CHAPTER VI

Discussion

Due to the large nature of this project, depicting 2,125 days would be rather disingenuous to mother nature should a printed copy need exist somewhere. Randomly selecting 5 months keeps this number down to 150, along with first-of-month depictions created in ArcGIS Pro. It was imperative that all seasons were captured in this section; random months for each season were selected with two months being selected from summer seasons. After the month was selected, a year was randomly associated with it. January 2019, October 2020, and April 2023 depict Winter, Fall, and Spring respectively while July 2021 and June 2023 depict Summer.

Given the low variance in terrain, except around mountainous areas, many of the urban populations are in basins allowing for the cumulation of surface O3 after its generation from higher elevations surrounding Phoenix and Tucson. The full daily outputs for each month are depicted starting on Map VIII.MAP.X V.2.2. and on. Only the first of each month was shown in detail using ArcGIS Pro; while high quality, these maps are left as example layouts to use for larger AOIs. Averages for each county with XGBRK are compared to monitor statistics followed by a brief analysis of potential health outcomes due to exposures at concentrations greater than the EPA Standard of 70 ppb. Full applications, processing of the dataset and future project management are also discussed before concluding with general comments in Chapter VII.

A Brief Surface O3 Case Study in Arizona

The many maps created for this section are dedicated to expanding the who, when, and where of surface O3 into what potential outcomes can occur in areas exposed to high concentrations. While these thesis could delve more into the how, much of this has already been discussed (e.g Literature et al., 2020-2024) As mentioned in Chapter II.3.4, O3 is an oxidizing agent, participating in redox reactions while simultaneously reducing itself due to instability (Marmett et al. 2023; Qiu et al. 2025; Yang et al. 2024). Using TD with extreme gradient boost (XGB), models predicting surface O3 concentrations are combined with basic population and income metrics from the US Census Bureau to show clear discrepancies in affected demographics. The initial goal of this was to create a unique depiction of urban density within the AOI. Final inspection of the predicted outputs reveals clear transport trends which favor dense urban locations, little change in elevation, and large sources of healthy vegetation.

These interactions can be seen across daily images provided in Maps VIII.3.11-3.161. Daily values within the time range often depict extreme changes in surface O3 concentrations across rural areas dedicated to farming, golfing, and tourism like Casa Grande, Rio Verde, and Mount Lemmon. Areas near the basins of the Rincon and Santa Catalina Mountain ranges would also see prolonged aftereffects post ozone production, likely stemming from nearby developing areas. During winter seasons, settling can be seen settling in the suburbs of both Phoenix and Tucson post-production. While the lower end of concentrations are well below the EPA’s 70 ppb standard during off-production seasons, these same areas typically see high risk to surface O3 during summer and spring. This is likely due to CO2 from healthy vegetation and VoCs found near predominantly urban areas. Along the boundary of these sources are mainly in areas lacking in vegetation due to the natural desert-like environment found across the AOI.

VI.1. Trends Over PHOTUC for Five Months

Aside from high altitudes, which see many high concentrations in general, most of these areas are exposed to ample heat, and result in the larger RK corrections. While certain urban areas of the AOI remain stable around 40-60ppb, Maps XI.3.6-XI.3.11 utilizing XGBRK predictions show clear splits in areas exposed to upwards of 80ppb. Some of the more exposed urban census tracts scattered throughout Phoenix and Tucson show below average income and have a higher number of people living in these areas; further showing that research across different AOIs with accurate, high-resolution surface O3 predictions is necessary to identify these communities.

The randomly selected days mainly highlight communities which tend to have higher income, larger mean/median skew and see higher than average surface O3 concentrations. The overall predicted concentration of O3 for each county was compared to its average monitor value. It’s worth noting that the distribution of monitors per count was skewed towards Maricopa; with it having 20 monitors compared to Pima (5) and Pinal (3). It’s no surprise the distribution of average concentrations was slightly skewed towards Maricopa. However, both Pheonix and Tucson showed similar trends where higher concentrations were found post increase in either heat or NO2.

VI.2. Maricopa

A map of the city of san francisco

AI-generated content may be incorrect.Distributions of surface O3 for Maricopa County were the most spread out with values ranging from 8.78 ppm to 107.09 ppm. This county houses Phoenix, the most populous city in Arizona as per census counts and the number of households. The estimated concentrations ranged from 10.11 ± 3.4 ppb to 91.67 ± 3.4 ppb. The distribution of highly populous areas with smaller amounts of occupied homes can be seen closer to Peoria and Glendale west of Phoenix. The coloring scheme shows many green shaded census tracks near the city center, typically surrounded by counties which have little variations in their mean and median income. Noting the surface O3 maps, the urban setting in Maricopa sees the most diversity in concentration distributions.

A map of the united states

AI-generated content may be incorrect.When overlaid with corresponding demographic information, many of the census tracts which have a high population, number of occupied households, and low deviation in their overall mean vs. median income are affected by higher concentrations. In addition, during low concentration months such as January, many of the trends show similar tendencies to weather patterns which tend to wrap around certain communities in the area. These same patterns can be seen during the high concentration months like October as well. The effects of both urban heath island effects and high-quality vegetative areas show the trends mentioned in Chapter II.3 where in O3 tends to settle in dry, undermaintained areas where the reaction is not stemming from.

Areas to the Northwest of Phoenix had a stronger weight towards population per capita with a lower weight in high occupancy housing population per capita. This suggests that people living in these areas are either more densely populated in occupied houses or potentially homeless. To the East and Southeast, closer towards Tempe and Paradise valley, there is less weight towards population per capita, meaning there are less people per occupied household. Many of the areas which have an equal proportion of population per capita and occupied households live in larger counties denoting potential suburbs of Phoenix. Many of these areas have scattered communities which exist as common stopping points across interstate highways and freeways.

Areas closer to the mountains like Scottsdale, Paradise valley, Rio Verde, and Foothills tend to see higher concentrations of surface O3, likely due to high sources of albedo and vegetation cycles. Low concentration seasons such as Winter and Spring show heavier levels of O3 likely due to natural cycles and high elevations in these areas. During high concentration seasons, these are slightly lower while exacerbating certain areas of Pheonix. Glendale, Youngtown, and Sun City West, which tend to see a brunt of high concentrations during the summer post-production at high elevations.

VI.4. Pinal

Pinal sits in-between Pima and Maricopa with a mean and median income of ……. Housing part of the Santa Catalina Mountain, many of these communities have equal distribution of population per capita and occupied housing. In terms of income, they have seen linear growth and consistent development. The cities and suburbs of Pima see concentrations of ozone from numerous sources during high production seasons. During low concentration seasons, surface O3 can be seen settling closer towards the Southeast of Maricopa. This county is situated in between the Northeastern part of Pima and Southeastern part of Maricopa. The estimated concentrations ranged from 10.11 ± 3.4 ppb to 91.67 ± 3.4 ppb based on gradient boosted fields. To the North of Tucson and Southeast of Phoenix lies Casa Grande, an old mining town which happens to stand in the middle of Pheonix and Tucson. Confusingly, Maricopa City sits within Pinal. This county has many areas dedicated to golf courses and farmland.

VI.3. Pima

Pima county is one of the original four counties in Arizona and is the oldest of the three in this thesis. While known mainly for the University of Arizona, Distributions of surface O3 for Pima county were the most spread out with values ranging from 8.78 ppm to 107.09 ppm. The estimated concentrations ranged from 10.11 ± 3.4 ppb to 91.67 ± 3.4 ppb based on gradient boosted fields.

When overlaid with corresponding demographic information, many of the census tracts which have a high population, number of occupied households, and low deviation in their overall mean vs. median income are affected by higher concentrations. In addition, during low concentration months such as January, many of the trends show similar tendencies to weather patterns which tend to wrap around certain communities in the area. These same patterns can be seen during the high concentration months like October as well. The effects of both urban heath island effects and high-quality vegetative areas show the trends mentioned in Chapter II.3 where in O3 tends to settle in dry, undermaintained areas where the reaction is not stemming from.

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Areas closer to the mountains like Scottsdale, Paradise valley, Rio Verde, and Foothills tend to see higher concentrations of surface O3, likely due to high sources of albedo and vegetation cycles. Low concentration seasons such as Winter and Spring show heavier levels of O3 likely due to natural cycles and high elevations in these areas. During high concentration seasons, these are slightly lower while exacerbating certain areas of Pheonix. Glendale, Youngtown, and Sun City West, which tend to see a brunt of high concentrations during the summer post-production at high elevations. The University of Arizona is within Tucson, along with the four major elevation spikes in the AOI. Many of the higher concentrations of ozone at and above the mean of 58.64 ± 3.4 ppb can be seen near Superior and Casa Blanca.

VI.5. Final Exposure Concerns and Mean Aoi Trends

Health outcomes related to short- and long-term surface ozone have been investigated to find worrying evidence that supports O3 tends to disproportionally affect vulnerable populations based on surrounding environments. (Bell, Zanobetti, and Dominici 2014; Turner et al. 2016a; Malley et al. 2017b; Tessum et al. 2021; Hsu et al. 2021; Ermagun, Smith, and Janatabadi 2024). Outcomes such as chronic obstructive pulmonary disease (COPD), elderly cognitive impairment, pro-thrombosis, pediatric asthma, and general inflammation are suspected to stem from exacerbated long-term exposure to surface O3 reactions (Balmes 2019; Gao et al. 2022; Niu et al. 2022). In short-term ozone studies, pre-teen and post-retirement age groups are more at risk while young, healthy populations varying results due to interactions with oxidative systems in the body. (Barath et al. 2013; C. Chen et al. 2023, 2023; Díaz et al. 2018; Goodman et al. 2018; Raza et al. 2018; Roth, Hwang, and Li 2008).

Short-term ambient exposure to surface O3 may also impact the risk of multiple sclerosis (MS) by increasing triglycerides, cholesterol, and blood pressure in predisposed populations. Women and older adults (especially those over 75) seem to be more affected by short-term ozone exposures (C. Chen et al. 2023; Fuller et al. 2022). Many of these outcomes occur at or above the EPA standard of 70ppb. Maricopa county, which houses Phoenix, saw high averages of income, population density, and surface O3 concentrations. In addition, areas with better kept greenspace near both Phoenix and Tucson would see the brunt of high concentrations in the area. While January and October showed averages lover than the EPA standard, these areas spiked, with potential exposures above 70ppb according to both in-situ and modelled measurements. Further improvements to the overall code, pre-processing methods, and applications of RK are needed to better depict harmful substances and exposures in urban areas at high resolutions.

VI.6. Insights Into Historical Exposures and Concentrations

The historical feasibility of high-resolution ozone modeling, particularly from 1980 to 2000, relies heavily on the RK method’s ability to accurately capture residual spatial dependencies. With RK, historical data from sources like TOMS can be spatially refined to produce monthly average ozone concentrations, filling a critical gap in historical ozone exposure records. This capability is invaluable for public health research, as it allows for the retrospective analysis of exposure patterns over time, linking long-term ozone trends with health outcomes in different populations. The RK method’s refinement of historical datasets can thus support an unprecedented level of detail in exposure mapping, fostering a new understanding of how ozone exposure has evolved in response to environmental and socio-economic changes. From 2000 onwards, with the advent of advanced satellite data from instruments like Sentinel-5P, the RK method can facilitate daily average ozone models by enabling granular spatial predictions, making high-resolution daily models feasible for the first time.

One of the most promising aspects of the RK method lies in its potential to improve existing statistical models, estimating predictions before 2005. By predicting geospatial error within a larger temporal range, RK can enhance the predictive accuracy of ML/AI corrections used for understanding trends over large decades if collected imagery. Statistical models, when combined with residual kriging, are empowered to deliver predictions that reflect both large-scale trends and localized variations. This integration enables a new generation of high-resolution spatial datasets that offer valuable insights for epidemiological studies, allowing for a more precise estimation of the impacts associated with different O3 exposure levels and more. The RK method provides a structured means of adjusting for the inherent variability in ozone concentrations that traditional statistical models cannot easily account for. This adjustment is critical in capturing the ozone’s complex behavior across diverse landscapes, which is essential for accurate long-term health impact assessments.

VI.7. Implications For Public Health and Policy

Enhanced ozone modeling has significant implications for public health. By addressing spatial and temporal variability more effectively, RK and ensemble methods can support targeted interventions to reduce ozone exposure, particularly in vulnerable populations. Policies informed by high-resolution ozone models can prioritize areas with high exposure, guiding infrastructure development and resource allocation for air quality improvement initiatives. Furthermore, the capacity of RK to capture fine-scale ozone variations holds potential for advancing urban planning, where localized emission control measures could significantly impact public health (Jerrett et al., 2009; Bell et al., 2014).

This study’s findings underscore the need for high-resolution models to achieve accurate exposure assessments that inform public health strategies and urban expansion plans. The RK method provides an advanced tool for mapping not only surface O3 concentrations, but many air pollutants and aerosols at resolutions finer than 300m in need be. If the dataset for surface O3 is expanded upon, it can offer the ability to rapidly estimate exposure risks for participants in exposure studies, especially in densely populated urban centers. Public health officials and policymakers could leverage this to implement localized interventions and standards, such as regulating vehicular emissions and industrial pollutants via emission credits, ultimately reducing health burdens associated with ozone and air pollution exposures.

VI.8. Advancing Surface O3 Mapping with RK Regression

The RK method emerged as a standout approach, offering robust spatial refinement to all baseline models by accounting for residual spatial dependencies. While some base ensembles out predicted SMaRK based estimations due to a stronger complex property, the overall SMaRK version of that ensemble still shows stronger associations with the in-situ value at each location. This approach successfully captured O3 concentrations across diverse anthropogenic environments with similar meteorological conditions as well as if not better than current ensemble approaches to correcting imagery.

If the associated instrument can be correlated to a monitor of the same type which is properly gathered (e.g. Dobson Monitors and TOMS/OMI imagery or high-resolution drone imagery corrected with GCPs and NDVI imagery from Landsat in-between retrievals), then predictive ensembles using remotely sensed data would inherently benefit from the reduced error in imagery. SMaRK’s low error rates and enhanced spatial precision offers novel solutions to correcting high-resolution imagery beneficial for numerous sectors; like public health research, urban chemical transport studies, and local weather mapping, where fine-scale exposure assessments are critical (Kong et al. 2023; Lo et al. 2024; Northeim, Tiwari, and Oppong 2021; Yin et al. 2019).

RK can be used to mitigate the Modifiable Areal Unit Problem (MAUP) and a unique advantage for remotely sensed imagery, providing more accurate, localized predictions of retrieval from current and historical technologies. By modelling the relative distance an observation is from its predicted value, the SMaRK approach can be thought of as a mathematical implementation of Tobler’s Law in ML/AI models. Each residual geo-atom, a representation of a complex trend based on geo-atoms within a set field, dictates the amount of similarity between the source and estimated value. By including this in modern imagery, large sets of geo-spatial uncertainty can be accounted for.

VI.8.1 RK Enhancement of Satellite Imagery

In tandem, the enhancement of remote sensing monitoring systems through RK underscores the potential for a more comprehensive air pollution monitoring network that combines satellite data with ground-level measurements. This approach addresses a key limitation of remote sensing: the lack of fine-scale spatial detail required for accurate exposure predictions in urban and rural microenvironments. RK can improve the spatial accuracy of satellite data by integrating it with in-situ measurements, thereby creating a more precise depiction of ozone concentrations near densely populated areas. Such high spatial resolution is essential for not only quicky estimating exposures, but also highlighting affected areas due to geographic location, socio-economic status, underlying health vulnerabilities given surroundings, or a combination of all three. By refining satellite-based O3 estimates and numerical models, RK can also facilitate more responsive public health interventions, allowing for the timely identification and mitigation of high-exposure areas.

Multi-disciplinary GIS modeling techniques such as SMaRK have become more widespread because of this most recent data revolution (Goodchild 2018). Brought about by the exponential growth in data storage and processing capacities via advancements in Big Data, new-found spatial and temporal analysis of both micro- and macro- ecologies have spurred the need for simplified, sound methodologies. The SMaRK approach significantly enhanced the predictive accuracy of traditional ML/AI models by spatially interpolating residuals from features at a given point and adding the predicted error back into the model. Satellite imagery in the PHOTUC region via SMaRK provides transformative capabilities for surface O3 mapping, CTMs, and exposure studies by including known values detected at the surface. The incorporation of spatial uncertainty into ML/AI methods for the proper display of geospatial information is critical to the progression of GIS programs. It enables finer, more nuanced depictions of any independent variable of interest across any temporal and geographic scale with the appropriate coverage of monitors. These fine-grained enhancements are critical for uncovering the full spectrum of micro- and macro-effects of the many pollutants threatening human health, ecosystems, and air quality.

VI.9. Necessity of Residual Kriging

The advent of satellite monitoring systems has also contributed significantly to ozone modeling by supplying remote sensing data that is crucial for large-scale atmospheric studies. Instruments like the total ozone mapping spectrometer (toms) and the more recent Sentinel-5P satellite offer invaluable datasets that track ozone and its precursors at a global level. These data, however, are subject to spatial limitations and are constrained by their resolution, particularly in densely populated or topographically diverse regions where ozone variability can be substantial. Satellite data alone cannot achieve the spatial and temporal precision needed for accurate, localized exposure assessments. However, the integration of satellite data with the RK method opens new possibilities. By applying residual kriging to the baseline satellite data, we can account for local variability and improve upon the spatial resolution, rendering the dataset much more useful for high-resolution historical and current-day models. This enhancement is particularly promising for bridging the gap in ozone data quality from 1980 to the present, enabling continuous historical models that track monthly and daily ozone variations across decades. The pursuit of high spatial resolution O3 models may represent a landmark methodology for GIS users. This ambition, driven by the imperative need for readily available, accurate, spatial-temporal based data has only become attainable due to advances in technology. Particularly, the availability of Big Data like TOAR/Google Earth Engine, application of spatial uncertainty into ML/AI representations of satellite data, and overall improvement of programming language syntaxes (Python 3.12.x, Java 8.x, R 4.x, SQL Server 2022, etc.).

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