Linking Nitrogen Oxide Emissions and Future Urban Growth:

How Present Day Land Use Development Choices Influence Future Emissions

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Summary
The world's population is becoming increasingly urbanized, with 66% of the global population expected to reside in urban areas by 2050. City planners and policy makers must consider how cities can accommodate such growth to minimize the city's contribution to climate change through greenhouse gas emissions and the consumption of ecologically valuable and agriculturally productive lands. On a regional scale, the horizontal expansion of urban areas creates fragmentation of agricultural lands and endangers vulnerable plants and animals by encroaching upon natural habits and biodiversity corridors The concentration of transportation networks and industry in heavily urbanized areas cause cities to point sources of pollution on a global scale. Numerous polluting gases that can lead to climate change are produced in cities: sulphur dioxide, carbon dioxide, volatile organic carbons, and nitrogen oxides. Nitrogen oxides, produced largely through the combustion of fossil fuels in automobiles, are of particular concern as they lead to a host of other gases that pose significant risk to human and environmental health. The projected growth of cities has already been modeled with consideration for agriculture lands, urban sprawl and biodiversity, but the emissions associated with the changes in land use associated with such growth have not been thoroughly investigated. A land-use regression (LUR) model can be utilized to calculate future NO_2 emissions associated with changes in land use in an urban setting. For Los Angeles County, nine predictor variables on five spatial scales were selected to be correlated to the two-week average NO_2 concentrations. The developed LUR model was used to calculate NO_2 emissions for five future growth scenarios for Los Angeles County. The Smart Growth scenario demonstrated the lowest average NO_2 concentration, suggesting that city development constrained to already urban areas will preserve green spaces that reduce emissions and restricts the urban sprawl associated with higher NO_2 emissions. However, urban density was not included in this study and could play a vital role in determining NO_2 emissions on a finer spatial scale.

I. Introduction

The world's population is increasingly concentrated in urban areas and cities, with 54% of the total global population residing in urban areas in 2014, a figure projected to be 66% by 2050 (UN, 2014). The concentration of transportation networks and industry in heavily urbanized areas cause cities to be point sources of pollution on a global scale (Grimm, 2008). Indeed, the world's 8038 urban areas with more than 50,000 residents produce approximately 40% of the anthropogenic pollution of nitrogen oxides (NO_x), volatile organic carbons (VOCs), and sulphur dioxide (SO_2), three potent polluting gases (Sarzynski, 2012). These are only three of a whole host of polluting gases and compounds produced by cities; carbon monoxide (CO), carbon dioxide (CO_2), ozone (O_3), and fine particulate matter (PM_{10}) are also produced in large quantities in urban areas due to high resource use, extensive land development, and high reliance on vehicles (Molina, 2004). As the world's population shifts towards urban areas, it becomes more pressing to make city development decisions today that will limit future emissions.

In particular, the family of compounds known as nitrogen oxides (NO_x) pose a significant risk to human and environmental health (W.H.O., 2003). NO_x is a family of compounds that includes nitrogen dioxide (NO_2) and nitric oxide (NO); as the most stable of these compounds this family is often referred to NO_x/NO_2, or simply NO_2. Nitrogen oxide (NO) is formed through the combustion of fossil fuels, which then quickly oxidizes in the atmosphere to form nitrogen dioxide. In the presence of sunlight, NO_2 breaks down into nitric oxide (NO) and an oxygen radical (O). The free oxygen radical again quickly reacts with atmospheric oxygen (O_2) to form ozone (O_3). This chain of chemical reactions is instigated by the burning of fossil fuels, and thus decreasing these emission at the source will in turn decrease a host of other harmful gases.

NO_x/NO_2 produced by vehicular traffic is linked to respiratory problems and is significantly associated with increasing all- cause mortality (Gauderman et al., 2002; Stieb, Judek, & Burnett, 2002). Additionally, NO_x is a precuser for a host of other harmful and long lasting greenhouse gases including ozone (O_3), acid rain (HNO_3) and smog, all of which pose a significant risk to both human and environmental health (Environmental Protection Agency, 1999). In the United States, despite the fact that the US Environmental Protection Agency (EPA) has taken action to curb NO emissions from combustion in vehicles the weekday ambient air concentration of ozone is projected to remain unchanged from 2012 to 2020 due to the availability of NO_x in the atmosphere (Fujita, Campbell, Stockwell, & Lawson, 2012). In addition to the United States several western nations have enacted policies to reduce NO_x/NO_2 emissions from vehicles; however, the effects of today's NO_x/NO_2 emissions will last into the future as secondary gases and compounds persist in densely populated areas.

As with all gases, the concentration and reaction rate of traffic produced NO_2 emissions in the atmosphere is dependent upon a host of atmospheric, topographic, and human behavior variables. For example, sunnier days will instigate the reaction of NO_2 into ozone. Wind speed and direction also move polluting gases from their origin point (a car) to nearby development, making exposure estimation less predictable and more complex. Traffic behavior also influences the amount of NOx emissions; in a 2014 study in Seoul, South Korea it was found that the greatest increase in NOx emissions was when the vehicle transitioned from idling to acceleration than in any other transition state (Kim, Lee, Woo, & Bae, 2014). Different landscapes also alter NOx concentrations; in Taipei, green space has been shown to significantly decrease NOx exposure, while monitoring stations located in street canyons (ie, streets with buildings of five or more stories on either side) recorded higher concentrations (Lee, et. al., 2014). It has also been shown that urban trees in street canyons help to remove air pollutants at ground level by filtering pollutive gases such as sulphur dioxide, nitrogen dioxide, and particulate matter (Nowak, Crane, & Stevens, 2006). With these many variables influencing NO_2 concentrations, a way to model the interaction of emissions, the atmosphere, and various types of land use is needed to inform present day decisions for future urban growth that will minimaze the concentration of NO_2.

To understand the ramifications of the world's incresingly urban areas, city planners and policy makers utilize models that can project how a city can develop depending on the needs of the future population. Cities can grow without restraint, can develop to limit urban sprawl, preserve native wildlife, or can adapt and grow with consideration for future climate change effects. The future urban landscape and how avialble land is utilized will change as choices are made today as to how cities will develop. As urban areas change, so too will its effect on emissions. To understand the influence of future urban landscapes on NOx/NO_2 emissions, a land use regression model has high potential. This study tested the applicability of land use regression model in projecting future emissions based on changes in land use while also investigating the difference in NO_2 concentration for five growth scenarios in an urban setting. The land use regression model utilized should be statisitcially comparable to existing land use regression models in urban areas of similar size. Due to the ability of green space to reduce emissions, it is expected that the growth scenario favoring to protect and enchance green space will result in the lowest concentration of NO_2, while the growth scenario favoring intensive urban development will result in the least amount of NO_2.

II. Methodology

Study Area

To project the effect of changes in land use in urban areas on NO_x/NO_2 emissions a land use regression model was applied to the outputs of the UPlan land use change model for the chosen study area of Los Angeles. Specifically, the county of Los Angeles rather than just the city of Los Angeles was chosen to maximize the available sample size from the air monitoring network and to include data on a variety of urban densities. Los Angeles and the surrounding area are of particular interest for a study on NO_x/NO_2 emissions as it is one of the mega cities of the world, is notoriously reliant on the automobile, and is known for heavy pollution. Additionally, this area provides a good contrast in land use types with residential, industrial, commercial, a large water body (i.e. the Pacific Ocean) and open green space in fairly close proximity to each other. With an area of 12,305 km^2, Los Angeles County had a population of 9.8 million in the base year of 2010, with a projected population of 13.5 million in 2050 (Census.gov; Thorne, Bjorkman, & Roth, 2012).

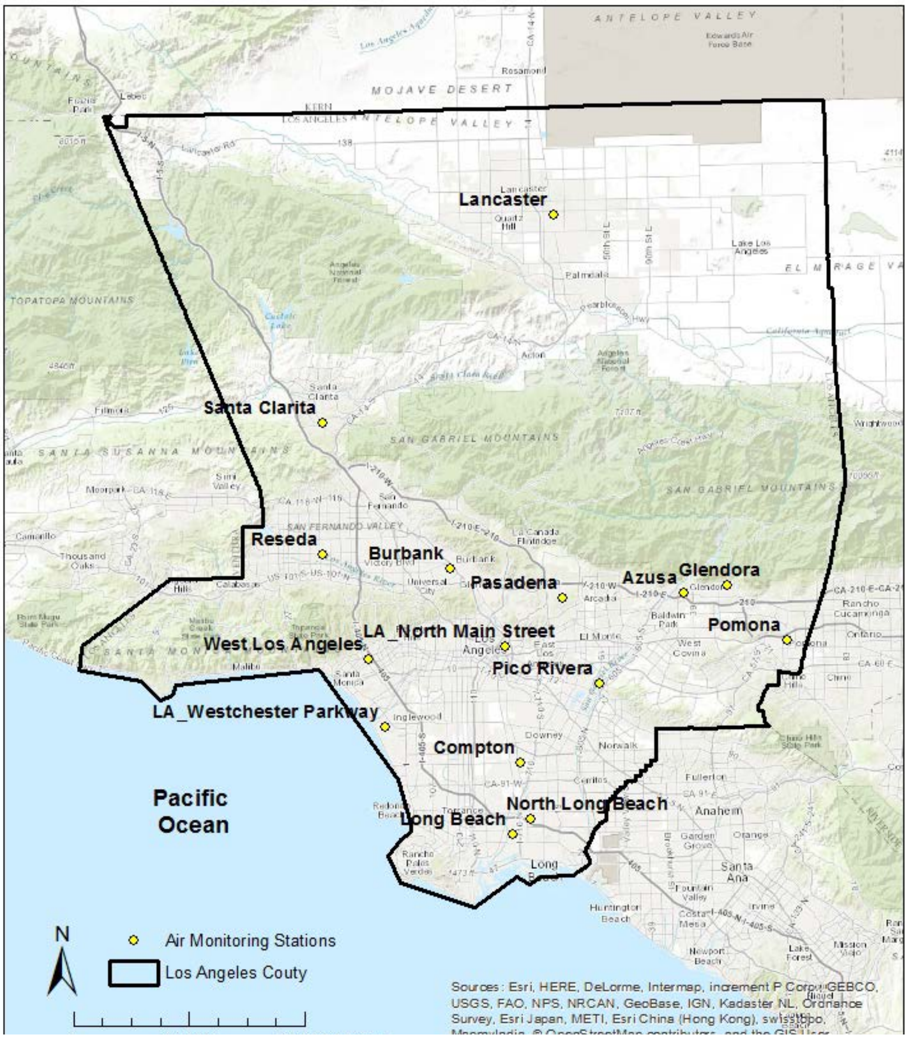

Figure 1: Study Area of Los Angeles County with air monitoring stations

Data Collection

A set of variables was chosen based on the geography of the study and from studies of NO_x/NO_2 land use regression models applied to similar sized urban areas. These variables were then combined in a linear regression equation that represents the relationship between a set of predictor variables and recorded NO_2 in the base year of 2010. This relationship was then used to calculate NO_2 in 2050 for several growth scenarios for the city of Los Angeles given data on the predictor variables. All data processing and collection was done through ESRI's Geographic Information System (GIS) application. The predictor variables chosen were:

- Length of Major Road (km)
- Length of Road (km)
- Length of All Roads (km)
- Distance to Major Road (km)
- Distance to Road (km)
- Distance to Pacific Ocean (km)
- Elevation (km)
- Urban Area (km^2)
- Green Space (km^2)

Future Urban Growth

The UPlan land use change model is a rule based GIS application that allocates different land use type categories following the rules set by a defined growth scenario or a preference for a certain type of land (Table 1). In this model, the urban area extent (no distinction between type of land use) in the year 2000 is chosen as the base year; land use types are then allocated following the rules set by each scenario to areas available for (re)development given the projected social demographic data for 2050. For each scenario, then, an output is generated which shows the distribution of land use by type in the year 2050. The land use types used by UPlan are:

- Industrial
- Commercial High
- Commercial Low
- Residential of varying densities: 50, 20, 10, 5, 1, .5, and .1

For residential areas, "50" denotes apartments with 50+ units at one end of the spectrum while ".1" denotes a single family home on 10+ acres of land. A 50m x 50m resolution raster is generated for each scenario, with each pixel representing one of the above land use types. The published version of the UPlan outputs were utilized (Thorne, Bjorkman, & Roth, 2012).

To maintain the same predictor variables between the base year of 2000 and the projected year of 2050, for 2050 all land types were generalized as urban. This allows for the relationship established for the year 2000 to be applied to 2050.

The UPlan model has a base year of 2000, but for this study the base year was adjusted to 2010 as several external data sets were only available beginning that year. The urban extent was adjusted to reflect any growth that may have occurred in those ten years by masking the NDVI raster layer for 2010 with the urban area raster layer for 2000 to generate a combined NDVI/urban area raster layer that was then used to collect data on Urban Area and Green Space for the base year of 2010.

Table 1: The Five Growth Scenarios utilized in the UPlan land use model

Scenario	Definition
Agriculture	Preference for preserving climate change sensitive agricultural areas
Biodiversity	Focus on the conservation of native California plant species; includes future climate change ramifications
Business as Usual (BAU)	No policy effort made to restrict growth from sprawling outside of city limits
Infill/Redevelopment	Intensive measures towards compact growth and reduction of sprawl; new development occurs within the existing urban extent
Smart Growth	Policy efforts somewhat restrict growth into rural areas and encourage growth closer to city centers; encourage reduction of urban sprawl

Green Space

A 50m x 50m NDVI raster layer was created in GIS by processing a Landsat 4-5 satellite image for the Los Angeles area for February 2010 (https://earthexplorer.usgs.gov/). The original three band Landsat image with a 60m resolution was recolored
to create an NDVI image; the original band 1 (green), band 2 (red), and band 3 (near infrared) were processed via the NDVI tool in GIS. The NDVI tool is a standardized index which generates an image displaying greenness (relative biomass) by visualizing the contrast of the chlorophyll pigment absorption of the red band and high reflectively of the plant materials in the near infrared band (desktop.arcgis.com). The NDVI image was then reclassified to create a raster layer with four land cover categories: water, non-organic (buildings, roads, and other built areas), light vegetation, and heavy vegetation (Table 2). The NDVI raster layer was also resized to a 50m resolution to match the resolution of the UPlan raster layers. Finally, the NDVI raster layer was then masked with each of the UPlan growth scenario raster layers to create a combined Urban and NDVI layer for each scenario containing the following land cover categories: Water, non-organic (now representing just roads), light vegetation, heavy vegetation, Industrial, Commercial High, Commercial Low, and Residential of varying densities: 50, 20, 10, 5, 1, .5, and .1. For each buffer, the zonal histogram tool was then run to collect the number of pixels of each type of land cover. Finally, the area of Green Space (consisting of light vegetation and heavy vegetation pixels) and Urban area (consisting of the UPlan land use type pixels) were calculated. It was assumed that the NDVI in February would not greatly differ between 2010 and 2050 leading to the same NDVI being used for both base year 2010 and projected year 2050.

Table 2: Range of NDVI values assigned to each Land Use Category

Land Use Category	NDVI value
Water	-.984 – -.098
Non-Organic	-.098 – 0.113
Light Vegetation	113 – .318
Heavy Vegetation	.318 – 1

Nitrogen Dioxide

The recorded nitrogen dioxide (NO_2) concentration for fifteen monitoring stations across the study area was collected for a two-week period in February 2010. Nitrogen dioxide was chosen as it is the most stable nitrogen oxide and the recorded values were therefore the most reliable. The reported value for each day is the maximum one hour average concentration. Recorded data on greenhouse gas emissions is freely available on the California Air Resources Board website (https://www.arb.ca.gov/adam/index.html). The collected NO_2 values were then averaged to create a two-week average concentration at each of the fifteen stations.

To test the influence of the surrounding area on the recorded NO_2 values, several buffers around each station were chosen: 250m, 500m, 1000m, 1500m, and 3000m. These specific radii were chosen based on what has been done in other NO_2 linear regression studies.

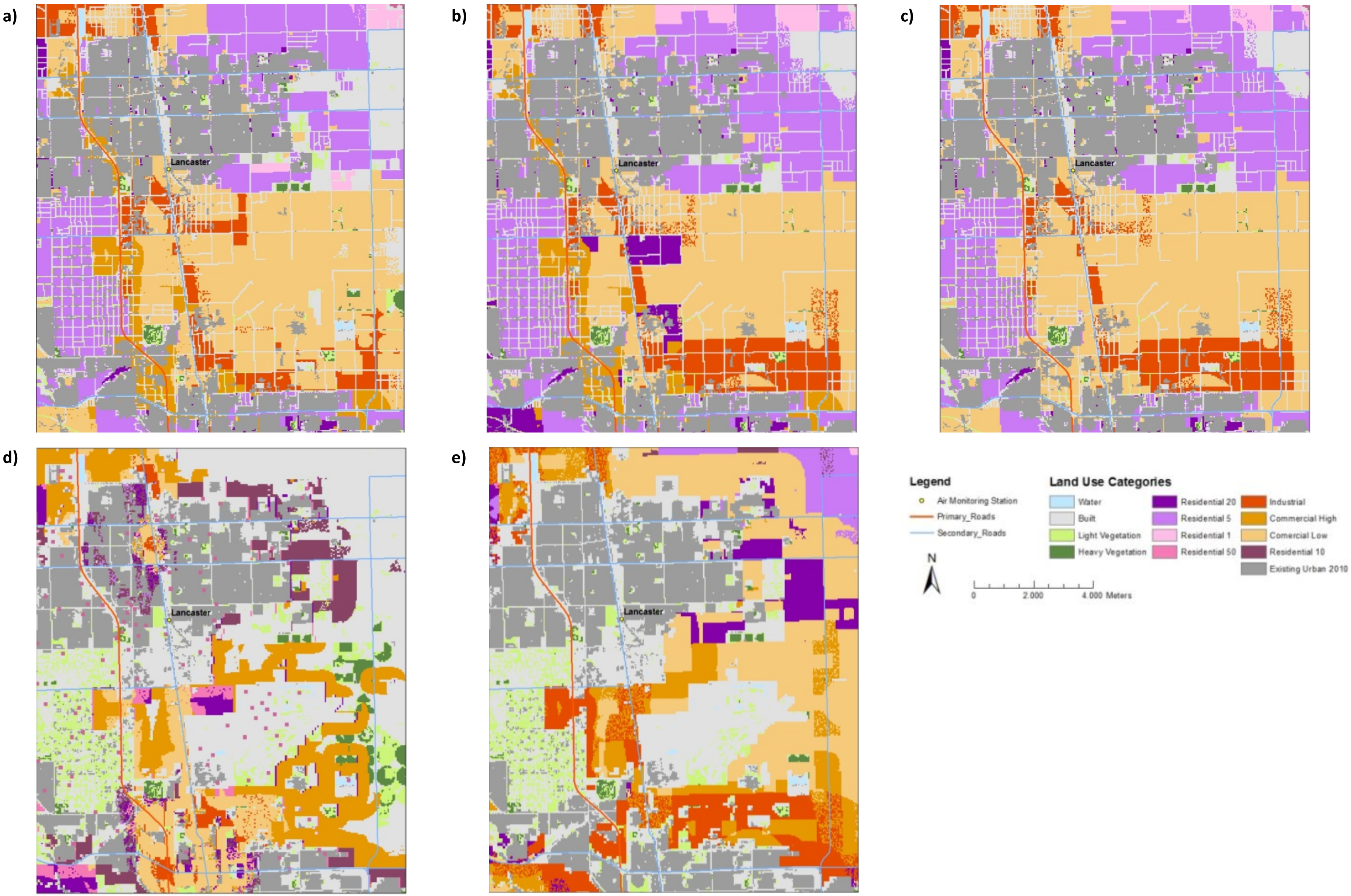

Figure 2: Combined NDVI and UPlan Land Use raster layers for a) Agriculture, b) Business As Usual, c) Biodiveristy, d) Redevelopment, and e) Smart Growth

Road Network
The Tigerline shapefiles provided by the U.S. Census Bureau were used to generate a road network for the year 2010 (https://www.census.gov/geo/maps-data/data/tiger-line.html). The Tigerline class codes of “Primary” and “Secondary” were categorized as Major Roads, while the class codes of “Local Neighborhood Roads” and “Ramps” were categorized as Roads. From this road network, length of road and length of major road were calculated within each buffer; additionally, length of all roads was recorded to test the a priori assumption that major roads produce more emissions than standard roads.

Road length was used as a proxy for traffic as traffic count data for 2050 on the spatial scale required by this study was not freely available. Several studies have similarly also used road length in lieu of traffic count data with generally positive results (Hoek et. al., 2008). A distinction was made between road types to reflect traffic intensities. Distance to road and distance to major road from stations was also recorded to take note of how far the nearest source of traffic emissions was. Finally, no major road construction projects are planned for the greater Los Angeles area in the coming decades. Therefore, the road network used for 2010 was also used for 2050.

Elevation and Ocean Proximity
Elevation was recorded at each monitoring station to account for the effects of the proximity to the San Gabriel mountain range on the edge of the Los Angeles downtown area. Elevation of each station was available from the California Air Resource Board website (https://www.arb.ca.gov/adam/index.html). The distance of each station to the ocean was also recorded to account for the effects of sea breeze (ie, humidity and wind). Coastal winds blowing from the west shift air pollution eastwards, causing stations near the coast to receive relatively clean ocean air while stations further away receive air and pollution from all areas westwards; Ross et. al. included distance to coast for the same reason in San Diego County (Ross et. al., 2006). Distance to Ocean was calculated in GIS from each monitoring station to the coast. Both Elevation and Distance to Ocean are static variables in that they remain the same at each spatial scale of data collection.

Overall, nine predictor variables were selected. The variables Elevation and Distance to Ocean do not vary as the buffers change and are therefore static; the remaining seven variables do change depending on the buffer. Seven variables were then recorded at five different spatial scales, while the remaining two variables remained the same each time. Data was recorded for each of the nine variables for the base year of 2010 and for projected year of 2050.

Statistical Analysis
Statistical analysis was done in SPSS. First, each predictor variable was investigated for normality by running the Shapiro-Wilk test. Predictor variables were considered normally distributed when the significance is greater than 0.05. Variables that are not normally distributed are transformed until normality was achieved.

Univariate regression analysis was conducted such that each predictor variable at each spatial scale was regressed against the recorded NO_2 concentration. The ANOVA test was used as a part of the univariate regression to test the null hypothesis. Predictor variables are considered to be significantly correlated to NO_2 concentration when $R^2 > 0.25$ and the P-value < 0.05. The predictor variables meeting these standards were selected for the initial model, with the same model tested at five spatial scales. Adjustments to the model were made through a leave one out process; one predictor variable would be excluded from the model at a time to investigate its statistical significance in combination with other variables. Multivariate regression analysis was conducted for each rendition of the model until the highest possible R^2 was achieved.

Two models in particular were investigated to test the influence of road types. Model one consisted of Urban Area, Green Space, Distance from Ocean, Length of Major Road, Length of Road, and Elevation. Model Two consisted of Urban Area, Green Space, Distance from Ocean, Length of All Roads, and Elevation. These models were run for the 1000m, 1500m, and 3000m buffers.

The model with the highest R^2 was then utilized to calculate NO_2 concentrations for five growth scenarios for Los Angeles County.

III. Results

Statistical Results

Out of all variables elevation, length of all roads, green space, and distance to ocean have a significant relationship to the recorded two-week average NO_2 concentration. Elevation and Distance to Ocean demonstrate this relationship in all buffers. The three remaining variables with a recorded significant linear relationship to recorded NO_2 values are Length of All Roads in the 1500m and 3000m buffer and Green Space in the 1500m buffer.

The 250m and 500m buffers both had predictor variables that did not obey normality, even after extensive data transformation. This is largely due in part to both buffers having a high number of recorded zeros in several variables. These zeros highly skewed the data, and did not lend itself to any regression that would also fit the other buffers. As such, the 250m and 500m buffers were excluded from subsequent analysis.

Elevation did not exhibit normality in any buffer, and was log transformed to achieve normality. Similarly, Distance to Major Road did not obey normality and was log transformed. Green Space in the 1000m and 3000m buffers also did not obey normality, and were also log transformed. Urban Area in the 1000m buffer was also log transformed to attain normality. These transformed variables were used for further analysis.

Out of all variables, Elevation has the strongest correlation with NO_2 (R^2=0.327), while Distance to Major Road has the lowest (R^2=0.012). Length of All Roads in the 1500m and 3000m buffer are the variables most highly correlated with NO_2 (R^2=0.300 and R^2=0.293 respectively), followed by Green Space in the 1500m buffer (R^2=0.283). Of all the buffers, the 1500m and 3000m buffers have the most variables with the highest R^2 value.

Of the nine variables tested, four variables show a significant relationship to recorded NO_2 values as indicated by the p-value: Elevation in every buffer (p=.026), Length of All Roads in the 1500m and 3000m buffers (p=.034 and p=.037 respectively), Green Space in the 1500m buffer (p=.041), and Distance to Ocean (p=.042) in all buffers.

Urban Area and Green Space demonstrated the expected relationship to NO_2 concentration with Urban Area increasing NO_2 and Green Space decreasing NO_2 concentration (Figure 3).

Table 3: Results of Univariate Regression Analysis

Buffer	Variable	R^2	P-Value
	Length of Major Road	0.019	0.621
	Length of Road	0.227	0.072
	Length of All Roads	0.243	0.062
	Distance to Major Road	0.012	0.703
1000	Distance to Road	0.185	0.109
	Distance to Ocean	**0.281**	**0.042**
	Elevation	**0.327**	**0.026**
	Green Space	0.047	0.439
	Urban Area	0.080	0.308
	Length of Major Road	0.200	0.095
	Length of Road	0.217	0.080
	Length of All Roads	**0.300**	**0.034**
	Distance to Major Road	0.012	0.703
1500	Distance to Road	0.185	0.109
	Distance to Ocean	**0.281**	**0.042**
	Elevation	**0.327**	**0.026**
	Green Space	**0.283**	**0.041**
	Urban Area	0.138	0.173
	Length of Major Road	0.226	0.073
	Length of Road	0.249	0.058
	Length of All Roads	**0.293**	**0.037**
	Distance to Major Road	0.012	0.703
3000	Distance to Road	0.185	0.109
	Distance to Ocean	**0.281**	**0.042**
	Elevation	**0.327**	**0.026**
	Green Space	0.208	0.088
	Urban Area	0.229	0.071

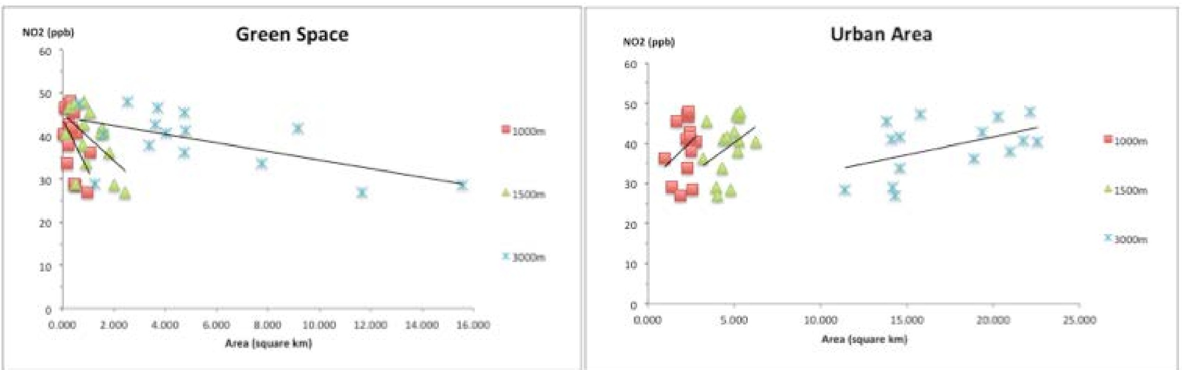

Figure 3: Correlation of Green Space and Urban Area to recorded NO_2 concentrations for the 1000m, 1500m and 3000m buffers

Two linear regression models were created from the predictor variables with the highest statistical significance. Model one consisted of Urban Area, Green Space, Distance from Ocean, Length of Major Road, Length of Road, and Elevation. Model Two consisted of Urban Area, Green Space, Distance from Ocean, Length of All Roads, and Elevation. In both model one and two, the 1500m buffer demonstrates statistical significance with a high R^2 value in addition to having the lowest p-value. Between model 1 and model 2 in the 1500m buffer, model 1 demonstrates the best fit with the highest R^2 value (R^2=.721) and lowest p-value (p=.055). Model one in the 1500m buffer is then statistically most suited for application to the five UPlan growth scenarios and NO_2 calculation.

Table 4: Results of final two linear regression models

Model	Buffer	R^2	P-Value
1	1000m	0.542	0.269
	1500m	**0.721**	**0.055**
	3000m	0.707	0.065
2	1000m	0.43	0.324
	1500m	0.567	0.124
	3000m	0.549	0.144

Table 5: Linear Regression Equation for Model 1 for the 1000m, 1500m, and 3000m buffers; MR_L =Length of Major Road, R_L =Length of Road, O_D =Distance to Ocean, E_{log} =Elevationlog, GS =Green Space, UA =Urban Area

Model	Buffer	Linear Equation	R^2	P-Value
1	1000m	$30.965+(0.572*MR_L)+(-0.064*R_L)+(0.172*O_D)+(-0.714*E_{log})+(-0.222*GS)+(-0.454*UA)$	0.542	0.269
	1500m	$12.076+(0.612* MR_L)+(0.057* R_L)+(-0.121* O_D)+(-0.166* E_{log})+(-0.143* GS)+(0.5* UA)$	**0.721**	**0.055**
	3000m	$-5.812+(0.68* MR_L)+(-0.363* R_L)+(0.482* O_D)+(-0.75* E_{log})+(0.162* GS)+(0.973* UA)$	0.707	0.065

Future Urban Growth & NO_2 Concentration

Nitrogen dioxide was calculated for each of the five growth scenarios at each of the fifteen monitoring station using the aforementioned linear regression model in the 1500m buffer. Calculated NO_2 was nearly identical at each station in the Agriculture, Business as Usual (BAU) and Biodiversity scenarios. The redevelopment scenario demonstrated a slight decrease in calculated NO_2 at most stations compared to the Agriculture, BAU, and Biodiversity scenarios. In comparing the Redevelopment and Biodiversity scenarios (with Biodiversity representing Agriculture and BAU as data is identical), the greatest percent decrease in calculated NO_2 is at the Lancaster station (10.4% decrease) while the greatest percent increase was at the LA_North Main Street station (5.1% increase). Out of all five growth scenarios, the Smart Growth Scenario demonstrated the least amount of calculated

NO_2 at every station. When compared to the Biodiversity scenario, the Smart Growth scenario demonstrates the largest percent decrease at the Lancaster station, and the least percentage decrease at the Compton station.

The calculated average NO_2 was identical for the Agriculture and Biodiversity scenarios, and the Business as Usual scenario was nearly identical. The Redevelopment scenario demonstrated a slightly lower average NO_2, while the Smart Growth scenario demonstrated the lowest average NO_2 (Figure 4).

Table 6: Calculated NO_2 concentration at each monitoring station for each growth scenario

Station	Agriculture	BAU	Biodiversity	Redevelopment	Smart Growth
Azusa	16.248	16.248	16.248	16.156	15.817
Burbank	23.380	23.380	23.380	23.356	23.134
Compton	20.673	20.673	20.673	20.572	20.531
Glendora	13.461	13.461	13.461	12.936	13.105
Lancaster	10.528	10.528	10.528	9.431	9.393
Long Beach	22.919	22.919	22.919	22.976	22.501
LA_North Main Street	22.914	22.914	22.914	24.074	22.542
LA_Westchester Parkway	20.755	20.755	20.755	20.449	20.438
North Long Beach	22.031	22.031	22.031	22.364	21.792
Pasadena	14.924	14.924	14.924	14.788	14.627
Pico Rivera	21.890	21.890	21.890	22.154	21.642
Pomona	17.602	17.602	17.602	18.134	17.311
Reseda	20.983	20.983	20.983	20.692	20.682
Santa Clarita	15.478	15.472	15.478	14.883	14.793
West Los Angeles	23.388	23.388	23.388	23.697	23.129

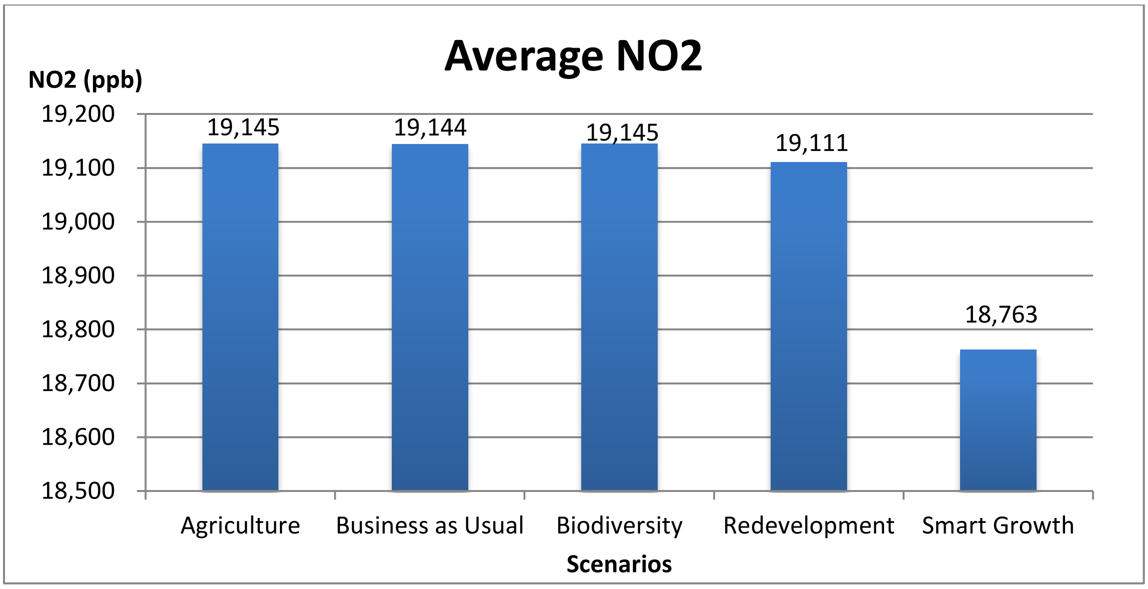

Figure 4: Average NO_2 in 2050 for each of the growth scenarios

As expected the growth scenarios that limit urban sprawl and encourage growth in existing urban areas demonstrate the lowest concentration of NO_2. The Smart Growth scenario restricts growth into rural areas and encourages growth closer to city centers (Thorne, Santos, & Bjorkman, 2017); this policy results in urban areas that are more densely populated and built up rather than allowing available space to be use; in other words, growth is upwards instead of outwards (Thorne, Santos, & Bjorkman, 2013). As such, green space in urban areas is not developed upon. Similarly, the redevelopment scenario encourages compact growth and the reduction of urban sprawl; growth and development occurs in spaces that are already urban but are not filled being fully utilized. Again, green space in urban areas is not developed upon. The availability of green space in both these scenarios, then, reduces the average NO_2.

Over all, a land use regression model is a useful means to projecting future emissions based on land use change in an urban setting. The statistical significance of the final model (R^2=0.72) is comparable to that of similar NO_2 land-use regression models in similar sized urban areas (Table 7).

Table 7: Studies that have utilized land-use regression models for projecting NO_2; adapted from Hoek et al., 2008

Reference	Study Area	Variables in Final Model	R^2 of model
Briggs et al. (1997)	Amsterdam	Length major roads 50,200,350m + Distance major road + built up land, 100m	0.62
	Huddersfield	Traffic volume 300m + land cover factor, 300m + altitude + sampling height	0.61
	Prague	Traffic volume, 60m + traffic volume 60-120m + land cover factor + altitude	0.72
Ross et al. (2006)	San Diego County	Traffic Density, 40-300m + traffic density, 300-1000m + road length, 40m + distance to Pacific coast	0.79
Jerrett et al. (2007)	Toronto	Expressway, 200m + major road, 50m + industrial land use, 750m + household density, 2000m + X-coordinate + downwind within 1500m expressway + traffic density, 500m	0.69
Henderson et al. (2007)	Vancouver	Length expressway, 100m + length expressway, 1000m + length major roads, 200m + population density, 2500m + commercial area, 750m + altitude + X-coordinate	0.56

IV. Discussion

This study explored the effects of changes in land use on nitrogen dioxide (NO_2) concentrations in an urban setting. A land-use regression model was built using six predictor variables that were proven to be significantly correlated to NO_2 concentration. This model was used in conjunction with five future growth scenarios for Los Angeles county to project NO_2 concentrations. Results showed that the Smart Growth scenario produced the lowest average NO_2 concentration.

The elevation at each monitoring station and the distance to the ocean were used as a proxy for the possible collection of air pollution shifted eastwards by the coastal winds. As a coastal valley, Los Angeles county experiences a complex interaction of sea breeze and mountain circulation conditional of changing temperatures and winds. Within the same day, changing temperatures and shifts in wind direction can cause pollution lifted into the troposphere earlier in the day to be circulated back over the valley basin by night time (Lu & Turco, 1995). With elevation and distance to ocean both showing a high degree of correlation to recorded NO_2 concentrations, this suggests that both these predictor variables are a useful, if perhaps oversimplified, proxy for the sea breeze and mountain circulation interaction in the Los Angles downtown area. Generally, stations located in the valley basin record higher NO_2 concentrations as air pollution collects there, while those near the coast have generally lower NO_2.

Roads were important predictors of NO_2 concentrations. Length of roads (major and overall) were used as a proxy for traffic intensity to predict its current and future effect on NO_2 emissions. This was shown to be a good proxy as model results are comparable to models applied in similar sized urban areas (Hoek et al., 2008). Henderson et. al. also showed that in the absence of traffic count data, road length can effectively be used to represent the traffic variable in a LUR model as both road length and traffic count were equally able to explain small-scale variability in pollutant concentrations (Henderson et. al, 2007). Model performance improved when length of major road and length of road were included separately as opposed to one category for all roads. Congestion is also a large contributing factor, as stop and go traffic produces more NO emissions than vehicles traveling at a constant speed (Seakins et al., 2002). Major roads (highways and multilane roads) produce more NO_2 emissions (Westerdahl et al., 2005; Seakins et al., 2002); accounting for this fact by dividing roads into major and minor more accurately captures the higher emissions from major roads than from smaller roads.

Urban Area and Green Space demonstrated the expected relationship to NO_2 concentration, with Urban Area increasing NO_2 and Green Space decreasing NO_2 concentration. This relationship became more pronounced at larger spatial scales, suggesting that small-scale variations in land use do not heavily influence NO_2 concentrations at a point recording station. Instead, larger areas of urban or green space may be necessary to influence air pollution levels. However, NO_2 can vary on a fine spatial scale and a large buffer could dilute this variability, allowing NO_2 to be more highly correlated to the two-week average that was used in this study. The results could have been affected by the two-week average values for NOx, as averaging might lead to higher correlation between a land use and NO_2 concentration.

The small sample size of the record stations within Los Angeles restricted the power and generalizability of this study. Fifteen sampling sites across a 12,305 km2 study area of over 10 million people was not a dense enough network to accurately capture the small scale variations in air pollution. Other similar studies have had the ability to set up their own monitoring networks, with between 37 and 107 monitoring stations across the study area (Hoek et. al, 2008). This suggests that interpretation of the results needs to be careful and future studies should consider own instrumentation or augmenting existing instrumentation network. For example, NASA's Megacities Project is developing their network of sensors which could complement the state recording stations (https://megacities.jpl.nasa.gov/portal/).

Different types of urban land use could also influence NOx emissions. However, the distinction between types of urban land use (i.e., commercial, residential, or industrial) was not made due to lack of information on their representation in the base year of 2010. It would have been interesting to separate the relative contributions of each urban and use type in, for example, assessing the influence of industry on NO_2 concentrations. Additionally, making a distinction between types of urban land use would allow for estimate exposure risks in residential areas.

The smaller scale buffers could not be considered for analysis because of the lack of fine scale predictor data. This is unfortunate as NO_2 concentrations might vary on a fine spatial scale, and I could not disentangle such dynamics from my results. In some areas, NO_2 can decrease to background levels with 100m from major urban roads or 500m from a major freeway (Hoek et. al, 2008).

Surprisingly, the Agriculture, and Biodiversity growth scenarios had nearly identical calculated NO_2 concentrations at all fifteen monitoring stations, and these values were similar to the Business-as-usual values. This is likely because both the agriculture and the biodiversity scenarios are about responses to climate change, and these mostly occur outside of already developed urban areas. Additionally, Los Angeles has very few patches of urban agriculture. The biodiversity scenario looked into potential movement corridors for plants to move as a response to changes in their preferred climatic conditions. Moving through a city like Los Angeles would be quite difficult for plants, however, other studies have shown that this is possible in the San Francisco Bay area for plants and butterflies (Weiss, 1999).

Among the five growth scenarios investigated, the Smart Growth scenario demonstrated the lowest average NO_2 concentration. This likely resulted from this scenario having the most green space in comparison to the other scenarios. However, the urban density of each scenario was not incorporated in the LUR model, but the inclusion of this variable may have generated different results. Indeed, in a study by Thorne, Santos, and Bjorkman published in 2013 the Smart Growth scenario preserved only marginally more open space than the Business-as-Usual Scenario in the San Francisco Bay Area. It is possible that more green space was conserved in the Los Angeles area than in the San Francisco Bay Area in the Smart Growth scenario. However, this deduction requires further investigation into the area of green space in both regions within this scenario before a definite conclusion can be reached. A repeat of this study with a predictor variables for urban density and land use type would likely generate different results. The inclusion of urban density could be a pathway to including heavier traffic due to higher population densities within the same area. A high urban density could also lead to taller buildings that can create street canyons; on a small scale this would alter NO_2 concentrations. Land use type would also allow for the inclusion of the effects of industrial areas, which can also produce NO_x/NO_2 emissions from the combustion of fossil fuels.

V. References

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