

```

183         ,bb = bb
184         ,crs = crs
185         ,static = static
186         ,pm_df = pm_df
187         ,scale_neph = scale_neph))
188     # parallelization takes place within each loop (faster)
189     ,cl = detectCores()-1
190 ))
191
192 return(df)
193 gc()
194 }
195
196 # Running our function on multiple days
197
198 extract_time <- system.time(df <- extractDailyPredictors(start_date =
199     start_date
200     #start_date
201     = "2018-09-01"
202     ,end_date =
203     end_date
204     #,end_date =
205     "2018-02-16" # for quick profiling
206     ,crs = crs
207     ,study_area =
208     study_area
209     ,bb = bb
210     ,pm_df = pm_
211     df
212     ,scale_neph =
213     scale_neph))
214
215 saveRDS(extract_time, paste0("./models/extract_time/", clean_time, "_
216     extract_time.RDS"))
217
218 head(df)
219 df <- df[complete.cases(df),]
220 saveRDS(df, paste0("./models/df/", clean_time, "_df.RDS"))

```

Source/modeling.R

```

1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2019-02-21
5 # Train RF model on predictor stack
6
7 # needed for nvim-R

```

```
8  if (basename(getwd()) == "src") {
9    setwd("../")
10   getwd()
11 }
12
13 # load the necessary packages


---


14 if (!require(pacman)) {
15   install.packages("pacman")
16   library(pacman)
17 }
18
19 p_load(plyr
20        ,dplyr
21        ,magrittr
22        ,tools
23        ,rgdal
24        ,raster
25        ,rasterVis
26        ,corrplot
27        ,sp
28        ,rgeos
29        ,ggplot2
30        ,stringr
31        ,RColorBrewer
32        ,pbapply
33        ,parallel
34        ,randomForest
35        ,ranger
36        ,tibble
37        ,broom
38        ,lubridate
39        #,mlr # one of these conflicts with raster somewhere...
40        #,tuneRanger
41        ,breakDown # visualize ranger model
42        ,car
43        ,lm.beta
44        ,PerformanceAnalytics
45        ,Matrix
46        ,xgboost
47        ,data.table
48        ,mltools
49        ,caret
50        #,sjmisc
51        #,sjPlot
52        )
53
54
```

```
55 # Load in global variables
56 source("../src/init.R")
57
58 # Load in misc function
59 source("../src/functions.R")
60
61 # CV plotting function
62 source("../src/ggRegression.R")
63
64
65 # Modeling


---


66
67 # Load in our most recent dataset by timestamp
68 # clean_time <- print_clean_time()
69 clean_time <- readRDS("../models/clean_time/clean_time.RDS")
70 # clean_time <- "2019-04-12_09_43_08"
71 # clean_time <- "2019-04-15_22_56_59"
72 # clean_time <- "2019-04-22_20_43_46"
73 # clean_time <- "2019-04-26_15_20_16"
74 # clean_time <- "2019-04-28_15_15_11"
75
76 # TODO Change this back later!
77 df <- readRDS(paste0("../models/df/", clean_time, "_df.RDS"))
78 # df <- readRDS(paste0("../models/df/df.RDS"))
79
80 # Exclude negative values in response variable
81 df <- df[df$Y>0,]
82
83
84 # Add constant to all elevation to avoid negative values
85 elev <- raster("../data/buf_static/elev.100m.tif")
86 min_elev <- min(values(elev))
87
88 # Setting up log transformed predictors for later
89 df$log_pm2.5.median <- log(df$pm2.5.median+1e-6)
90 df$log_fwy.100m <- log(df$fwy.100m+1e-6)
91 df$log_fwy.300m <- log(df$fwy.300m+1e-6)
92 df$log_fwy.500m <- log(df$fwy.500m+1e-6)
93 df$log_fwy.1000m <- log(df$fwy.1000m+1e-6)
94 df$log_elev.100m <- log(df$elev.100m+1e-6+abs(min_elev))
95 df$log_elev.300m <- log(df$elev.300m+1e-6+abs(min_elev))
96 df$log_elev.500m <- log(df$elev.500m+1e-6+abs(min_elev))
97 df$log_elev.1000m <- log(df$elev.1000m+1e-6+abs(min_elev))
98 df$log_pbl.min <- log(df$pbl.min+1e-6)
99 df$log_railroad.100m <- log(df$railroad.100m+1e-6)
100 df$log_railroad.300m <- log(df$railroad.300m+1e-6)
```

```

101 df$log_railroad.500m <- log(df$railroad.500m+1e-6)
102 df$log_railroad.1000m <- log(df$railroad.1000m+1e-6)
103 df$log_rmin <- log(df$rmin+1e-6)
104
105 saveRDS(df, paste0("./models/df/df.RDS"))
106
107 # setting seed for reproducibility
108 set.seed(6489)
109
110 # 70/30 Holdout
111 sub <- sample(1:nrow(df), floor(0.7*nrow(df)))
112 train <- df[sub,]
113 test <- df[-sub,]
114
115 saveRDS(train, paste0("./models/train/", clean_time, "_train.RDS"))
116 saveRDS(test, paste0("./models/test/", clean_time, "_test.RDS"))
117 # train <- readRDS(paste0("./models/train/", clean_time, "_train.RDS"))
118 # test <- readRDS(paste0("./models/test/", clean_time, "_test.RDS"))
119
120 # Correlation Plot EDA

```

```

121
122 # Loop through each base var and develop individual corrplot

```

```

123 vars <- df %>% select_if(is.numeric) %>% colnames() %>%
124   str_replace_all("\\\\.\\d{1,4}m$", "") %>% unique()
125
126 lapply(vars, function(i) {
127   try({
128     cmatrix <- data.frame(df[,grep1(paste0("^Y$|^", i), names(df))])
129     names(cmatrix)[names(cmatrix) == 'pm2.5.median'] <- 'neph'
130     # Exclude columns that all contain zero (produces NaN error later)
131     cmatrix <- cmatrix[, colSums(cmatrix != 0) > 0]
132     col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD", "#4477AA"))
133     res1 <- cor.mtest(cmatrix, conf.level = 0.95, na.rm=T)
134     p.mat <- cor.mtest(cmatrix)$p
135     corrplot(cor(cmatrix), col = rev(col(200)), order = "hclust",
136       number.cex = 0.7
137       ,addCoef.col = "black"
138       ,tl.col = "black", tl.srt = 90
139       ,p.mat = p.mat
140       ,sig.level = 0.05, insig = "blank", diag = F)
141     png(filename = paste0("./figures/corrplot/", clean_time, "_", i,
142       '_corrplot.png'))

```

```

141         ,height = 8
142         ,width = 8
143         ,units = "in"
144         ,res = 300)
145     dev.off()
146 })
147 })
148
149 # buffers <- c("25m", "50m", "100m", "300m", "500m", "1000m")
150 #
151 # lapply(buffers, function(i) {
152 #   try({
153 #     cmatrix <- data.frame(df[,grep1(paste0("^Y$|pm2.5.median|pbl.max|
154 #       pbl.min|",i), names(df))])
155 #     names(cmatrix)[names(cmatrix) == 'pm2.5.median'] <- 'neph'
156 #     cmatrix <- cmatrix[, colSums(cmatrix != 0) > 0]
157 #     col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77
158 #       AADD", "#4477AA"))
159 #     res1 <- cor.mtest(cmatrix, conf.level = 0.95, na.rm=T)
160 #     p.mat <- cor.mtest(cmatrix)$p
161 #     corrplot(cor(cmatrix), col = rev(col(200)), order = "hclust",
162 #       number.cex = 0.7
163 #       ,addCoef.col = "black"
164 #       ,tl.col = "black"
165 #       ,tl.srt = 90
166 #       ,p.mat = p.mat
167 #       ,sig.level = 0.05
168 #       ,insig = "blank"
169 #       ,diag = F)
170 #     png(filename = paste0('./figures/corrplot/', clean_time, '_', i,
171 #       '_corrplot.png')
172 #       ,height = 8
173 #       ,width = 8
174 #       ,units = "in"
175 #       ,res = 300)
176 #     dev.off()
177 #   })
178 # })
179
180 # Summer/Winter sensitivity analysis
181
182 # # eda w/ Meena
183 # spring <- df %>% filter(month %in% c(4, 5, 6))
184 # forestfire <- df %>% filter(month %in% c(8,9))
185 # winter <- df %>% filter(month %in% c(10,11,12))
186 #
187 # spring$class <- "spring"

```

```

184 # forestfire$class <- "ff"
185 # winter$class <- "winter"
186 #
187 # season_df <- rbind(spring, forestfire, winter)
188 #
189 # season_df %>% ggplot(aes(y = Y, x = class)) +
190 #   geom_boxplot()
191 #
192 # df %>% ggplot(aes(y = Y, x = season)) +
193 #   geom_boxplot()
194 #
195 # quantile(spring$Y)
196 # quantile(forestfire$Y)
197 # quantile(winter$Y)
198 #
199 # quantile(df$arterial)
200 # quantile(df$Y[df$arterial > 1.37 & df$arterial < 2.27])
201 #
202 # asdf <- df %>% mutate(qart = ntile(arterial, 4), qmaj_art = ntile(
203 #   maj_art, 4)) %>%
204 #   group_by(qart, qmaj_art, month) %>%
205 #   summarise(Y_q = mean(Y), n = n(), art_mean = mean(arterial), maj_
206 #     art_mean = mean(maj_art))
207 #
208 # asdf <- df %>% mutate(qart = ntile(arterial, 4), qmaj_art = ntile(
209 #   maj_art, 4)) %>%
210 #   group_by(qmaj_art, month) %>%
211 #   summarise(pm_mean = mean(Y), n = n(), art_mean = mean(arterial),
212 #     maj_art_mean = mean(maj_art))
213 #
214 # asdf$month <- as.integer(asdf$month)
215 #
216 # mod <- lm.beta(Y~arterial*evi, data = df)
217 # summary.lm.beta(mod)
218 # summary(mod)
219 # lm.beta(mod)
220 # Hyperparameter Tuning with Cross Validation
221
222 # Begin caret hyperparam tuning
223
224 # fit <- caret::train(
225 #   x = train[, predictors]
226 #   ,y = response
227 #   ,method = 'ranger'
228 #   ,tuneGrid = grid
229 #   ,trControl = fitControl
230 #   ,importance = "permutation"
231 #   ,num.trees = 500

```

```

226 # ,respect.unordered.factors = T
227 # ,keep.inbag = T
228 # )
229 #
230 # # Print tuning duration in minutes
231 # (proc.time() - ptm)/ 60
232 #
233 # # Let's plot RMSE ~ mtry
234 # plot(fit)
235 #
236 # # Store the best performing model in a new object
237 # rfr_caret <- fit$finalModel
238 # rfr_caret
239
240 # Can't get the formula notation to work with caret
241 # rfr_caret_formula <- caret::train(
242 #   data = train
243 #   ,form = Y_scaled~.-Y-weekday-season
244 #   ,method = 'ranger'
245 #   #,tuneGrid = grid
246 #   #,trControl = fitControl
247 #   ,num.trees = 500
248 #   ,importance = 'permutation'
249 #   ,mtry = ceiling((length(which(predictors==T))/3)*1.0)
250 #   ,respect.unordered.factors = T
251 #   ,keep.inbag = T
252 #   ,splitrule = 'variance'
253 #   ,min.node.size = 5 # regression
254 # )
255
256 # breakDown::broken(rfr_caret, train)
257
258 # # Checkpoint our model objects
259 # saveRDS(fit, paste0("./models/fit/", clean_time, "_fit.RDS"))
260 # saveRDS(rfr, paste0("./models/rfr/", clean_time, "_rfr.RDS"))
261
262 # Ranger

```

```

263
264 # Following the DataCamp course principles for repeatedcv
265 fitControl <- caret::trainControl(method = "repeatedcv"
266                                   ,number = 5 # K-folds
267                                   ,repeats = 3
268                                   ,verboseIter= T)
269
270 # store start time
271 ptm <- proc.time()

```



```

272 # Train model differently depending on scale_neph
273
274 # Manually select predictors to train model on (scale_neph handles
    pm2.5.median)
275 # Select single buffer for each predictor based on the strongest
    correlation and instinctive sign
276 initial_predictor_names <- c("fwy.100m" # largest buffer to smooth
    data
277                                , "elev.300m" # maybe smooth this out to larger
    buffer prevent overfitting?
278                                , "streets.100m" # include or not?
279                                #, "arterial" # negative relationship all buffers
280                                , "pr" # pr is one of the better correlated
    predictors, but may be introducing noise...
281                                #, "th" # ignore wd because of resolution!
282                                #, "maj_art" # negative relationship/non-
    relationship for buffers
283                                , "pbl.max"
284                                , "pbl.min"
285                                , "railroad.1000m" # strongest predictor
286                                #, "railyards.1000m" # negative relationship
287                                , "rmin.1000m" # rh and temp are introducing
    noise to the model
288                                , "rmax.1000m"
289                                , "tmmn.1000m"
290                                , "tmmx.1000m" # Strong positive relationship,
    dominated by forest fires...
291                                , "vs.1000m" # Strong negative relationship, but
    data quality/resolution issues...
292                                #, "th.1000m" # omit entirely due to poor
    resolution?
293                                , "weekday"
294                                , "season"
295                                , "month"
296                                , "weekend"
297                                #, "barren_land.1000m"
298                                #, "cultivated_crops.100m" # Positive correlation
    with PM
299                                , "pop_dens.2000m" # Larger buffers don't make a
    difference!
300                                #, "developed_high_intensity.500m" # no
    correlation with PM
301                                #, "developed_low_intensity.500m" # positive
    correlation at 500m, negative at 1000m
302                                #, "developed_medium_intensity.500m" # positive
    correlation for all buffers
303                                #, "developed_open_space.1000m" # take out later?

```

```

304         , "ndvi.100m" # largest buffer with negative
      correlation
305         , "evi.100m" # largest buffer with negative
      correlation
306         , "deciduous_forest.1000m"
307         , "evergreen_forest.1000m"
308         , "mixed_forest.1000m"
309         # , "shrub_scrub.100m" # Exclude?
310         # , "hay_pasture.1000m" # positive correlation?
      exclude?
311         # , "herbaceous.500m" # negative at 500m,
      positive at 1000m
312         # , "emergent_herbaceous_wetlands.1000m"
313         # , "open_water.100m" # LUR overfits this! (
      correlated with railroads...)
314         # , "woody_wetlands" # positive correlation for
      all buffers
315         , "lon"
316         , "lat"
317     )
318
319 # Use hclust to determine which predictor to select for each
      collinear group

```

```

320 # cmatrix <- data.frame(df[,grep1(paste0("^Y$|^", paste0(initial_
      predictor_names, collapse = '|'), "$"), names(df))])
321 cmatrix <- df[, names(df) %in% c("Y", "pm2.5.median", initial_
      predictor_names)]
322 names(cmatrix)[names(cmatrix) == 'pm2.5.median'] <- 'neph'
323 # Exclude columns that all contain zero (produces NaN error later)
324 cmatrix <- cmatrix[, colSums(cmatrix != 0) > 0]
325 cmatrix <- dplyr::select_if(cmatrix, is.numeric)
326 col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD",
      "#4477AA"))
327 res1 <- cor.mtest(cmatrix, conf.level = 0.95, na.rm=T)
328 sp.mat <- cor.mtest(cmatrix)$p
329
330 saveRDS(cor(cmatrix), paste0("./models/cmatrix/", clean_time, "_
      cmatrix.RDS"))
331
332 # Checkpoint our correlation matrix
333 cdf <- as.data.frame(as.table(cor(cmatrix)))
334 cdf %>% dplyr::filter(Var1 != Var2 & Var1 == "Y") %>% arrange(desc(
      Freq))
335
336 # Figure out something better later
337 ggplot(cdf, aes(reorder(Var2, Freq, sum), Freq)) +

```

```

338   geom_col() +
339   coord_flip() +
340   theme_bw()
341
342   corrplot(cor(cmatrix), col = rev(col(200)), order = "hclust", number.
      cex = 0.5
343           ,addCoef.col = "black"
344           #,type = "lower"
345           ,method = "color"
346           ,tl.col = "black"
347           ,tl.srt = 90
348           #,p.mat = p.mat
349           #,sig.level = 0.10
350           #,insig = "blank"
351           ,diag = F)
352
353   abbr_names <- paste0({
354     names(cmatrix) %>% sub(pattern = "\\\\.\\d+m$", replacement = "") %>%
355     sub(pattern = "_", replacement = "") %>%
356     sub(pattern = "[[:punct:]]+", replacement = "") %>% abbreviate(
      minlength = 3)
357   }, ".", str_extract(names(cmatrix), "\\d+m$")
358   )
359
360   abbr_names <- str_replace_all(abbr_names, "\\\\.NA$", "")
361   names(cmatrix) <- abbr_names
362
363   # chart.Correlation(cmatrix, histogram = T)
364   cmatrix <- cmatrix[, colSums(cmatrix != 0) > 0]
365   col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD",
      "#4477AA"))
366   res1 <- cor.mtest(cmatrix, conf.level = 0.95, na.rm=T)
367   p.mat <- cor.mtest(cmatrix)$p
368
369   png(filename = paste0("./figures/corrplot/", clean_time, "_initial_
      corrplot.png")
370       ,height = 6
371       ,width = 8
372       ,units = "in"
373       ,res = 300
374       )
375   corrplot(cor(cmatrix), col = rev(col(200)), order = "hclust"
376           ,addCoef.col = "black"
377           ,tl.col = "black"
378           ,tl.srt = 90
379           #,number.cex = 0.5
380           #,p.mat = p.mat
381           #,sig.level = 0.05

```

```

382         #,insig = "blank"
383         ,addrect = 7 # objectively set this somehow?
384         ,diag = F)
385 dev.off()
386
387 # Checkpoint our correlation matrix
388 cdf <- as.data.frame(as.table(cor(cmatrix)))
389 cdf %>% dplyr::filter(Var1 != Var2 & Var1 == "Y") %>% arrange(desc(
    Freq))
390
391 # Figure out something better later
392 ggplot(cdf, aes(reorder(Var2, Freq, sum), Freq)) +
393   geom_col() +
394   coord_flip() +
395   theme_bw()
396
397 #

```

```

398
399 # Prune predictor list based on corrplot hclust results? Or conduct
    two-step RF for variable selection?
400 predictor_names <- c("elev.100m" # maybe smooth this out to larger
    buffer prevent overfitting?
401                       , "log_fwy.100m" # largest buffer to smooth data
402                       , "fwy.100m" # largest buffer to smooth data
403                       , "streets.100m" # include or not?
404                       , "arterial" # negative relationship all buffers
405                       , "pr" # pr is one of the better correlated
    predictors, but may be introducing noise...
406                       , "th" # ignore wd because of resolution!
407                       , "maj_art" # negative relationship/non-
    relationship for buffers
408                       , "pbl.max"
409                       , "pbl.min"
410                       , "ndvi.100m" # largest buffer with negative
    correlation
411                       , "evi.100m" # largest buffer with negative
    correlation
412                       , "railroad.1000m" # strongest predictor
413                       , "log_railroad.1000m" # strongest predictor
414                       , "railyards.1000m" # negative relationship
415                       , "pop_dens.2000m" # Should I exclude this and
    just use NLCD?
416                       , "rmin" # rh and temp are introducing noise to
    the model
417                       , "rmax.1000m"
418                       , "tmmn.1000m"

```

```

419         , "tmmx.1000m"
420         # , "vs.1000m"
421         # , "th.1000m" # omit entirely due to poor
422     resolution?
423         # , "weekday"
424         # , "season"
425         # , "month"
426         # , "weekend"
427         # , "barren_land.1000m"
428         # , "cultivated_crops.100m" # Positive correlation
429     with PM
430         # , "deciduous_forest.1000m"
431         # , "developed_high_intensity.500m" # no
432     correlation with PM
433         # , "developed_low_intensity.100m" # positive
434     correlation at 500m, negative at 1000m
435         # , "developed_medium_intensity.300m" # positive
436     correlation for all buffers
437         # , "developed_open_space.1000m" # take out later?
438         # , "evergreen_forest.1000m"
439         # , "hay_pasture.1000m" # positive correlation?
440     exclude?
441         # , "herbaceous.500m" # negative at 500m,
442     positive at 1000m
443         # , "emergent_herbaceous_wetlands.1000m"
444         # , "mixed_forest.1000m"
445         # , "open_water.100m" # overfits?
446         # , "shrub_scrub.100m"
447         # , "woody_wetlands" # positive correlation for
448     all buffers
449         , "lon"
450         , "lat"
451     )
452 }
453
454 if (scale_neph) {
455     predictors <- names(train) %in% predictor_names
456     form <- as.formula(paste0("Y_scaled~", paste(predictor_names,
457         collapse = "+")))
458 } else {
459     predictors <- names(train) %in% c("pm2.5.median", predictor_names)
460     form <- as.formula(paste0("Y~pm2.5.median+", paste(predictor_names,
461         collapse = "+")))
462 }
463
464 # Temporary kitchen-sink formula!
465 # form <- as.formula("Y~.-lat-lon-Y_scaled-pm2_5_cf_x-date-node")

```

```

456 # predictor_names <- train[, names(train) %!in% c("lat", "lon", "Y",
457   "Y_scaled", "node", "date", "pm2_5_cf_x")] %>% names
458 # predictors <- names(train) %in% predictor_names
459 cmatrix <- df[, names(df) %in% c("Y", "pm2.5.median", predictor_names
460   )] %>% dplyr::select_if(is.numeric)
461 col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD",
462   "#4477AA"))
463 res1 <- cor.mtest(cmatrix, conf.level = 0.95, na.rm=T)
464 p.mat <- cor.mtest(cmatrix)$p
465 png(filename = paste0("./figures/corrplot/", clean_time, "_final_
466   corrplot.png"),
467   ,height = 6
468   ,width = 8
469   ,units = "in"
470   ,res = 300
471 )
472 corrplot(cor(cmatrix), col = rev(col(200)), order = "hclust"
473   #,addCoef.col = "black"
474   ,tl.col = "black"
475   ,tl.srt = 90
476   #,number.cex = 0.5
477   #,p.mat = p.mat
478   #,sig.level = 0.05
479   #,insig = "blank"
480   ,addrect = 7 # objectively set this somehow?
481   ,diag = F)
482 dev.off()
483 # Checkpoint our model formula (ease of reproducibility later)
484 saveRDS(form, paste0("./models/form/", clean_time, "_form.RDS"))
485 # Define our conditional response variable (absolute or scaled PM)
486 if(scale_neph) {
487   response <- train[, names(train) == 'Y_scaled'] # Scaled Response
488 } else {
489   response <- train[, names(train) == 'Y'] # Scaled Response
490 }
491 # Ensure the correct predictors are selected
492 names(train[, predictors])
493
494
495
496

```

```

497 # LUR


---


498
499 # Exclude weird negative PA value
500 # df <- df[df$Y>0,]
501 # sub2 <- sample(1:nrow(df), 5000) # limit of shapiro test
502 # df2 <- df[sub2,]
503 # df2 <- train
504
505
506 # Independent Variable Transformations


---


507
508 # Limit influence of outliers via log transform
509 lapply(c("pm2.5.median", predictor_names), function(n) {
510   if (is.numeric(train[[n]])) {
511     par(mfrow=c(1,2))
512     hist(train[[n]], main = n, xlab="")
513     boxplot(train[[n]], main = n)
514   }
515 })
516
517 # Predictors with outliers
518 # df2$log_pm2.5.median <- log(df2$pm2.5.median+1e-6)
519 # df2$log_fwy.100m <- log(df2$fwy.100m+1e-6)
520 # df2$log_elev.100m <- log(df2$elev.100m+1e-6)
521 # df2$log_pbl.min <- log(df2$pbl.min+1e-6)
522 # df2$log_railroad.100m <- log(df2$railroad.100m+1e-6)
523 # df2$log_rmin <- log(df2$rmin+1e-6)
524
525 log_predictors <- dplyr::select(train, starts_with("log")) %>%
526   colnames()
527
528 lapply(log_predictors, function(n) {
529   if (is.numeric(train[[n]])) {
530     par(mfrow=c(1,2))
531     hist(train[[n]], main = n, xlab="")
532     boxplot(train[[n]], main = n)
533   }
534 })
535
536 par(mfrow=c(1,1))
537
538 # Response Variable Transformation


---


539

```

```

540 # Response variable's residuals normally distributed?
541 qqnorm(train$Y)
542 qqline(train$Y, col = "red", lwd = 2)
543
544 # TODO make sure this still makes sense...
545 # Formula for independent variables
546 # iv <- "log_pm2.5.median+log_fwy.100m+log_elev.100m+log_pbl.min+ndvi
547       .100m+log_railroad.100m+pop_dens.100m+log_rmin+month"
547 iv <- "pm2.5.median+log_fwy.100m+elev.100m+pbl.min+ndvi.100m+log_
       railroad.100m+pop_dens.100m+rmin+season"
548
549 # Create a landuse regression model too?
550 # form_raw <- paste0("Y~", iv)
551 # lm <- lm(form_raw, data = train)
552 lm <- lm(form, data = train)
553 summary(lm)
554 par(mfrow=c(2,2))
555 plot(lm)
556 par(mfrow=c(1,1))
557
558 # Box-Cox Transformation
559 bc <- MASS::boxcox(object=lm, data = train)
560 best_lambda <- bc$x[which(bc$y==max(bc$y))]
561
562 train$Y_bc <- train$Y^best_lambda
563 qqnorm(train$Y_bc)
564 qqline(train$Y_bc, col = "red", lwd = 2)
565 # form_bc <- as.formula(paste0('Y_bc~pm2.5.median+', paste(predictor_
566       names, collapse = '+')))
566 # form_bc <- "Y_bc~log_pm2.5.median+log_fwy.100m+log_elev.100m+log_
567       pbl.min+ndvi.100m+log_railroad.100m+pop_dens.100m+log_rmin+month"
567 form_bc <- paste0("Y_bc~", iv)
568 lm_bc <- lm(form_bc, data = train)
569 summary(lm_bc)
570 par(mfrow=c(2,2))
571 plot(lm_bc)
572 par(mfrow=c(1,1))
573
574 # Log Transformation
575 train$Y_log <- log(train$Y+1e-6)
576 # form_log <- "Y_log~log_pm2.5.median+log_fwy.100m+log_elev.100m+log_
577       pbl.min+ndvi.100m+log_railroad.100m+pop_dens.100m+log_rmin+season+
578       month"
577 # form_log <- as.formula(paste0('Y_log~pm2.5.median+', paste(
578       predictor_names, collapse = '+')))
578 form_log <- paste0("Y_log~", iv)
579 qqnorm(train$Y_log)
580 qqline(train$Y_log, col = "red", lwd = 2)

```



```
581 lm_log <- lm(form_log, data = train)
582 summary(lm_log)
583 par(mfrow=c(2,2))
584 plot(lm_log)
585 par(mfrow=c(1,1))
586
587 # Normality of residuals -----
588 hist(residuals(lm))
589 hist(residuals(lm_bc))
590 hist(residuals(lm_log))
591
592 boxplot(residuals(lm))
593 boxplot(residuals(lm_bc))
594 boxplot(residuals(lm_log))
595
596 # We will always reject null when sample size is too great! Rely on
    graphical assessment instead!
597 try(shapiro.test(residuals(lm)))
598 try(shapiro.test(residuals(lm_bc)))
599 try(shapiro.test(residuals(lm_log)))
600
601
602 # Heteroscedasticity of residuals -----
603
604 # We will always reject null when sample size is too great!
605
606 split_lm <- median(lm$fitted) #find a median of residuls
607 g1_lm <-lm$resid[lm$fitted<split_lm] #divide all residuls into two
    groups with an equal sample size
608 g2_lm <-lm$resid[lm$fitted>split_lm]
609 var.test(g1_lm, g2_lm) #test the equal variance assumption
610
611 split_bc <- median(lm_bc$fitted) #find a median of residuls
612 g1_bc <-lm$resid[lm_bc$fitted<split_bc] #divide all residuls into two
    groups with an equal sample size
613 g2_bc <-lm$resid[lm_bc$fitted>split_bc]
614 var.test(g1_bc, g2_bc) #test the equal variance assumption
615
616 split_log <- median(lm_log$fitted) #find a median of residuls
617 g1_log <-lm$resid[lm_log$fitted<split_log] #divide all residuls into
    two groups with an equal sample size
618 g2_log <-lm$resid[lm_log$fitted>split_log]
619 var.test(g1_log, g2_log) #test the equal variance assumption
620
621 # Multicollinearity -----
622 try(car::vif(lm))
623 try(car::vif(lm_bc))
624 try(car::vif(lm_log))
```

```

625
626 # Reduce full model to parsimonious model _____
627
628 # TODO verify model
629
630 # Hybrid Approach
631 lm_step <- step(lm, direction="both")
632 lm_step <- MASS::stepAIC(lm, direction = "both")
633 lm_step <- caret::train(as.formula(form), data = train, method = "
    lmStepAIC")
634 lm_step$finalModel
635 summary(lm_step$finalModel)
636 summary(lm)
637 car::vif(lm_step$finalModel) # nice, lower VIFs now
638 # anova(lm_step$finalModel, lm_log) # caret messes with response
    variable name...
639
640 # Checkpoint our explanatory model _____
641 lm_final <- lm_step$finalModel
642 summary(lm_final)
643
644 # TODO manually exclude insignificant variables before stepAIC?
645 # TODO handle categorical variables after stepAIC?
646 # TODO handle categorical variables significance?
647
648 # Fixing this by hand for now...
649 # lm_final <- lm("Y~pm2.5.median+elev.100m+log_fwy.100m+pbl.min+ndvi
    .100m+log_railroad.100m+rmin+season+weekend+lat", train)
650 form <- "Y~pm2.5.median+elev.100m+pbl.min+log_railroad.1000m+rmax
    .1000m+tmx.1000m+season+weekend+lat"
651 lm_final <- lm(form, train)
652 summary(lm_final)
653
654 # # TODO stepVif with initial_predictors instead of hclust?
655 # df2$Y_log <- log(df2$Y+1)
656 # form_log <- as.formula(paste0('Y_log~pm2.5.median+', paste(
    predictor_names, collapse = '+')))
657 # lm_log <- lm(form_log, data = df2)
658 # summary(lm_log)
659 # summary(lm)
660
661 # Old method (without IV inspection, assumptions, and explanatory
    model)
662 # lm_final <- lm(form, data = df)
663
664 # summary(lm) # how to get standardized effects?
665 summary.lm.beta(lm_final, standardized = F)
666

```

```

667 # Checkpoint our LUR
668 saveRDS(lm_final, paste0("./models/lm/", clean_time, "_lm.RDS"))
669
670 # Build grid of possible hyperparam combos


---


671 grid <- expand_grid(mtry = c(ceiling((length(which(predictors==T))/3)
    * 1.0)
672                        , ceiling((length(which(predictors==T))/
    3)* 1.5)
673                        , ceiling((length(which(predictors==T))/
    3)* 2.0)
674                        , ceiling((length(which(predictors==T))/
    3)* 2.5)
675                        , ceiling((length(which(predictors==T))/
    3)* 2.7))
676                        , num.trees = c(100, seq(500, 10000, 500))
677                        , splitrule = c("variance"
678                        #,"extratrees" # No OOB-ER or R2!
679                        #,"maxstat"
680                        )
681                        , min.node.size = c(5 # Default for regression
682                        #,3 # Default for survival
683                        #,1 # Default for classification
684                        ))
685
686 # Train a single ranger model
687 rfr <- ranger(
688   #data = train
689   #,form # memory inefficient
690   data = cbind(train[, predictors], Y = response)
691   ,dependent.variable.name = 'Y'
692   ,num.trees = 500
693   ,importance = 'permutation'
694   ,mtry = ceiling((length(which(predictors==T))/3)* 1.0)
695   ,respect.unordered.factors = T
696   ,keep.inbag = T
697   ,splitrule = 'variance'
698   ,min.node.size = 5 # regression
699 )
700
701 rfr
702
703 # Checkpoint our model objects
704 saveRDS(rfr, paste0("./models/rfr/", clean_time, "_rfr.RDS"))
705
706 # # Here's how to use ranger with the index notation
707 # rfr2 <- ranger(

```

```

708 # #data = train
709 # #Y~.-Y_scaled-weekday-season-pm2_5_cf_x
710 # #data = cbind(train[, predictors], Y_scaled = train$Y_scaled)
711 # #,dependent.variable.name = 'Y_scaled'
712 # data = cbind(train[, predictors], Y = response)
713 # ,dependent.variable.name = 'Y'
714 # ,num.trees = 500
715 # ,importance = 'permutation'
716 # ,mtry = ceiling((length(which(predictors==T))/3)*1.0)
717 # ,respect.unordered.factors = T
718 # ,keep.inbag = T
719 # ,splitrule = 'variance'
720 # ,min.node.size = 5 # regression
721 # )
722 # rfr2 # Not good right now! Fix predictor indexing to match formula!
723 # !!
724 # XGBoost

```

```

725 x_train <- train[,predictors] %>% as.data.table() %>% mltools::one_
  hot(dropUnusedLevels = F)
726 y_train <- train$Y
727 x_test <- test[,predictors] %>% as.data.table() %>% mltools::one_hot(
  dropUnusedLevels = F)
728 y_test <- test$Y
729
730 # Test that factor encoding is preserved with month subset
731 # df_dt_test <- df_dt %>% filter(month == "1") %>% as.data.table()
732 # df_oh_test <- mltools::one_hot(df_dt_test, dropUnusedLevels = F)
733
734 xgb_trcontrol = trainControl(
735   method = "cv",
736   number = 5,
737   allowParallel = TRUE,
738   verboseIter = FALSE,
739   returnData = FALSE
740 )
741
742 xgbGrid <- expand.grid(nrounds = c(100,200), # this is n_estimators
  in the python code above
743                       max_depth = c(10, 15, 20, 25),
744                       colsample_bytree = seq(0.5, 0.9, length.out =
745                       5),
746                       ## The values below are default values in the
  sklearn-api.
747                       eta = 0.1,
  gamma=0,

```

```

748             min_child_weight = 1,
749             subsample = 1
750         )
751
752     xgb_model <- caret::train(x_train, y_train, method = "xgbTree"
753                             ,trControl = xgb_trcontrol, tuneGrid =
754                               xgbGrid, type="prob")
755     xgb_model$bestTune
756
757     predicted <- predict(xgb_model, x_test)
758     residuals <- y_test - predicted
759     RMSE <- sqrt(mean(residuals^2))
760     cat('The root mean square error of the test data is ', round(RMSE,3),
761         '\n')
762
763     y_test_mean = mean(y_test)
764     # Calculate total sum of squares
765     tss = sum((y_test - y_test_mean)^2 )
766     # Calculate residual sum of squares
767     rss = sum(residuals^2)
768     # Calculate R-squared
769     rsq = 1 - (rss/tss)
770     cat('The R-square of the test data is ', round(rsq,3), '\n')
771     saveRDS(xgb_model, paste0("./models/xgb/", clean_time, "_xgb.RDS"))
772
773     # Random Forest
774
775     # Save a randomForest version too
776     rf <- randomForest(x = train[, predictors]
777                       ,y = response
778                       ,ntree = 500
779                       ,importance = T
780                       ,mtry = rfr$mtry # just grab the best mtry from
781                         the ranger hyperparam tuning for now...
782                       ,nodesize = 5
783                       ,nPerm = 1
784                       ,do.trace = F
785                       ,na.action = na.fail
786                       ,keep.inbag = T
787     )
788
789     varImpPlot(rf)
790     plot(rf)
791     rf
792
793     # Checkpoint our model output

```

```

791 saveRDS(rf, paste0("./models/rf/", clean_time, "_rf.RDS"))
792
793
794 # Variable importance plots


---


795
796 # Top 20 predictors
797 rfr$variable.importance %>%
798   as.data.frame() %>%
799   rownames_to_column() %>%
800   dplyr::select(variable = "rowname", IncNodePurity = ".") %>%
801   arrange(IncNodePurity) %>%
802   tail(n = 20) %>%
803   mutate(variable = forcats::fct_inorder(variable)) %>%
804   ggplot() +
805   geom_col(aes(x = variable, y = IncNodePurity)) +
806   coord_flip() +
807   theme_bw()
808
809 ggsave(plot = last_plot()
810        , filename = paste0("./figures/variable_importance/", clean_
811          time, "_varImpPlot20.png")
812        )
813
814 # Top 50 predictors
815 rfr$variable.importance %>%
816   as.data.frame() %>%
817   rownames_to_column() %>%
818   dplyr::select(variable = "rowname", IncNodePurity = ".") %>%
819   arrange(IncNodePurity) %>%
820   tail(n = 50) %>%
821   mutate(variable = forcats::fct_inorder(variable)) %>%
822   ggplot() +
823   geom_col(aes(x = variable, y = IncNodePurity)) +
824   coord_flip() +
825   theme_bw()
826
827 ggsave(plot = last_plot()
828        , filename = paste0("./figures/variable_importance/", clean_
829          time, "_varImpPlot50.png")
830        )
831
832 # Convert relative PM to Absolute if scale_neph is T


---


833 if (scale_neph) {
834   # Add Neph median to predicted spatial residual

```

```

835 predictions <- predict(rfr , test[,predictors])$predictions+test$pm2
      .5.median
836 predict_full <- predict(rfr , df[,predictors])$predictions+df$pm2.5.
      median
837
838 # Add Neph median to observed spatial residual
839 test$X <- test$Y_scaled + test$pm2.5.median
840
841 df$X <- df$Y_scaled + df$pm2.5.median
842
843 # Build test regression dataframe
844 cvr <- data.frame(x = test$X, y = predictions)
845 cvr_full <- data.frame(x = df$X, y = predict_full)
846
847 # Create test regression model
848 rfr_cv <- lm(y~x, data = cvr)
849 rfr_cv_full <- lm(y~x, data = cvr_full)
850
851 } else {
852
853 # Build test regression dataframe
854 cvr <- data.frame(x = test$Y, y = predict(rfr , test[,predictors])$
      predictions)
855 cvr_full <- data.frame(x = df$Y, y = predict(rfr , df[,predictors])$
      predictions)
856
857 # Create regression validation model
858 rfr_cv <- lm(y~x, data = cvr)
859 rfr_cv_full <- lm(y~x, data = cvr_full)
860
861 # Build another test regression with lm instead of rfr
862 cv_lm <- data.frame(x = test$Y, y = predict(lm_final , test[,
      predictors]))
863 cv_xgb <- data.frame(x = y_test , y = predicted)
864 # rank-deficit warning ignored for now...
865
866 }
867
868 # Store summary of model as new object
869 modr <- summary(rfr_cv)
870 modr
871 # modr_full <- summary(rfr_cv_full)
872 # modr_full
873
874 # Checkpoint our regression validation model object summary
875 saveRDS(modr, paste0("./models/mod_summary/", clean_time , "_mod_
      summary.RDS"))

```

```

876 # modr <- readRDS(paste0("./models/mod_summary/", clean_time, "_mod_
      summary.RDS"))
877
878 # TODO verify p-value thing... lmp() should be suffice
879
880 # Compute RMSE on test data versus predictions
881 rmse <- sqrt(mean((cvr$y - cvr$x)^2))
882 rmse
883
884 # Plot Validation Regression
      

---


885 testRegression(df = cvr, x = "x", y = "y", outdir = "./figures/lm_obs
      _pred/", clean_time = paste0(clean_time, "_rf"), reduced = F)
886 testRegression(df = cv_xgb, x = "x", y = "y", outdir = "./figures/lm_
      obs_pred/", clean_time = paste0(clean_time, "_xgb"), reduced = F)
887 testRegression(df = cv_lm, x = "x", y = "y", outdir = "./figures/lm_
      obs_pred/", clean_time = paste0(clean_time, "_lm"), reduced = F)
888 # testRegression(df = cvr, x = "x", y = "y", outdir = "./figures/misc
      /", clean_time = clean_time, reduced = F)
889 # testRegression(df = cvr_full, x = "x", y = "y", outdir = "./figures
      /lm_obs_pred/full_", clean_time = clean_time, reduced = F)
890
891 # Plot regression with train and test data
892 # TODO Store model summary stats in table for safe keeping
893
894 # LOOCV
      

---


895
896 # Determine viable nodes
897 n_obs_node <- train %>% group_by(node) %>% summarise(n = n())
898
899 n_threshold <- 100
900
901 p <- ggplot(n_obs_node, aes(x = reorder(node, -n), y = n)) +
902   geom_col() +
903   geom_hline(yintercept = n_threshold, col = "firebrick", linetype =
     "dashed") +
904   theme_minimal() +
905   theme(axis.text.x = element_text(angle = 90, vjust = 0.5)
     , axis.title.x = element_blank())
906
907
908 p
909
910 png("./figures/loocv/n_threshold/n_threshold.png"
     , width = 8
     , height = 6
     , units = "in"

```



```

914     ,res = 300)
915 p
916 dev.off()
917
918 # Exclude nodes with too few observations
919 n_obs_node %>% filter(n >= n_threshold)
920
921 # Extract names from remaining nodes
922 nodes <- unique(n_obs_node$node)
923
924 # Loop through each node during LOOCV
925
926 # TODO keep low n nodes during modeling or not?
927 loocv_results <- Reduce(rbind, pblapply(nodes, function(n) {
928
929   # Exclude node of interest
930   df_loocv <- filter(train, node %!in% n)
931
932   # Run models -----
933   # TODO log transform lm predictors???
934   # TODO include k-folds during modeling?
935   lm_loocv <- lm(form, df_loocv)
936   rf_loocv <- ranger(
937     data = df_loocv
938     ,form
939     #x = train[, predictors]
940     #y = response
941     #,dependent.variable.name = 'Y_scaled'
942     ,num.trees = 500
943     ,importance = 'permutation'
944     ,mtry = ceiling((length(which(predictors==T))/3)*1.0)
945     ,respect.unordered.factors = T
946     ,keep.inbag = T
947     ,splitrule = 'variance'
948     ,min.node.size = 5 # regression
949   )
950
951
952   # Predict holdout node -----
953   holdout_loocv <- filter(train, node %in% n)
954
955   holdout_loocv$pred_lm <- predict(lm_loocv, holdout_loocv)
956   holdout_loocv$pred_rf <- predict(rf_loocv, holdout_loocv)$
957     predictions
958
959   # Clean up the node name -----
960   n <- str_replace_all(n, "[[:punct:]]", " ")
961   n <- str_squish(n)

```

```

961   n <- str_replace_all(n, "\\s+", "_")
962
963   # Checkpoint these models for ensemble predicting
964   saveRDS(lm_loocv, paste0("./models/loocv_models/lm/", clean_time, "_", n, "_lm_loocv.RDS"))
965   saveRDS(rf_loocv, paste0("./models/loocv_models/rf/", clean_time, "_", n, "_rf_loocv.RDS"))
966
967   # Visualize CV
968   testRegression(df = holdout_loocv, x = "Y", y = "pred_lm", outdir =
969     "./figures/loocv/lm/", clean_time = paste0(clean_time, "_lm_lo_", n),
970     reduced = F)
971   testRegression(df = holdout_loocv, x = "Y", y = "pred_rf", outdir =
972     "./figures/loocv/rf/", clean_time = paste0(clean_time, "_rf_lo_", n),
973     reduced = F)
974
975   # Store obs-predicted model results
976   mod_lm <- lm(pred_lm~Y, data = holdout_loocv)
977   mod_rf <- lm(pred_rf~Y, data = holdout_loocv)
978
979   summary_lm <- broom::glance(mod_lm)
980   summary_rf <- broom::glance(mod_rf)
981
982   summary_lm$slope <- mod_lm$coef[[2]]
983   summary_rf$slope <- mod_rf$coef[[2]]
984
985   summary_lm$intercept <- mod_lm$coef[[1]]
986   summary_rf$intercept <- mod_rf$coef[[1]]
987
988   summary_lm$model_type <- "lm"
989   summary_rf$model_type <- "rf"
990
991   summary_df <- rbind(summary_lm, summary_rf)
992   summary_df$out_node <- n
993
994   return(summary_df)
995
996 })
997
998 # EDA LOOCV
999
1000 loocv_results_lm <- loocv_results %>% filter(model_type == "lm")

```

```

1000 loocv_results_rf <- loocv_results %>% filter(model_type == "rf")
1001
1002 loocv_results %>% group_by(model_type) %>% summarise_if(is.numeric,
1003   mean)
1004
1005 loocv_results %>% ggplot(aes(x = model_type, y = adj.r.squared, fill
1006   = model_type)) +
1007   geom_violin() +
1008   guides(fill = F) +
1009   theme_minimal() +
1010   theme(axis.text = element_text(face = "bold"),
1011     axis.title = element_text(face = "bold"))
1012
1013 loocv_results %>% ggplot(aes(x = model_type, y = sigma, fill = model_
1014   type)) +
1015   geom_violin() +
1016   guides(fill = F) +
1017   theme_minimal() +
1018   ylab("rmse") +
1019   theme(axis.text = element_text(face = "bold"),
1020     axis.title = element_text(face = "bold"))
1021
1022 loocv_results %>% ggplot(aes(x = model_type, y = slope, fill = model_
1023   type)) +
1024   geom_violin() +
1025   guides(fill = F) +
1026   theme_minimal() +
1027   theme(axis.text = element_text(face = "bold"),
1028     axis.title = element_text(face = "bold"))
1029
1030 loocv_results %>% ggplot(aes(x = model_type, y = intercept, fill =
1031   model_type)) +
1032   geom_violin() +
1033   guides(fill = F) +
1034   theme_minimal() +
1035   theme(axis.text = element_text(face = "bold"),
1036     axis.title = element_text(face = "bold"))
1037
1038 # LOOCV Ensemble predicting the holdout

```

```

1034 lm_mods <- lapply(list.files("./models/loocv_models/lm/", paste0(
1035   clean_time, ".*\\.RDS$"), full.names = T), readRDS)
1036 rf_mods <- lapply(list.files("./models/loocv_models/rf/", paste0(
1037   clean_time, ".*\\.RDS$"), full.names = T), readRDS)
1038
1039 lm_preds <- lapply(1:length(lm_mods), function(m) {

```

```

1038   cv_lm <- data.frame(x = test$Y, y = predict(lm_mods[[m]], test[,
1039     predictors]), i = seq(1:length(test$Y)))
1040   return(cv_lm)
1041 })
1042 rf_preds <- lapply(1:length(rf_mods), function(m) {
1043   cv_rf <- data.frame(x = test$Y, y = predict(rf_mods[[m]], test[,
1044     predictors])$predictions, i = seq(1:length(test$Y)))
1045   return(cv_rf)
1046 })
1047 # Compute mean of ensemble prediction

```

```

1048 ens_lm_cv <- data.table::rbindlist(lm_preds[,lapply(.SD, mean), list
1049   (i)])
1050 ens_rf_cv <- data.table::rbindlist(rf_preds[,lapply(.SD, mean), list
1051   (i)])
1052 testRegression(df = ens_lm_cv, x = "x", y = "y", outdir = "./figures/
1053   lm_obs_pred/", clean_time = paste0(clean_time, "_lm_ensemble"),
1054   reduced = F)
1055 testRegression(df = ens_rf_cv, x = "x", y = "y", outdir = "./figures/
1056   lm_obs_pred/", clean_time = paste0(clean_time, "_rf_ensemble"),
1057   reduced = F)
1058 # testRegression(df = ens_xgb_cv, x = "x", y = "y", outdir = "./
1059   figures/lm_obs_pred/", clean_time = paste0(clean_time, "_xgb_
1060   ensemble"), reduced = F)

```

Source/predict.R

```

1  # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2  # Canopy Continuum Project, USFS
3  # PI Dr. Linda George
4  # 2019-02-21
5  # Predict PM2.5 surfaces with RF model
6
7  # needed for nvim-R
8  if (basename(getwd()) == "src") {
9    setwd("../")
10   getwd()
11 }
12
13 # load the necessary packages

```

```

14 if (!require(pacman)) {
15   install.packages("pacman")
16   library(pacman)

```

```
17 }
18
19 p_load(plyr
20       ,dplyr
21       ,magrittr
22       ,tools
23       ,rgdal
24       ,raster
25       ,rasterVis
26       ,corrplot
27       ,sp
28       ,rgeos
29       ,ggplot2
30       ,stringr
31       ,RColorBrewer
32       ,pbapply
33       ,parallel
34       ,randomForest
35       ,ranger
36       ,tibble
37       ,broom
38       ,lubridate
39       #,mlr # one of these conflicts with raster somewhere...
40       #,tuneRanger
41       ,breakDown # visualize ranger model
42       ,data.table
43       ,mltools
44       ,xgboost
45       ,caret
46       ,formula.tools
47       )
48
49 # Load in global variables
50 source("./src/init.R")
51
52 # Load in misc function
53 source("./src/functions.R")
54
55 clean_time <- readRDS("./models/clean_time/clean_time.RDS")
56 # clean_time <- "2019-04-12_09_43_08"
57 # clean_time <- "2019-04-15_22_56_59"
58 # clean_time <- "2019-04-22_20_43_46"
59 # clean_time <- "2019-04-26_15_20_16"
60 # clean_time <- "2019-06-10_15_31_05"
61
62 # These are used to extract predictor names... must match the LOOCV
   models!
63 rfr <- readRDS(paste0("./models/rfr/", clean_time, "_rfr.RDS"))
```

```

64 rf <- readRDS(paste0("./models/rf/", clean_time, "_rf.RDS"))
65 lm <- readRDS(paste0("./models/lm/", clean_time, "_lm.RDS"))
66 xgb <- readRDS(paste0("./models/xgb/", clean_time, "_xgb.RDS"))
67
68 # Ensemble mod lists
69 lm_mods <- lapply(list.files("./models/loocv_models/lm/", paste0(
    clean_time, ".*\\.RDS$"), full.names = T), readRDS)
70 # rf_mods <- lapply(list.files("./models/loocv_models/rf/", paste0(
    clean_time, ".*\\.RDS$"), full.names = T), readRDS)
71
72 # Scale extracted elevation data based on global minima
73 elev <- raster("./data/buf_static/elev.100m.tif")
74 min_elev <- min(values(elev))
75
76 # Predictions

```

```

77 predictRasters <- function(date = date
78                             #, crs = crs
79                             #, rf = rf
80                             , scale_neph = scale_neph
81                             #, predictors = predictors
82                             , static = static
83                             #, rfr = rfr
84                             ) {
85
86   # TODO stack list of desired predictors instead of all of them?
87   # read in each date's raster stack previously created in
    extractPredictors
88   s <- stack(list.files("./data/buf_vars", pattern = date, full.names
    = T))
89
90   # strip date from daily predictor layer names
91   names(s) <- gsub(x = names(s), pattern = paste0("^X", date, "\\."),
    replacement = "")
92
93   static <- stack(list.files("./data/buf_static", pattern = "\\..tif$"
    , full.names = T))
94   s <- stack(s, static)
95
96   # Reduce stack size to increase performance
97   lm_names <- names(lm$coefficients)
98   rf_names <- names(rfr$variable.importance)
99   # xgb_names <- names(xgb$pred) # should match RF model
100
101   mod_names <- unique(c(lm_names, rf_names))
102   mod_names <- sub("^log_", "", mod_names)
103   suppressWarnings(s <- subset(s, mod_names))

```

```

104
105 # Predict -----
106 # convert to dataframe before prediction
107 df <- as.data.frame(s, xy = T, na.rm=T)
108
109 # This takes ~6-minutes per stack!
110 # system.time(df <- as.data.frame(s, xy = T, na.rm = T))
111
112 # Is this faster than converting the whole stack?
113 # system.time({
114 #   df <- Reduce(cbind, pblapply(1:nlayers(s), function(n) {
115 #     if(n < nlayers(s)) {
116 #       asdf <- as.data.frame(s[[n]], na.rm = T)
117 #       # asdf <- dplyr::select(asdf, -c("x", "y"))
118 #     } else {
119 #       asdf <- as.data.frame(s[[n]], xy = T, na.rm = T)
120 #     }
121 #     # print(names(asdf))
122 #     return(asdf)
123 #   })
124 #   ,cl=detectCores()-1
125 # ))
126 # })
127
128
129 # Change x, y columns to lon, lat
130 names(df)[names(df) == "x"] <- "lon"
131 names(df)[names(df) == "y"] <- "lat"
132
133 # -----
134 # Setting up log transformed predictors for later
135 df$log_pm2.5.median <- log(df$pm2.5.median+1e-6)
136 df$log_fwy.100m <- log(df$fwy.100m+1e-6)
137 # df$log_fwy.300m <- log(df$fwy.300m+1e-6)
138 # df$log_fwy.500m <- log(df$fwy.500m+1e-6)
139 # df$log_fwy.1000m <- log(df$fwy.1000m+1e-6)
140 df$log_elev.100m <- log(df$elev.100m+1e-6+abs(min_elev))
141 # df$log_elev.300m <- log(df$elev.300m+1e-6+abs(min_elev))
142 # df$log_elev.500m <- log(df$elev.500m+1e-6+abs(min_elev))
143 # df$log_elev.1000m <- log(df$elev.1000m+1e-6+abs(min_elev))
144 df$log_pbl.min <- log(df$pbl.min+1e-6)
145 # df$log_railroad.100m <- log(df$railroad.100m+1e-6)
146 # df$log_railroad.300m <- log(df$railroad.300m+1e-6)
147 # df$log_railroad.500m <- log(df$railroad.500m+1e-6)
148 df$log_railroad.1000m <- log(df$railroad.1000m+1e-6)
149 # df$log_rmin <- log(df$rmin+1e-6)
150
151 # Add lat and lon to stack?

```

```

152 # s$lat <- df$lat
153 # s$lon <- df$lon
154
155 # system.time({
156 #   s_extract <- raster::extract(s, extent(bb))
157 #   s_extract_sp <- raster::extract(s, extent(bb), sp=T, na.rm = T,
158 #     method = 'bilinear')
159 #   df <- s_extract %>% raster::as.data.frame() %>% na.omit()
160 #   df_sp <- s_extract_sp %>% raster::as.data.frame() %>% na.omit()
161 # })
162
163 # So we need to add lat, lon, and temporal variables to our df
164 # after converting from stack
165 clean_date <- hyphenDate(date)
166
167 # Add DayOfWeek variable
168 df$weekday <- lubridate::wday(clean_date) %>% factor(levels = c
169 (1:7))
170
171 # Add Season variable
172 df$season <- getSeason(clean_date) %>% factor(levels = c(1:4))
173
174 # # Add Month Variable? Captures phenological differences in PM
175 # from vegetation?
176 df$month <- lubridate::month(clean_date) %>% factor(levels = c
177 (1:12))
178
179 # Weekend/Weekday Captures differences in on-road mobile emissions?
180 df$weekend <- ifelse(lubridate::wday(clean_date) %in% c(6,7), 1, 0)
181 %>% factor(levels = c(0:1))
182
183 # Store Neph data in separate vector (it is deleted in following
184 # line!)
185 pm2.5.median <- df$pm2.5.median
186
187 # Exclude any extra predictors from input data not required by
188 # ranger.predict (pm2.5.median)
189 df %>% dplyr::select(names(rfr$variable.importance)) # dplyr to
190 # the rescue
191
192 # Determine the difference in predictors between input data and
193 # ranger.predict
194 missing_model_predictors <- names(rfr$variable.importance[which(
195 names(rfr$variable.importance) %!in% colnames(df))])
196 extra_input_predictors <- colnames(df[which(colnames(df) %!in%
197 names(rfr$variable.importance))])
198
199 # Confirm there are no missing expected predictors in our df

```



```

188   if (length(missing_model_predictors) > 0 || length(extra_input_
189     predictors) > 0) {
190     print(paste0("Number of missing expected predictors: ", missing_
191       model_predictors))
192     print(paste0("Number of extra input predictors: ", extra_input_
193       predictors))
194     stop()
195   } else {
196
197     # Single model predictions
198
199     # Index our input data on the predictors expected by the model!
200     system.time(pred_rfr <- predict(rfr
201       , data = df[, names(rfr$variable.
202         importance)]
203       , verbose = T
204       , type = "response"
205       , type = "se"
206     ))
207
208     # # Figure out how to predict raster with linear model...
209     # system.time(pred_lm <- predict(lm, df, se.fit = T))
210
211     # system.time(pred_rf <- predict(model = rf
212       , object = s
213       , type = "response"
214       , progress = "text"
215     ))
216
217     # TODO figure out 1d predict time with xgb???
218     # # XGBoost
219     # df_xgb <- df %>% as.data.table() %>%
220     #   mltools::one_hot(dropUnusedLevels = F) %>%
221     #   # feature order is necessary for xgb!!!!
222     #   dplyr::select(xgb$finalModel$feature_names)
223     # system.time(pred_xgb <- predict(xgb, df_xgb))
224
225     # Ensemble predictions
226
227     lm_preds <- lapply(1:length(lm_mods), function(m) {
228       pred_m <- predict(lm_mods[[m]], df, se.fit = T)
229       ens_df <- data.frame(i = seq(1:nrow(df)), fit = pred_m$fit, se
230         = pred_m$se.fit)
231       return(ens_df)
232     })

```

```

227
228   # RF ensemble predictions requires too much memory!
229   # rf_preds <- lapply(1:length(rf_mods), function(m) {
230   #   pred_m <- predict(rf_mods[[m]], data = df[,names(rfr$variable
231   .importance)], type = "se")
232   #   ens_df <- data.frame(i = seq(1:nrow(df)), fit = pred_m$
233   predictions, se = pred_m$se)
234   #   return(ens_df)
235   # })

236   # # Compute mean of ensemble predictions
237
238   ens_lm <- data.table::rbindlist(lm_preds)[,lapply(.SD, mean),
239   list(i)]
240   # ens_rf <- data.table::rbindlist(rf_preds)[,lapply(.SD, mean),
241   list(i)]
242
243   # if neph data is an offset
244   if(scale_neph) {
245
246     # Single model method -----
247     # if the neph data scales the prediction
248     s$"pm2.5.rf" <- pred_rfr$predictions + pm2.5.median
249     # s$"pm2.5.lm" <- pred_lm + pm2.5.median
250     # s$"pm2.5.xgb" <- pred_xgb + pm2.5.median
251
252     # Ensemble method -----
253     # s$"pm2.5.rf" <- ens_rf$fit + pm2.5.median
254     s$"pm2.5.lm" <- ens_lm$fit + pm2.5.median
255
256     # All of these methods return the same plot
257     # # trying Jackson's methods (returns the same looking raster
258     layer)
259     # template <- s[[1]]
260     # template[complete.cases(df)] <- pred_rfr$predictions + pm2.5.
261     median
262     # plot(template)
263     # values(template) <- pred_rfr$predictions + pm2.5.median
264     # plot(template)
265     # plot(s$pm2.5.predicted)
266
267   } else {
268
269     # Single model predictions -----
270     # if neph data is a predictor
271     s$"pm2.5.rf" <- pred_rfr$predictions
272     # s$"pm2.5.lm" <- pred_lm$fit

```

```

267     # s$ "pm2.5.xgb" <- pred_xgb
268
269     # ensemble predictions -----
270     # s$ "pm2.5.rf" <- ens_rf$fit
271     s$ "pm2.5.lm" <- ens_lm$fit
272   }
273
274   # Return prediction SE for each model
275   -----
276   s$pm2.5.rf.se <- pred_rfr$se
277   # s$pm2.5.lm.se <- pred_lm$se
278
279   # # Ensemble error method -----
280   # s$pm2.5.rf.se <- ens_rf$se
281   s$pm2.5.lm.se <- ens_lm$se
282   # s$pm2.5.xgb.se <- ""
283
284   # # extract just the prediction layer
285   # pred_rf <- s$pm2.5.rf
286   # names(pred_rf) <- paste0(date, ".pm2.5.rf.")
287   # pred_lm <- s$pm2.5.lm
288   # names(pred_lm) <- paste0(date, ".pm2.5.lm.")
289   # pred_xgb <- s$pm2.5.xgb
290   # names(pred_xgb) <- paste0(date, ".pm2.5.xgb.")
291
292   pm_stack <- s[[ which(grepl("pm2.5.", names(s))) ]] %>% dropLayer("
pm2.5.median")
293   names(pm_stack) <- paste0(date, ".", names(pm_stack))
294
295   rm(s)
296   rm(df)
297   gc()
298
299   writeRaster(pm_stack, filename = paste0("./data/predicted_raster/
", names(pm_stack), ".tif")
300             , bylayer = T
301             , format = "GTiff"
302             , overwrite = T
303             )
304
305   rm(pm_stack)
306   gc()
307 }
308
309 # writeRaster(crop(mod
310 #             , extent(readRDS(study_area) %>% raster(crs=crs,
res =1000, vals = 0)))

```

```

311     # ,filename = paste0("./data/predicted_raster/", names
      (mod), ".", date, ".tif")
312     # #,bylayer=T
313     # ,format = "GTiff"
314     # ,overwrite = T # will this throw an error?
315     # )
316
317 }
318
319 # loop prediction function over each day
320 predictDailyRasters <- function(start_date = start_date
321                                ,end_date = end_date
322                                #,crs = epsg_26910
323                                ,scale_neph = scale_neph
324                                ,rfr = rfr) {
325
326     dates <- sequenceDates(start_date = start_date, end_date = end_date
327                             )
328
329     # preds <- Reduce(rbind, pblapply(dates, function(x) {
330     #   predictRasters(date = x
331     #                   #,crs = crs
332     #                   ,rf = rf)})
333     #   ,cl = detectCores()-1))
334
335     # Clear out existing files before writing new predictions
336     f <- list.files("./data/predicted_raster", ".tif", full.names = T)
337     lapply(f, file.remove)
338
339     pblapply(dates, function(x) {
340       predictRasters(date = x
341                     #,crs = crs
342                     #,rfr = rfr
343                     ,scale_neph = scale_neph
344                     )}
345     ,cl = detectCores()-1
346     #,cl = 6
347     )
348 }
349
350 # calling the function
351 predict_time <- system.time(predictDailyRasters(
352     start_date = start_
353     #start_date =
354     "2017-10-10"
355     ,end_date = end_date

```

```

355                                     #,end_date =
        "2017-10-10"
356                                     #,crs = crs
357                                     ,scale_neph = scale_
        neph
358                                     #,rfr = rfr
359                                     ))
360
361 print("predictDailyRasters completed!")
362
363 # Checkpoint stack
364 s <- stack(list.files("./data/predicted_raster/", "rf.tif", full.
        names = T))
365 saveRDS(s, paste0("./data/predicted_stack/", clean_time, "_stack_pm2_
        5_rf.RDS"))
366
367 s <- stack(list.files("./data/predicted_raster/", "lm.tif", full.
        names = T))
368 saveRDS(s, paste0("./data/predicted_stack/", clean_time, "_stack_pm2_
        5_lm.RDS"))
369
370 # s <- stack(list.files("./data/predicted_raster/", "xgb.tif", full.
        names = T))
371 # saveRDS(s, paste0("./data/predicted_stack/", clean_time, "_stack_
        pm2_5_xgb.RDS"))
372
373 print("Saving rf, lm, xgb stacks!")
374
375 # r <- raster("./data/predicted_raster/X2017.10.10.pm2.5.predicted.
        tif")
376 # levelplot(r, margin = F)
377
378 saveRDS(predict_time, paste0("./models/predict_time/", clean_time, "_
        predict_time.RDS"))
379
380
381 index <- eval(parse(text = "1:16"))
382 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
        index), "_", max(index), ".png")
383     ,width = 12
384     ,height = 8
385     ,res = 300
386     ,units = "in"
387 )
388 levelplot(s[[index]])
389 dev.off()
390
391

```

```
392 index <- eval(parse(text = "70:85"))
393 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
394     ,width = 12
395     ,height = 8
396     ,res = 300
397     ,units = "in"
398 )
399 levelplot(s[[index]])
400 dev.off()
401
402
403 index <- eval(parse(text = "90:105"))
404 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
405     ,width = 12
406     ,height = 8
407     ,res = 300
408     ,units = "in"
409 )
410 levelplot(s[[index]])
411 dev.off()
412
413
414 index <- eval(parse(text = "105:120"))
415 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
416     ,width = 12
417     ,height = 8
418     ,res = 300
419     ,units = "in"
420 )
421 levelplot(s[[index]])
422 dev.off()
423
424 # This one usually looks really weird!
425 index <- eval(parse(text = "200:215"))
426 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
427     ,width = 12
428     ,height = 8
429     ,res = 300
430     ,units = "in"
431 )
432 levelplot(s[[index]])
433 dev.off()
434
435 index <- eval(parse(text = "300:315"))
```

```

436 png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
437       ,width = 12
438       ,height = 8
439       ,res = 300
440       ,units = "in"
441     )
442   levelplot(s[[index]])
443   dev.off()
444
445   index <- eval(parse(text = "370:395"))
446   png(paste0("./figures/levelplot/", clean_time, "_levelplot_", min(
      index), "_", max(index), ".png")
447       ,width = 12
448       ,height = 8
449       ,res = 300
450       ,units = "in"
451     )
452   levelplot(s[[index]])
453   dev.off()

```

Source/vectorToRaster.R

```

1  vectorToRaster <- function(layer = NULL # shapefile name w/ file
      extension
2                                ,indir = "./data/rlls/" # directory path
3                                ,outdir = "./data/rlls/" # output directory
4                                ,buf_res = sp_res # 50 m buffer
5                                ) {
6
7    # Grab the layer name without file extension
8    var <- basename(tools::file_path_sans_ext(layer))
9
10   # Create outfile
11   outfile <- paste0(outdir, var, ".tif")
12
13   # Check to see if the outfile already exists
14   if(!file.exists(outfile)) {
15
16     print(paste0(outfile, " is being processed."))
17
18     # read in shapefile and reproject
19     vector <- readOGR(dsn = indir, layer = var) %>% spTransform(
      CRSobj = proj4string(df))
20
21     # create an empty raster

```

```

22   template_rst <- raster(extent(gBuffer(df, width = buf_res)), crs
= projection(df), res = buf_res)
23
24   # determine the density of a feature in each cell
25   density <- pbsapply(1:ncell(template_rst), function(x) {
26
27     # create placeholder raster
28     tmp_rst <- template_rst
29
30     # add placeholder value
31     tmp_rst[x] <- 1
32
33     # convert single cell extent to vector
34     tmp_vec <- rasterToPolygons(tmp_rst)
35
36     # Check to see if the feature is within the raster cell
37     if (gIntersects(vector, tmp_vec)) {
38
39       # Crop feature by the extent of a single raster cell
40       vector_crp <- crop(vector, tmp_vec)
41
42       # Perform different calculation for Points, Lines, and
Polygons
43       if ("SpatialLinesDataFrame" %in% class(vector)) {
44         cell_value <- gLength(vector_crp)
45       } else if ("SpatialPolygonsDataFrame" %in% class(vector)) {
46         cell_value <- gArea(vector_crp)
47       } else if ("SpatialPointsDataFrame" %in% class(vector)) {
48         cell_value <- gIntersection(vector_crp, tmp_vec) %>% length
() %>% as.integer()
49       } else {
50         print("Object not of class Spatial*DataFrame!")
51         next
52       }
53       return(cell_value)
54     } else {
55       # If the feature does not intersect with the cell, assign 0
56       return(0)
57     }
58   }, cl = detectCores()-1
59   )
60
61   # set the cell value to the kernel density
62   template_rst[] <- density
63
64   # write to file
65   writeRaster(template_rst

```



```

67         ,filename = outfile
68         ,format = "GTiff"
69         ,overwrite = T)
70     } else {
71         print(paste0(outfile , " already exists!"))
72     }
73 }
74
75 # # list of shape files in rlis
76 # layers <- list.files("./data/rlis", pattern = "\\\\.shp$")
77 #
78 # # call our processing function
79 # pblapply(layers , function(x) {
80 #     vectorToRaster(x)
81 # })

```

Source/purpleair_id_key.py

```

1  # pull 3rd part purpleair data from json api
2  import json
3  import urllib
4  import requests
5  import time
6  from datetime import datetime
7  import calendar
8  import sys
9  import itertools
10 import os
11 import pandas as pd
12
13 file_name = "pa_id_key.txt"
14 dir_name = "/data/pa_id_key/"
15 full_path = os.getcwd() + "/" + dir_name + "/" + file_name
16 row = 0
17
18 d = datetime.utcnow()
19 unixtime = calendar.timegm(d.utctimetuple())
20
21 df = pd.DataFrame(columns=[ 'datetime'
22     , 'ID'
23     , 'ParentID'
24     , 'Label'
25     , 'DEVICE_LOCATIONTYPE'
26     , 'THINGSPEAK_PRIMARY_ID'
27     , 'THINGSPEAK_PRIMARY_ID_READ_KEY'
28     , 'THINGSPEAK_SECONDARY_ID'
29     , 'THINGSPEAK_SECONDARY_ID_READ_KEY'
30     , 'Lat'

```



```

78         ,ParentID = sensor[ 'ParentID' ]
79         ,Label = sensor[ 'Label' ]
80         ,DEVICE_LOCATIONTYPE = sensor[ 'DEVICE_LOCATIONTYPE' ]
81         ,THINGSPEAK_PRIMARY_ID = sensor[ 'THINGSPEAK_PRIMARY_ID' ]
82         ,THINGSPEAK_PRIMARY_ID_READ_KEY = sensor[ '
THINGSPEAK_PRIMARY_ID_READ_KEY' ]
83         ,THINGSPEAK_SECONDARY_ID = sensor[ '
THINGSPEAK_SECONDARY_ID' ]
84         ,THINGSPEAK_SECONDARY_ID_READ_KEY = sensor[ '
THINGSPEAK_SECONDARY_ID_READ_KEY' ]
85         ,Lat = sensor[ 'Lat' ]
86         ,Lon = sensor[ 'Lon' ]
87         ,PM2_5Value = sensor[ 'PM2_5Value' ]
88         #,LastSeen = sensor[ 'LastSeen' ]
89         ,State = sensor[ 'State' ]
90         ,Type = sensor[ 'Type' ]
91         ,Hidden = sensor[ 'Hidden' ]
92         ,Flag = sensor[ 'Flag' ]
93         ,isOwner = sensor[ 'isOwner' ]
94         ,A_H = sensor[ 'A_H' ]
95         ,temp_f = sensor[ 'temp_f' ]
96         ,humidity = sensor[ 'humidity' ]
97         ,pressure = sensor[ 'pressure' ]
98         ,AGE = sensor[ 'AGE' ]
99         ,Stats= sensor[ 'Stats' ]
100     )
101 )
102
103     print df.loc[[row]]
104     row += 1
105     df.to_csv( full_path , sep = ",", index = False , encoding = '
utf-8' )
106 except Exception as e:
107     print '[*] Error, no data was written to file'
108     print e

```

Source/create_observation.sql

```

1 create table observation (
2     created_at varchar(20)
3     ,id varchar(10)
4     ,sensor char(1)
5     ,label varchar(100)
6     ,temp_f numeric
7     ,humidity numeric
8     ,pm1_0_atm numeric
9     ,pm2_5_atm numeric
10    ,pm10_0_atm numeric

```

```

11      ,pm1_0_cf_1 numeric
12      ,pm2_5_cf_1 numeric
13      ,pm10_0_cf_1 numeric
14      ,p_0_3_um numeric
15      ,p_0_5_um numeric
16      ,p_1_0_um numeric
17      ,p_2_5_um numeric
18      ,p_5_0_um numeric
19      ,p_10_0_um numeric
20      ,geom geometry
21      );

```

Source/create_pdx_cf.sql

```

1  create table pdx_cf (
2      year varchar(4)
3      ,month varchar(3)
4      ,id integer
5      ,label varchar(100)
6      ,r_squared numeric
7      ,adj_r_squared numeric
8      ,sigma numeric
9      ,statistic_r2 numeric
10     ,p_value_r2 numeric
11     ,df numeric
12     ,logLik numeric
13     ,AIC numeric
14     ,BIC numeric
15     ,deviance numeric
16     ,df_residual numeric
17     ,term_m varchar(100)
18     ,estimate_m numeric
19     ,std_error_m numeric
20     ,statistic_m numeric
21     ,p_value_m numeric
22     ,term_b varchar(100)
23     ,estimate_b numeric
24     ,std_error_b numeric
25     ,statistic_b numeric
26     ,p_value_b numeric
27     ,geom geometry
28 );

```

Source/thingspeakCollect.R

```

1  # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2  # Canopy Continuum Project , USFS
3  # PI Dr. Linda George
4  # 2018-08-31

```

```

5 # pull PurpleAir data from thingspeak API and upload to Postgres
  database
6
7 # thingspeak read function
  

---


8 # create function to collect purpleair data ~8000 rows at a time
9 thingspeak_collect <- function(row, start = "2017-01-01", end = as.
  character(Sys.Date())) {
10
11   # for testing
12   #start_date <- "2018-06-01"
13   #end_date <- "2018-06-08"
14
15   # 5-min resolution required for overlapping A & B sensors ...
16   time_resolution <- "5 min"
17   time_step <- 5 # same as time res without string "min"
18
19   # define align 5-minute time function
20
21   # for clean 5-min breaks
22   align.time.down = function(x,n) {
23     index(x) = index(x) - n
24     align.time(x,n)
25   }
26
27   # ignore rows without a ParentID
28   if (is.na(row$ParentID)) {
29     # next
30     print("parent ID is empty")
31   } else {
32
33     # API ID & KEYS
    

---


34
35     # grab parent row from pa_sf
36     parent_row <- pa_sf %>% filter(ID == row$ParentID)
37
38     # skip indoor air monitors!!!
39     if (parent_row$DEVICE_LOCATIONTYPE == "indoor") {
40       print(paste("Skipping indoor sensor", parent_row$Label))
41       next
42     }
43
44     # primary api id and key pairs A sensor
45     primary_id_a <- parent_row$THINGSPEAK_PRIMARY_ID
46     primary_key_a <- parent_row$THINGSPEAK_PRIMARY_ID_READ_KEY
47

```

```

48   # secondary api id and key pairs A sensor
49   secondary_id_a <- parent_row$THINGSPEAK_SECONDARY_ID
50   secondary_key_a <- parent_row$THINGSPEAK_SECONDARY_ID_READ_KEY
51
52   # primary api id and key pairs B sensor
53   primary_id_b <- row$THINGSPEAK_PRIMARY_ID
54   primary_key_b <- row$THINGSPEAK_PRIMARY_ID_READ_KEY
55
56   # secondary api id and key pairs B sensor
57   secondary_id_b <- row$THINGSPEAK_SECONDARY_ID
58   secondary_key_b <- row$THINGSPEAK_SECONDARY_ID_READ_KEY
59
60   # convert geometry to text
61   row$geometry <- st_as_text(row$geometry
62                             ,EWKT = TRUE)
63
64   # row$geometry <- st_as_sfc(row$geometry) # converts back to geom
65
66   # create a weekly sequence

```

```

67
68   # need to break up our entire request into 8000 length chunks...
69   weeks <- seq(from = as.Date(start)
70               ,to = as.Date(end)
71               ,by = "week") %>% as.data.frame()
72
73   # assign vector name
74   colnames(weeks) <- "date"
75
76   # API requests across weekly sequence

```

```

77   # make weekly request to api (need to vectorize this...)
78   for (i in 1:nrow(weeks)) {
79
80     # extract start and end dates from our weekly sequence
81     start_date <- weeks$date[i]
82     end_date <- weeks$date[i+1]
83
84     # if the end data is in the future, then use the current date
85     # as the final end point
86     if (is_empty(end_date) | is.na(end_date)) {
87       end_date <- Sys.Date()
88     }
89
90     # A sensor primary url to pull from api
91     primary_url_a <- paste0("https://api.thingspeak.com/channels/"
92                             ,primary_id_a
93                             ,"/feeds.json?api_key="

```

```
93         ,primary_key_a
94         ,"&start="
95         ,start_date
96         ,"%2000:00:00&end="
97         ,end_date
98         ,"%2023:59:59")
99
100 # A sensor secondary url to pull from api
101 secondary_url_a <- paste0("https://api.thingspeak.com/channels/
102
103         ,secondary_id_a
104         ,"/feeds.json?api_key="
105         ,secondary_key_a
106         ,"&start="
107         ,start_date
108         ,"%2000:00:00&end="
109         ,end_date
110         ,"%2023:59:59")
111
112 # B sensor primary url to pull from api
113 primary_url_b <- paste0("https://api.thingspeak.com/channels/"
114         ,primary_id_b
115         ,"/feeds.json?api_key="
116         ,primary_key_b
117         ,"&start="
118         ,start_date
119         ,"%2000:00:00&end="
120         ,end_date
121         ,"%2023:59:59")
122
123 # B sensor secondary url to pull from api
124 secondary_url_b <- paste0("https://api.thingspeak.com/channels/
125
126         ,secondary_id_b
127         ,"/feeds.json?api_key="
128         ,secondary_key_b
129         ,"&start="
130         ,start_date
131         ,"%2000:00:00&end="
132         ,end_date
133         ,"%2023:59:59")
134
135
136 # try pulling from thinspeak API
137
138 # exception handling API request
```

```
139     primary_request_a <- NULL
140     secondary_request_a <- NULL
141     primary_request_b <- NULL
142     secondary_request_b <- NULL
143
144     primary_attempt_a <- 0
145     secondary_attempt_a <- 0
146     primary_attempt_b <- 0
147     secondary_attempt_b <- 0
148
149     # request A sensor data


---


150     while(is.null(primary_request_a) && primary_attempt_a <= 3) {
151       try(primary_request_a <- jsonlite::fromJSON(primary_url_a))
152       print(paste0("Primary Attempt A: ", primary_attempt_a))
153       primary_attempt_a <- primary_attempt_a + 1
154       Sys.sleep(2)
155     }
156
157     if (is.null(primary_request_a)) {
158       print(paste0(primary_url_a, " failed!"))
159     }
160
161     while(is.null(secondary_request_a) && secondary_attempt_a <= 3)
162     {
163       try(secondary_request_a <- jsonlite::fromJSON(secondary_url_a
164       ))
165       print(paste0("Secondary Attempt A: ", secondary_attempt_a))
166       secondary_attempt_a <- secondary_attempt_a + 1
167       Sys.sleep(2)
168     }
169
170     if (is.null(secondary_request_a)) {
171       print(paste0(secondary_url_a, " failed!"))
172     }
173
174     # request B sensor data


---


175     while(is.null(primary_request_b) && primary_attempt_b <= 3) {
176       try(primary_request_b <- jsonlite::fromJSON(primary_url_b))
177       print(paste0("Primary Attempt B: ", primary_attempt_b))
178       primary_attempt_b <- primary_attempt_b + 1
179       Sys.sleep(2)
180     }
181
182     if (is.null(primary_request_b)) {
183       print(paste0(primary_url_b, " failed!"))
184     }
```



```

183
184     while(is.null(secondary_request_b) && secondary_attempt_b <= 3)
185     {
186         try(secondary_request_b <- jsonlite::fromJSON(secondary_url_b
187         ))
188         print(paste0("Secondary Attempt B: ", secondary_attempt_b))
189         secondary_attempt_b <- secondary_attempt_b + 1
190         Sys.sleep(2)
191     }
192
193     if (is.null(secondary_request_b)) {
194         print(paste0(secondary_url_b, " failed!"))
195     }
196
197     # next if request is NULL
198
199     if (is_empty(primary_request_a$feeds) | is_empty(secondary_
200     request_a$feeds) | is_empty(primary_request_b$feeds) | is_empty(
201     secondary_request_b$feeds)) {
202         print(paste0(start_date, "-", end_date, " ", parent_row$Label
203         , " is empty..."))
204         next
205     } else {
206
207         print(paste0(start_date, "-", end_date, " ", parent_row$Label
208         , " A & B are being processed..."))
209
210         # channel A field names
211
212         primary_fields_a <- c("created_at"
213         , "entry_id"
214         , "pm1_0_atm"
215         , "pm2_5_atm"
216         , "pm10_0_atm"
217         , "uptime_min"
218         , "rssi_wifi_strength"
219         , "temp_f"
220         , "humidity"
221         , "pm2_5_cf_1")
222
223         secondary_fields_a <- c("created_at"
224         , "entry_id"
225         , "p_0_3_um"
226         , "p_0_5_um"
227         , "p_1_0_um"
228         , "p_2_5_um"
229         , "p_5_0_um"

```

```

223         , "p_10_0_um"
224         , "pm1_0_cf_1"
225         , "pm10_0_cf_1")
226
227
228     #channel B field names

```

```

229     primary_fields_b <- c("created_at"
230         , "entry_id"
231         , "pm1_0_atm"
232         , "pm2_5_atm"
233         , "pm10_0_atm"
234         , "free_heap_memory"
235         , "analog_input"
236         , "sensor_firmware_pressure"
237         , "not_used"
238         , "pm2_5_cf_1")
239
240     secondary_fields_b <- c("created_at"
241         , "entry_id"
242         , "p_0_3_um"
243         , "p_0_5_um"
244         , "p_1_0_um"
245         , "p_2_5_um"
246         , "p_5_0_um"
247         , "p_10_0_um"
248         , "pm1_0_cf_1"
249         , "pm10_0_cf_1")
250
251
252     # read in primary data for A sensor

```

```

253     primary_df_a <- primary_request_a$feeds
254
255     # assign A field names for primary data
256     # colnames(primary_df) <- primary_fields_a # threw error when
    missing fields...
257
258     # assign primary A field names dynamically
259     names(primary_df_a)[names(primary_df_a) == 'field1'] <-
primary_fields_a[3]
260     names(primary_df_a)[names(primary_df_a) == 'field2'] <-
primary_fields_a[4]
261     names(primary_df_a)[names(primary_df_a) == 'field3'] <-
primary_fields_a[5]
262     names(primary_df_a)[names(primary_df_a) == 'field4'] <-
primary_fields_a[6]

```

```

263     names(primary_df_a)[names(primary_df_a) == 'field5'] <-
primary_fields_a[7]
264     names(primary_df_a)[names(primary_df_a) == 'field6'] <-
primary_fields_a[8]
265     names(primary_df_a)[names(primary_df_a) == 'field7'] <-
primary_fields_a[9]
266     names(primary_df_a)[names(primary_df_a) == 'field8'] <-
primary_fields_a[10]
267
268     # remove non-numeric columns before grouping by date
269     primary_df_a <- primary_df_a %>% dplyr::select(-c(entry_id,
uptime_min, rssi_wifi_strength))
270
271     # cast from character to numeric class
272     try({
273         primary_df_a$pm1_0_atm <- as.numeric(primary_df_a$pm1_0_atm
)
274         primary_df_a$pm2_5_atm <- as.numeric(primary_df_a$pm2_5_atm
)
275         primary_df_a$pm10_0_atm <- as.numeric(primary_df_a$pm10_0_
atm)
276         primary_df_a$temp_f <- as.numeric(primary_df_a$temp_f)
277         primary_df_a$humidity <- as.numeric(primary_df_a$humidity)
278         primary_df_a$pm2_5_cf_1 <- as.numeric(primary_df_a$pm2_5_cf
_1)
279     }, silent = TRUE)
280
281     # aggregate by clean 5-min breaks
282     primary_xts_a <- xts(primary_df_a[, -1]
, as.POSIXct(primary_df_a$created_at
, format = "%Y-%m-%dT%H:%M:%
SZ"
, tz = "GMT"
))
283
284     primary_means_a <- period.apply(primary_xts_a, endpoints(
primary_xts_a, "mins", k = time_step), mean)
285     primary_rounded_a <- align.time.down(primary_means_a, time_
step*60)
286     primary_df_a <- fortify(primary_rounded_a)
287     names(primary_df_a)[names(primary_df_a) == "Index"] <- "
created_at"
288
289     primary_df_a$created_at <- as.character(primary_df_a$created_
at)
290
291     # add sensor label
292     primary_df_a$sensor <- "A"

```

```

297
298     # read in secondary data for A sensor
299     secondary_df_a <- secondary_request_a$feeds
300
301     # assign A field names for secondary data
302     # colnames(secondary_df) <- secondary_fields_a # breaks when
    fields are missing
303
304     # assign secondary A field names dynamically
305     names(secondary_df_a)[names(secondary_df_a) == 'field1'] <-
secondary_fields_a[3]
306     names(secondary_df_a)[names(secondary_df_a) == 'field2'] <-
secondary_fields_a[4]
307     names(secondary_df_a)[names(secondary_df_a) == 'field3'] <-
secondary_fields_a[5]
308     names(secondary_df_a)[names(secondary_df_a) == 'field4'] <-
secondary_fields_a[6]
309     names(secondary_df_a)[names(secondary_df_a) == 'field5'] <-
secondary_fields_a[7]
310     names(secondary_df_a)[names(secondary_df_a) == 'field6'] <-
secondary_fields_a[8]
311     names(secondary_df_a)[names(secondary_df_a) == 'field7'] <-
secondary_fields_a[9]
312     names(secondary_df_a)[names(secondary_df_a) == 'field8'] <-
secondary_fields_a[10]
313
314
315     # remove non-numeric columns before grouping
316     secondary_df_a <- secondary_df_a %>% dplyr::select(-c(entry_
id))
317
318     # cast from character to numeric class
319     try({
320         secondary_df_a$p_0_3_um <- as.numeric(secondary_df_a$p_0_3_
um)
321         secondary_df_a$p_0_5_um <- as.numeric(secondary_df_a$p_0_5_
um)
322         secondary_df_a$p_1_0_um <- as.numeric(secondary_df_a$p_1_0_
um)
323         secondary_df_a$p_2_5_um <- as.numeric(secondary_df_a$p_2_5_
um)
324         secondary_df_a$p_5_0_um <- as.numeric(secondary_df_a$p_0_5_
um)
325         secondary_df_a$p_10_0_um <- as.numeric(secondary_df_a$p_10_
0_um)
326         secondary_df_a$pm1_0_cf_1 <- as.numeric(secondary_df_a$pm1_
0_cf_1)

```

```

327     secondary_df_a$pm10_0_cf_1 <- as.numeric(secondary_df_a$
pm10_0_cf_1)
328     }, silent = TRUE)
329
330     # aggregate by clean 5-min breaks
331     secondary_xts_a <- xts(secondary_df_a[, -1]
332         , as.POSIXct(secondary_df_a$created_at
333             , format = "%Y-%m-%dT%H:%M
:%SZ"
334                 , tz = "GMT"))
335
336     secondary_means_a <- period.apply(secondary_xts_a, endpoints(
secondary_xts_a, "mins", k = time_step), mean)
337     secondary_rounded_a <- align.time.down(secondary_means_a,
time_step*60)
338     secondary_df_a <- fortify(secondary_rounded_a)
339     names(secondary_df_a)[names(secondary_df_a) == "Index"] <- "
created_at"
340
341     secondary_df_a$created_at <- as.character(secondary_df_a$
created_at)
342
343     # add sensor label
344     secondary_df_a$sensor <- "A"
345
346
347     # read in primary data for B sensor

```

```

348     primary_df_b <- primary_request_b$feeds
349
350     # assign primary B field names for primary data
351     # colnames(primary_df) <- primary_fields_b # breaks when
fields are missing
352
353     # assign B field names dynamically
354     names(primary_df_b)[names(primary_df_b) == 'field1'] <-
primary_fields_b[3]
355     names(primary_df_b)[names(primary_df_b) == 'field2'] <-
primary_fields_b[4]
356     names(primary_df_b)[names(primary_df_b) == 'field3'] <-
primary_fields_b[5]
357     names(primary_df_b)[names(primary_df_b) == 'field4'] <-
primary_fields_b[6]
358     names(primary_df_b)[names(primary_df_b) == 'field5'] <-
primary_fields_b[7]
359     names(primary_df_b)[names(primary_df_b) == 'field6'] <-
primary_fields_b[8]

```

```

360     names(primary_df_b)[names(primary_df_b) == 'field7'] <-
primary_fields_b[9]
361     names(primary_df_b)[names(primary_df_b) == 'field8'] <-
primary_fields_b[10]
362
363     # remove non-numeric columns before grouping by date
364     primary_df_b <- primary_df_b %>% dplyr::select(-c(entry_id,
free_heap_memory, analog_input, sensor_firmware_pressure, not_used
))
365
366     # cast from character to numeric
367
368     try({
369         primary_df_b$pm1_0_atm <- as.numeric(primary_df_b$pm1_0_atm
)
370         primary_df_b$pm2_5_atm <- as.numeric(primary_df_b$pm2_5_atm
)
371         primary_df_b$pm10_0_atm <- as.numeric(primary_df_b$pm10_0_
atm)
372         primary_df_b$pm2_5_cf_1 <- as.numeric(primary_df_b$pm2_5_cf
_1)
373     }, silent = TRUE)
374
375
376     # aggregate by clean 5-min breaks
377     primary_xts_b <- xts(primary_df_b[, -1]
, as.POSIXct(primary_df_b$created_at
, format = "%Y-%m-%dT%H:%M:%
SZ"
, tz = "GMT"))
380
381
382     primary_means_b <- period.apply(primary_xts_b, endpoints(
primary_xts_b, "mins", k = time_step), mean)
383     primary_rounded_b <- align.time.down(primary_means_b, time_
step*60)
384     primary_df_b <- fortify(primary_rounded_b)
385     names(primary_df_b)[names(primary_df_b) == "Index"] <- "
created_at"
386
387     primary_df_b$created_at <- as.character(primary_df_b$created_
at)
388
389     # add sensor label
390     primary_df_b$sensor <- "B"
391
392     # read in secondary data for B sensor
393
secondary_df_b <- secondary_request_b$feeds

```

```

394
395     # assign B field names for secondary sensor
396     # colnames(secondary_df) <- secondary_fields_b
397
398     # assign B field names dynamically
399     names(secondary_df_b)[names(secondary_df_b) == 'field1'] <-
secondary_fields_b[3]
400     names(secondary_df_b)[names(secondary_df_b) == 'field2'] <-
secondary_fields_b[4]
401     names(secondary_df_b)[names(secondary_df_b) == 'field3'] <-
secondary_fields_b[5]
402     names(secondary_df_b)[names(secondary_df_b) == 'field4'] <-
secondary_fields_b[6]
403     names(secondary_df_b)[names(secondary_df_b) == 'field5'] <-
secondary_fields_b[7]
404     names(secondary_df_b)[names(secondary_df_b) == 'field6'] <-
secondary_fields_b[8]
405     names(secondary_df_b)[names(secondary_df_b) == 'field7'] <-
secondary_fields_b[9]
406     names(secondary_df_b)[names(secondary_df_b) == 'field8'] <-
secondary_fields_b[10]
407
408
409     # remove non-numeric columns before grouping
410     secondary_df_b <- secondary_df_b %>% dplyr::select(-c(entry_
id))
411
412     # cast character to numeric class
413     try({
414         secondary_df_b$p_0_3_um <- as.numeric(secondary_df_b$p_0_3_
um)
415         secondary_df_b$p_0_5_um <- as.numeric(secondary_df_b$p_0_5_
um)
416         secondary_df_b$p_1_0_um <- as.numeric(secondary_df_b$p_1_0_
um)
417         secondary_df_b$p_2_5_um <- as.numeric(secondary_df_b$p_2_5_
um)
418         secondary_df_b$p_5_0_um <- as.numeric(secondary_df_b$p_5_0_
um)
419         secondary_df_b$p_10_0_um <- as.numeric(secondary_df_b$p_10_
0_um)
420         secondary_df_b$pm1_0_cf_1 <- as.numeric(secondary_df_b$pm1_
0_cf_1)
421         secondary_df_b$pm10_0_cf_1 <- as.numeric(secondary_df_b$
pm10_0_cf_1)
422     }, silent = TRUE)
423
424

```

```

425     # aggregate by clean 5-min breaks
426     secondary_xts_b <- xts(secondary_df_b[, -1]
427                           , as.POSIXct(secondary_df_b$created_at
428                                         , format = "%Y-%m-%dT%H:%M
429                                         :%SZ"
430                                         , tz = "GMT"))
431
432     secondary_means_b <- period.apply(secondary_xts_b, endpoints(
433     secondary_xts_b, "mins", k = time_step), mean)
434     secondary_rounded_b <- align.time.down(secondary_means_b,
435     time_step*60)
436     secondary_df_b <- fortify(secondary_rounded_b)
437     names(secondary_df_b)[names(secondary_df_b) == "Index"] <- "
438     created_at"
439
440     secondary_df_b$created_at <- as.character(secondary_df_b$
441     created_at)
442
443     # add sensor label
444     secondary_df_b$sensor <- "B"
445
446
447     # add temp and humidity from primary A to primary B sensor
448
449     met_data <- primary_df_a %>%
450     dplyr::select(created_at, temp_f, humidity)
451
452     print("joining met data")
453     primary_df_b <- primary_df_b %>% left_join(met_data) # read
454     in primary data for B sensor
455
456
457     # attach PurpleAir API attributes to primary thingspeak data
458     primary_df_a$label <- parent_row$Label
459     primary_df_a$id <- parent_row$ID
460     secondary_df_a$label <- parent_row$Label
461     secondary_df_a$id <- parent_row$ID
462
463     primary_df_b$label <- row$Label
464     primary_df_b$id <- row$ID
465     secondary_df_b$label <- row$Label
466     secondary_df_b$id <- row$ID
467
468     # handle missing device location from B sensors!
469
470     # filter indoor air quality data
471
472     # grab location type only from parent ID

```



```

464     parent_location <- filter(pa_sf, ID == row$ParentID) %>%
dplyr::select(DEVICE_LOCATIONTYPE)
465
466     primary_df_a$DEVICE_LOCATIONTYPE <- parent_location$DEVICE_
LOCATIONTYPE
467     secondary_df_a$DEVICE_LOCATIONTYPE <- parent_location$DEVICE_
LOCATIONTYPE
468
469     primary_df_b$DEVICE_LOCATIONTYPE <- parent_location$DEVICE_
LOCATIONTYPE
470     secondary_df_b$DEVICE_LOCATIONTYPE <- parent_location$DEVICE_
LOCATIONTYPE
471
472     # filter out indoor purpleair data
473     primary_df_a <- primary_df_a %>% filter(DEVICE_LOCATIONTYPE !=
"inside")
474     primary_df_a <- primary_df_a %>% dplyr::select(-DEVICE_
LOCATIONTYPE) # threw error without dplyr::
475     primary_df_b <- primary_df_b %>% filter(DEVICE_LOCATIONTYPE !=
"inside")
476     primary_df_b <- primary_df_b %>% dplyr::select(-DEVICE_
LOCATIONTYPE) # threw error without dplyr::
477     #print("test point 5")
478
479     secondary_df_a <- secondary_df_a %>% filter(DEVICE_
LOCATIONTYPE != "inside")
480     secondary_df_a <- secondary_df_a %>% dplyr::select(-DEVICE_
LOCATIONTYPE) # threw error without dplyr::
481     secondary_df_b <- secondary_df_b %>% filter(DEVICE_
LOCATIONTYPE != "inside")
482     secondary_df_b <- secondary_df_b %>% dplyr::select(-DEVICE_
LOCATIONTYPE) # threw error without dplyr::
483     #print("test point 6")
484
485     print("joining primary_a secondary_a")
486     # create wide dataframe to use less rows (tidy 100k rows per
week per sensor)
487     df_wide_a <- inner_join(primary_df_a, secondary_df_a, by = c(
"created_at"
488
, "sensor"
489
, "label"
490
# , "geom"
491
, "id"))
492

```

```

493     # reorder columns
494     df_wide_a <- df_wide_a %>% dplyr::select(
495
496         created_at # put this first out of convention
497         #,entry_id
498         ,id
499         ,label
500         ,sensor
501         #,uptime_min # Channel A
502         #,rssi_wifi_strength # Channel A
503         ,temp_f # Channel A
504         ,humidity # Channel A
505         ,pm1_0_atm
506         ,pm2_5_atm
507         ,pm10_0_atm
508         ,pm1_0_cf_1
509         ,pm2_5_cf_1
510         ,pm10_0_cf_1
511         ,p_0_3_um
512         ,p_0_5_um
513         ,p_1_0_um
514         ,p_2_5_um
515         ,p_5_0_um
516         ,p_10_0_um
517         #,geom # put this last out of convention
518     )
519
520     print("joining primary_b secondary_b")
521     # create wide dataframe to use less rows (tidy 100k rows per
week per sensor) -----
522     df_wide_b <- inner_join(primary_df_b, secondary_df_b, by = c(
"created_at"
523
524     , "sensor"
525
526     , "label"
527
528     # , "geom"
529
530     , "id"))
531
532     # reorder columns
533     df_wide_b <- df_wide_b %>% dplyr::select(
534         created_at # put this first out of convention
535         #,entry_id
536         ,id
537         ,label
538         ,sensor

```

```

535     #,uptime_min # Channel A
536     #,rssi_wifi_strength # Channel A
537     ,temp_f # Channel A
538     ,humidity # Channel A
539     ,pm1_0_atm
540     ,pm2_5_atm
541     ,pm10_0_atm
542     ,pm1_0_cf_1
543     ,pm2_5_cf_1
544     ,pm10_0_cf_1
545     ,p_0_3_um
546     ,p_0_5_um
547     ,p_1_0_um
548     ,p_2_5_um
549     ,p_5_0_um
550     ,p_10_0_um
551     #,geom # put this last out of convention
552 )
553
554 #

```

```

555 # Join Primary and Secondary data and omit NAs
556 df_wide <- bind_rows(df_wide_a, df_wide_b)
557 df_wide <- df_wide[complete.cases(df_wide), ]
558 df_wide <- df_wide %>% na.omit()
559
560 # bring geom back

```

```

561 if (nrow(df_wide) == 0) {
562   print("df_wide is empty, skipping db upload")
563   next
564 }
565
566 print("adding geom")
567 df_wide$geom <- row$geometry
568 print(class(df_wide))
569 print(class(df_wide$geom))
570 #print('converting from character to wkt')
571 #df_wide$geom <- st_as_sfc(df_wide$geom)
572 print("converting to sf df")
573 df_wide <- st_as_sf(df_wide, wkt = "geom")
574 print(class(df_wide$geom))
575 print(class(df_wide))
576
577
578 observation <- df_wide %>% na.omit()

```

```

579
580     # open connection to our db
581     con <- dbConnect(drv = RPostgres::Postgres()
582                     ,dbname = db
583                     ,host = 'pgsql102.rc.pdx.edu' # not sure why
584                     ,port = port
585                     ,password = pw
586                     ,user = user)
587
588     # TODO update database without producing dupes!
589
590     # writes only new independences to db
591     print("writing to db")
592     st_write(dsn = con
593             ,obj = observation
594             ,query = "INSERT INTO pdx_local_slope ON CONFLICT
595 DO NOTHING;" # this isn't working, writes twice...
596             ,layer_options = "OVERWRITE=true"
597             ,drop_table = FALSE
598             ,try_drop = FALSE
599             ,debug = TRUE
600             ,append = TRUE
601             ,dataset_options = "GEOMETRY=AS_WKT"
602         )
603
604     # cleaning up
605     invisible(gc())
606 }
607 }
608 }

```

Source/uploadDailyThingspeak.R

```

1  # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2  # Canopy Continuum Project , USFS
3  # PI Dr. Linda George
4  # 2018-07-16
5  # pull PurpleAir data from thingspeak API and upload to Postgres
6  # database
7  # set up environment
8
9  # load the necessary packages
10 if (!require(pacman)) {
11   install.packages("pacman")

```

```
12   library(pacman)
13 }
14
15 p_load(readr
16         ,readxl
17         #,xlsx
18         ,ggplot2
19         ,plyr
20         ,dplyr
21         ,broom
22         ,reshape2
23         ,tidyr
24         ,stringr
25         ,magrittr
26         ,rlist
27         ,grid
28         ,gridExtra
29         ,tidyquant
30         ,scales
31         ,qdapRegex
32         ,sp
33         ,rgeos
34         ,sf
35         ,devtools
36         ,RColorBrewer
37         ,classInt
38         ,htmltools
39         ,scales
40         ,htmlwidgets
41         ,httr
42         ,jsonlite
43         ,rgdal
44         ,pbapply
45         ,snow
46         ,parallel
47         ,data.table
48         ,RPostgres
49         ,leaflet
50 )
51
52
53 # define global variables
54
55 # set timezone to UTC/GMT to match postgres
56 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
57 #   PDT!
57 # DEQ only uses PST!
```

```

58 Sys.setenv(TZ="GMT")
59
60 ## connecting to local db
61 host <- 'pgsql120.rc.pdx.edu'
62 db <- 'canopycontinuum'
63 user <- 'porlando'
64 port <- 5433
65 pw <- scan("./batteries.pgpass", what = "")
66
67
68 # initially connect to clear existing data
69 con <- dbConnect(drv = RPostgres::Postgres()
70                  ,dbname = db
71                  ,host = 'pgsql102.rc.pdx.edu' # not sure why object
72                  ,port = port
73                  ,password = pw
74                  ,user = user)
75
76
77 # create unanimous time resolution for all data
78 time_resolution <- "1 sec"
79
80 # CRS
81 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
82
83 # Albuquerque, NM, UTM 13N
84 utm_13N <- "+proj=utm +zone=13 +ellps=WGS84 +datum=WGS84 +units=m +no_
85 _defs "
86
87 # Sacramento, CA, UTM 10S, meters
88 epsg_26911 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
89 +no_defs "
90
91 # Oregon North NAD83 HARN meters
92 epsg_2838 <- "+proj=lcc +lat_1=46 +lat_2=44.33333333333334 +lat_
93 0=43.666666666666666 +lon_0=-120.5 +x_0=2500000 +y_0=0 +ellps=GRS80
94 +units=m +no_defs "
95
96 # Oregon North NAD83 Meters UTM Zone 10
97 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
98 +no_defs "
99
100 # Function definition
101
102
103 # creating a custom not-in function

```

```

99  '%!in%' <- function(x,y)!( '%!in%'(x,y))
100
101  # set path to output of python script (up to date purpleair list)
102  pa_path <- "./data/pa_id_key/pa_id_key.txt"
103
104  # sourcing thingspeak collect function
105  source("./src/thingspeakCollect.R")
106
107  # upload new data each day to db


---


108
109  # convert to char because of thingspeak_collect legacy code...
110  yesterday <- as.character(Sys.Date() - 1)
111  today <- as.character(Sys.Date())
112  tomorrow <- as.character(Sys.Date() + 1)
113
114  # grab up to date list of global PurpleAir network
115  system("python ./purpleair_id_key.py") # this unexpectedly crashes
    when running python within RStudio
116
117  # reading our scraped purpleair id data
118  pa <- read.csv(pa_path
119                ,stringsAsFactors = FALSE
120                ,header = TRUE)
121
122  # converting to simple features class
123  pa_sf <- st_as_sf(pa
124                  ,coords = c("Lon", "Lat")
125                  ,crs = wgs_84
126                  ,na.fail = FALSE)
127
128  # reading in urban growth boundary shapefile
129  portl <- readOGR(dsn = "./data/shape/ugb.shp") # n =
130  portl <- spTransform(portl, CRSobj = CRS(epsg_26910))
131  portl <- st_as_sf(portl)
132  pa_sf <- st_transform(pa_sf, crs = st_crs(portl))
133
134  # Buffer Portland Study Area to capture Urban-Rural Gradient!
135  portl_buf <- st_buffer(portl, dist = 1e5)
136
137  # subset purpleair that intersect ugb
138  pa_sf <- pa_sf[portl_buf,]
139
140  # same thing as above but with a progress bar
141  pbapply(pa_sf, 1, thingspeak_collect, start = yesterday, end =
    yesterday)

```

Source/uploadHistoricalThingspeak.R

```
1 # created by Philip Orlando @ Sustainable Atmospheres Research Lab
2 # Canopy Continuum Project, USFS
3 # PI Dr. Linda George
4 # 2018-07-16
5 # pull PurpleAir data from thingspeak API and upload to Postgres
  database
6
7 # set up environment
  

---


8
9 # load the necessary packages
10 if (!require(pacman)) {
11   install.packages("pacman")
12   library(pacman)
13 }
14
15 p_load(readr
16         ,readxl
17         ,ggplot2
18         ,plyr
19         ,dplyr
20         ,broom
21         ,reshape2
22         ,tidyr
23         ,stringr
24         ,magrittr
25         ,rlist
26         ,grid
27         ,gridExtra
28         ,tidyquant
29         ,scales
30         ,qdapRegex
31         ,sp
32         ,sf
33         ,devtools
34         ,RColorBrewer
35         ,classInt
36         ,htmltools
37         ,scales
38         ,htmlwidgets
39         ,httr
40         ,jsonlite
41         ,rgdal
42         ,pbapply
43         ,snow
44         ,parallel
45         ,data.table
46         ,RPostgres
```



```

47 )
48
49
50 # define global variables
    _____
51
52 # set timezone to UTC/GMT to match postgres
53 # otherwise, st_read() will convert timestamp to US/Pacific with PST/
    PDT!
54 # DEQ only uses PST!
55 Sys.setenv(TZ="GMT")
56
57 ## connecting to local db
58 host <- 'pgsql120.rc.pdx.edu'
59 db <- 'canopycontinuum'
60 user <- 'porlando'
61 port <- 5433
62 pw <- scan("./batteries.pgss", what = "")
63
64
65 # initially connect to clear existing data
66 con <- dbConnect(drv = RPostgres::Postgres()
67                  ,dbname = db
68                  ,host = 'pgsql102.rc.pdx.edu' # not sure why object
    host isn't working...
69                  ,port = port
70                  ,password = pw
71                  ,user = user)
72
73
74 # create unanimous time resolution for all data
75 time_resolution <- "1 sec"
76
77 # CRS
78 wgs_84 <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs "
79
80 # Albuquerque, NM, UTM 13N
81 utm_13N <- "+proj=utm +zone=13 +ellps=WGS84 +datum=WGS84 +units=m +no
    _defs "
82
83 # Sacramento, CA, UTM 10S, meters
84 epsg_26911 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
85
86 # Oregon North NAD83 HARN meters
87 epsg_2838 <- "+proj=lcc +lat_1=46 +lat_2=44.33333333333334 +lat_
    0=43.66666666666666 +lon_0=-120.5 +x_0=2500000 +y_0=0 +ellps=GRS80
    +units=m +no_defs "

```

```

88
89 # Oregon North NAD83 Meters UTM Zone 10
90 epsg_26910 <- "+proj=utm +zone=10 +ellps=GRS80 +datum=NAD83 +units=m
    +no_defs "
91
92
93 # Function definition
    

---


94
95 # creating a custom not-in function
96 '%!in%' <- function(x,y){ '%in%'(x,y)}
97
98 # set path to output of python script (up to date purpleair list)
99 pa_path <- "./data/pa_id_key/pa_id_key.txt"
100
101 # sourcing thingspeak collect function
102 source("./src/thingspeakCollect.R")
103
104 # loop begin
105 # upload new data each day to db
    

---


106
107 # grab up to date list of global PurpleAir network
108 system("python ./purpleair_id_key.py") # this unexpectedly crashes
    when running python within RStudio
109
110 # reading our scraped purpleair id data
111 pa <- read.csv(pa_path
112               ,stringsAsFactors = FALSE
113               ,header = TRUE)
114
115 # converting to simple features class
116 pa_sf <- st_as_sf(pa
117                  ,coords = c("Lon", "Lat")
118                  ,crs = wgs_84
119                  ,na.fail = FALSE)
120
121 # reading in urban growth boundary shapefile
122 portl <- readOGR(dsn = "./data/shape/ugb.shp") # n =
123 portl <- spTransform(portl, CRSobj = CRS(epsg_26910))
124 portl <- st_as_sf(portl)
125 pa_sf <- st_transform(pa_sf, crs = st_crs(portl))
126
127 # Buffer Portland Study Area to capture Urban-Rural Gradient!
128 portl_buf <- st_buffer(portl, dist = 1e5)
129
130 # subset purpleair that intersect ugb
131 pa_sf <- pa_sf[portl_buf,]

```

```

132
133 # invisible(apply(pa_sf
134 #             ,MARGIN = 1 # applies over rows
135 #             ,FUN = thingspeak_collect
136 #             ))
137
138 # same thing as above but with a progress bar
139 pbapply(pa_sf, 1, thingspeak_collect, start = "2017-07-01", end = as.
    character(Sys.Date()))
140     ,cl = detectCores()-1 # linux-specific (doesn't work on
    windows!)
141     )

```

Source/purpleair_watchdog.py

```

1 #
    #####

2 ##### PurpleAir Watchdog Algorithm
    #####

3 #
    #####

4
5 ##### Created by: Philip Orlando
6 ##### Sustainable Atmospheres Research Lab
7 ##### Portland State University
8 ##### 2018-02-15
9
10 import json
11 import urllib
12 import requests
13 import time
14 from datetime import datetime
15 import calendar
16 import smtplib
17 from email.mime.text import MIMEText
18 from email.mime.multipart import MIMEMultipart
19 import getpass
20 import pyfiglet
21 import termcolor
22 import itertools
23 import sys
24
25
26 ## program header
27 termcolor.cprint(pyfiglet.figlet_format('PurpleAir\nWatchdog', font='
    slant'),

```

```
28     'magenta', attrs=['bold'])
29
30 ## create send email Class
31 class Gmail(object):
32     def __init__(self, email, recipient, password):
33         self.email = email
34         self.password = password
35         self.recipient = recipient
36         self.server = 'smtp.gmail.com'
37         self.port = 587
38         session = smtplib.SMTP(self.server, self.port)
39         session.ehlo()
40         session.starttls()
41         session.ehlo
42         session.login(self.email, self.password)
43         self.session = session
44
45     def send_message(self, subject, body):
46
47         headers = [
48             "From: " + self.email,
49             "Subject: " + subject,
50             "To: " + self.recipient,
51             "MIME-Version: 1.0",
52             "Content-Type: text/html"]
53
54         headers = "\r\n".join(headers)
55         self.session.sendmail(
56             self.email,
57             self.recipient,
58             headers + "\r\n\r\n" + body)
59
60
61 ## define email parameters:
62 sender = 'phlp.orlando@gmail.com'
63
64 ##recipient = 'h6lg@pdx.edu'
65 recipient = 'psustarlab@pdx.edu'
66
67 ## secured raw_input for email password
68 email_password = getpass.getpass('[*] Enter the email server password
69     : ')
70
71 ## creating a list of sensor IDs
72 sensorID = [
73     # PDX Sites
74     3786 ## PSU Star Lab Cully
```

```
75 ,3787 ## PSU Star Lab Cully B
76 #,3357 ## Irvington
77 #,3358 ## Irvington B
78 #,5826 ## NE 12th & Tillamook
79 #,5827 ## NE 12th & Tillamook B
80 #,7018 ## Miller
81 #,7019 ## Miller B
82 #,2317 ## Portsmouth Portland
83 #,2318 ## Portsmouth Portland B
84 ,2037 ## PSU STAR Lab Hayden Island
85 ,2038 ## PSU STAR Lab Hayden Island B
86 ,1606 ## PSU STAR Lab Roof North
87 ,1607 ## PSU STAR Lab Roof North B
88 ,1569 ## PSU STAR Lab Roof South
89 ,1570 ## PSU STAR Lab Roof South B
90 #,7386 ## PSU STAR Lab Roof South SD
91 #,7387 ## PSU STAR Lab Roof South SD B
92 ,2045 ## PSU STAR Lab Rose City Park
93 ,2046 ## PSU STAR Lab Rose City Park B
94 ,2065 ## STAR Lab Hillsdale
95 ,2066 ## STAR Lab Hillsdale
96 ,2059 ## STAR Lab Aloha
97 ,2060 ## STAR Lab Aloha B
98 ,2055 ## STAR LAB BETHANY
99 ,2056 ## STAR LAB BETHANY B
100 ,2043 ## STAR Lab Creston Kenilworth
101 ,2044 ## STAR Lab Creston Kenilworth B
102 ,2057 ## STAR Lab Homestead Neighborhood
103 ,2058 ## STAR Lab Homestead Neighborhood B
104 ,2053 ## STAR Lab Powell–Hurst Gilbert
105 ,2054 ## Star Lab Powell–Hurst Gilbert B
106 ,3707 ## STAR Jesuit HS
107 ,3708 ## STAR Jesuit HS B
108 ,3729 ## PSU STAR Lab Edgewater
109 ,3730 ## PSU STAR Lab Edgewater B
110 ,3684 ## Lower Boones Ferry
111 ,3685 ## Lower Boones Ferry B
112 ,3775 ## PSU STAR Lab Lost Park
113 ,3776 ## PSU STAR Lab Lost Park B
114 #,2033 ## Star Lab Jesuit
115 #,2034 ## Star Lab Jesuit B
116
117 #,2566 ## VerdeVista
118 #,2567 ## VerdeVista B
119 #,3404 ## Woods Park
120 #,3405 ## Woods Park B
121 #,3281 ## Red Fox Hills
122 #,3282 ## Red Fox Hills B
```

```

123 #,3233 ## Marion Court Apartments
124 #,3234 ## Marion Court Apartments B
125 #,2741 ## College Park
126 #,2742 ## College Park B
127
128
129 # ABQ Sites
130 ,7366 # PSU STAR Lab Calle Suenos
131 ,7367 # PSU STAR Lab Calle Suenos B
132 ,9758 # PSU STAR Lab Homestead Trail ABQ
133 ,9759 # PSU STAR Lab Homestead Trail ABQ B
134 ,10304 # PSU STAR Lab Carrington
135 ,10305 # PSU STAR Lab Carrington B
136 ,9746 # PSU STAR Lab ABQIRAM
137 ,9747 # PSU STAR Lab ABQIRAM B
138 ,7370 # PSU STAR Lab Parkway
139 ,7371 # PSU STAR Lab Parkway B
140 ,7404 # PSU STAR Lab Old Town
141 ,7405 # PSU STAR Lab Old Town B
142 ,7420 # PSU STAR Lab ABQ Mark Twain
143 ,7421 # PSU STAR Lab ABQ Mark Twain B
144 ,10278 # PSU STAR Lab Bandelier
145 ,10279 # PSU STAR Lab Bandelier B
146 ,7406 # PSU STAR Lab Parkland Hills Albuquerque
147 ,7407 # PSU STAR Lab Parkland Hills ALbuquerque B
148 ,9730 # Elyse Pl. Albuquerque
149 ,9731 # Elyse Pl. Albuquerque B
150 ,9782 # PSU STAR Lab Sunstar Loop
151 ,9783 # PSU STAR Lab Sunstar Loop B
152 ,9754 # PSU STAR Lab – Loma del Rey
153 ,9755 # PSU STAR Lab – Loma del Rey B
154 ]
155
156
157 ## establish downtime intervals
158 downHour = int(60*2)
159 downDay = int(60*60*24)
160 #downDay = int(60)
161 #sleep_time = int(30)
162 sleep_time = int(60*15) ## 15-minute scan
163
164 ## wrap our algo into a while loop:
165 while True:
166
167     ## retrieving the current timestamp and converting it to unixtime
168     t = datetime.utcnow()
169     startTime = calendar.timegm(t.utctimetuple())
170     nextDay = startTime + downDay

```

```
171
172 try:
173     del(offline_sensors[:])
174
175 except Exception:
176     pass
177
178 offline_sensors = []
179
180 while calendar.timegm(datetime.utcnow().utctimetuple()) < nextDay:
181
182     d = datetime.utcnow()
183     unixtime = calendar.timegm(d.utctimetuple())
184
185     print
186
187     ## assigning PurpleAir API to url
188     url = "https://www.purpleair.com/json"
189
190     ## GET request from PurpleAir API
191     try:
192         r = requests.get(url)
193         print '[*] Connecting to API...'
194         print '[*] GET Status: ', r.status_code
195
196     except Exception as e:
197         print '[*] Unable to connect to API...'
198         print 'GET Status: ', r.status_code
199         print e
200     print
201
202
203     try:
204         ## parse the JSON returned from the request
205         j = r.json()
206     except Exception as e:
207         print '[*] Unable to parse JSON'
208         print e
209
210     try:
211
212         ## iterate through entire dictionary
213         for sensor in j['results']:
214
215             ## retrieve only the sensors from our list
216             if sensor['ID'] in sensorID:
217
218                 ## determine if a sensor has been down for a day
```

```

219     if (unixtime - int(sensor['LastSeen'])) > downHour and sensor['
ID'] not in [int(y) for x in offline_sensors for y in x.split()]:
220         print '[*] Sensor', sensor['Label'], 'went offline at',
datetime.fromtimestamp(sensor['LastSeen'])
221         down_sensor = str(sensor['Label'])
222         down_ID = str(sensor['ID'])
223         offline_sensors.append(down_ID) ## this could be better handled
with files, avoiding dupe emails when restarting the program more
than once per day (if needed due to an exception)
224         ## send email
225         msg = 'has been down since ' + str(datetime.fromtimestamp(
sensor['LastSeen']))
226         gm = Gmail(sender, recipient, email_password)
227         gm.send_message(down_sensor, msg)
228         print '[*] Notification sent.'
229
230     elif (unixtime - int(sensor['LastSeen'])) > downHour and sensor[
ID'] in [int(y) for x in offline_sensors for y in x.split()]:
231         print '[*] Sensor', sensor['Label'], 'has been down since',
datetime.fromtimestamp(sensor['LastSeen'])
232         print '[*] Notification has already been sent to', recipient
233
234     else:
235         print '[*]', str(sensor['Label']) + ': ', sensor['ID'], '
lastSeen', datetime.fromtimestamp(sensor['LastSeen'])
236
237         try:
238             offline_sensors.remove(sensor['ID']) # clear a sensor once it
goes back online!
239
240         except:
241             pass
242     print
243     print '[*] nextScan', datetime.fromtimestamp(unixtime + sleep_time
)
244     print '[*] startTime', datetime.fromtimestamp(startTime)
245     print '[*] unixtime', datetime.fromtimestamp(unixtime)
246     print '[*] nextDay', datetime.fromtimestamp(nextDay)
247     time.sleep(sleep_time)
248
249 except Exception as e:
250     print '[*] Delivery to ', recipient, 'failed!'
251     print e
252     print '[*] Will try again in one hour....'
253     time.sleep(sleep_time)
254
255 # empty our list of offline sensors each day
256 #offline_sensors[:] = []

```


Appendix B

ThingSpeak PurpleAir Field Descriptions

Channel A and B, primary and secondary ThingSpeak channels together provide 32 fields for each sensor. There are six μgm^{-3} values and six particle counts for each channel (laser) as well as temperature, humidity, WiFi signal (RSSI), sensor uptime, free memory and analog input.

B.1 Channel A

B.1.1 PrimaryData

field1: PM1.0 (CF=ATM) $\mu\text{g}/\text{m}^3$

field2: PM2.5 (CF=ATM) $\mu\text{g}/\text{m}^3$

field3: PM10.0 (CF=ATM) $\mu\text{g}/\text{m}^3$

field4: Uptime (Minutes)

field5: RSSI (WiFi Signal Strength)

field6: Temperature (F)

field7: Humidity (%)

field8: PM2.5 (CF=1) $\mu\text{g}/\text{m}^3$ This is the field to use for PM2.5

B.1.2 SecondaryData

field1: 0.3um particles/deciliter

field2: 0.5um particles/deciliter

field3: 1.0um particles/deciliter

field4: 2.5um particles/deciliter

field5: 5.0um particles/deciliter

field6: 10.0um particles/deciliter

field7: PM1.0 (CF=1) ug/m3 This is the field to use for PM1.0

field8: PM10 (CF=1) ug/m3 This is the field to use for PM10

B.2 Channel B**B.2.1 PrimaryData**

field1: PM1.0 (CF=ATM) ug/m3

field2: PM2.5 (CF=ATM) ug/m3

field3: PM10.0 (CF=ATM) ug/m3

field4: Free HEAP memory

field5: ADC0 (analog input) voltage

field6: SENSOR FIRMWARE 2.5 and up: Atmospheric Pressure

field7: (NOT USED)

field8: PM2.5 (CF=1) ug/m3 This is the field to use for PM2.5

B.2.2 SecondaryData

field1: 0.3um particles/deciliter

field2: 0.5um particles/deciliter

field3: 1.0um particles/deciliter

field4: 2.5um particles/deciliter

field5: 5.0um particles/deciliter

field6: 10.0um particles/deciliter

field7: PM1.0 (CF=1) ug/m3 This is the field to use for PM1.0

field8: PM10 (CF=1) ug/m3 This is the field to use for PM10