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ENVIRONMENTAL AND SOCIAL IMPACT ASSESSMENT (ESIA) FOR SAFER ROADS FOR SOCIO-ECONOMIC INTEGRATION IN MOZAMBIQUE (SRSEI) - MULTIPHASE PROGRAMMATIC APPROACH (MPA)

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Environmental and Social Impact Assessment

ENVIRONMENTAL AND SOCIAL IMPACT ASSESSMENT (ESIA) REPORT

Package 2: Gorongosa - Caia,
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Environmental and Social Impact Assessment for the Safer Roads for Socioeconomic Integration in Mozambique – Multiphase Programmatic Approach

This report consists of the following:

Volume 2A	Non-Technical Summary
Volume 2B	Main Report
Volume 2C	Annexes
Volume 2D	Public Consultation Report
Volume 2E	Environmental and Social Management Plan

ANNEX 1

Wildlife Permeability study

Road permeability study

From Inchope to Caia

For

Environmental and Social Assessment for the Safer Roads for Socioeconomic Integration in Mozambique – Multiphase Programmatic Approach

January, 2026

List of abbreviations

ENM	Ecological Niche Models
GBiF	Global Biodiversity Information Facility
GIS	Geographic Information Systems
GNP	Gorongosa Pational Park
MPA	Multiphase Programmatic Approach
QGIS	Quantum GIS

Contents

List of Figures

List of Tables

Introduction

This report outlines the landscape permeability assessment in Sofala and Manica provinces, conducted as part of the Environmental and Social Impact Assessment for the Safer Roads for Socioeconomic Integration in Mozambique – Multiphase Programmatic Approach.

As Mozambique progresses toward improving its infrastructure to foster economic growth and social development, the integration of environmental sustainability into this process has become paramount. The Landscape Permeability Assessment for Sofala and Manica provinces, conducted as part of the broader Environmental and Social Impact Assessment for the Safer Roads for Socioeconomic Integration in Mozambique – Multiphase Programmatic Approach (MPA), addresses the urgent need to balance development with the conservation of Mozambique's natural landscapes. These provinces, known for their rich biodiversity, vibrant ecosystems, and significant wildlife populations, are also vital corridors for regional connectivity. However, infrastructure development – particularly road networks –poses potential threats to the ecological integrity of these regions. Roads can fragment habitats, isolate wildlife populations, and create barriers that hinder natural movements, thereby affecting biodiversity conservation efforts. This fragmentation may also impact ecosystem services upon which local communities rely, exacerbating existing environmental and socio-economic vulnerabilities.

The primary goal of this landscape permeability assessment is to evaluate how infrastructure developments, such as road construction and rehabilitation, influence wildlife movement, habitat connectivity, and the natural flow of ecosystems. By examining key factors such as land use changes, habitat fragmentation, and the presence of natural corridors, this assessment aims to provide a comprehensive understanding of landscape permeability in Sofala and Manica provinces, for the sections of the N1 road to be rehabilitated. The study focuses on identifying critical barriers, determining areas where wildlife and ecosystems are most at risk, and proposing solutions to enhance connectivity and mitigate negative impacts.

This report outlines the methodology employed to conduct the assessment, which incorporates species habitat suitability, remote sensing data and Geographic Information

Systems (GIS). By integrating these methods, this assessment ensures that both ecological and socio-economic dimensions are considered. The findings offer valuable insights into the current state of landscape permeability in the region, highlighting the intersection of environmental conservation with human development. Furthermore, the report presents recommendations to ensure that future infrastructure projects, particularly those linked to the SRSEIP, do not compromise the ecological connectivity that is crucial for maintaining biodiversity and supporting resilient local communities. The recommendations emphasize the need for strategic planning, ecological corridors, and mitigation measures that facilitate coexistence between development initiatives and environmental sustainability. As Mozambique continues to invest in its road network to drive socioeconomic integration, ensuring that these projects promote ecological resilience will be vital in achieving long-term sustainability.

Material and methods

Overview of the study area

To account for appropriate results, a bounding box (Figure 1) stretching to the limits of the road (all three segments from Inchope to Caia), was created using the bounding box plugin in QGIS v. 3.30.2. This enabled a broader view of the landscape and can more accurately incorporate the movement of the species and the associated constrains within the landscape. The study area is located within the Greater Gorongosa ecosystem, one of Africa's most diverse and ecologically significant environments (E.O. Wilson, person communication). The park spans over 4,000 Km^2 and encompasses a rich mosaic of landscapes, including savannahs, woodlands, grasslands, wetlands, and rainforests.

Within the ecosystem, Mount Gorongosa stands tall, rising to nearly 1.900 meters and encompassing several rare and endemic species. This ecosystem is home to a wide array of wildlife, including elephants, lions, buffaloes, hippos, antelopes, and a variety of bird species, making it a critical conservation area. The park's rivers, particularly the Pungué and Vunduzi and its tributaries, create fertile floodplains that support abundant life, while the seasonal rain patterns sustain wetlands and lakes that are vital for migratory birds and aquatic life (Stalmans et al., 2008).

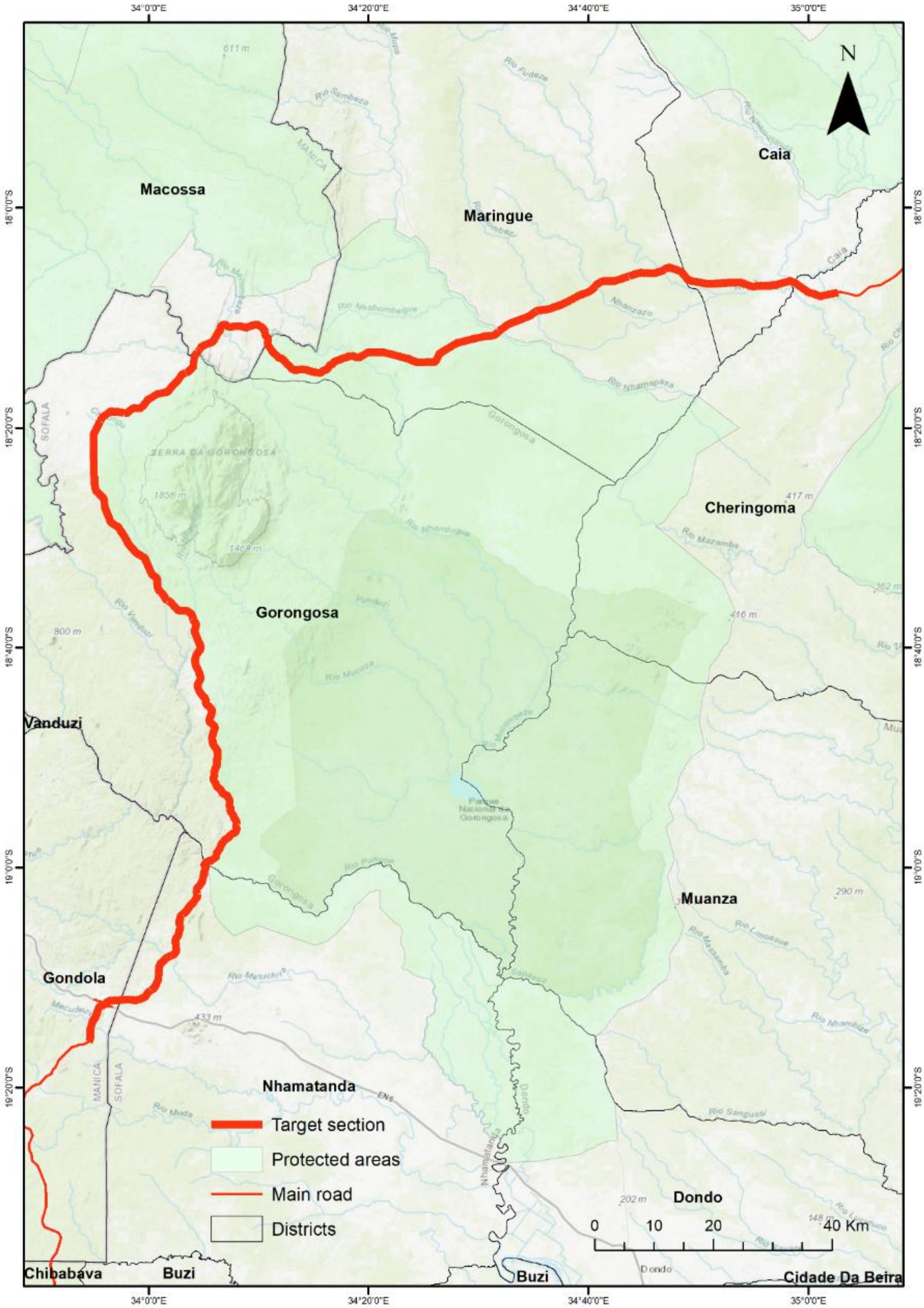

Figure 1: The study area for the landscape permeability assessment.

Species and occurrence records

Twenty-one species were considered in this study, aiming to provide a balance between large and medium species of mammals and different dispersal capacities (Table 1), with occurrence records retrieved from the Global Biodiversity Information Facility (GBIF), which provides broad-scale, publicly available biodiversity data repository and field records from Gorongosa National Park, which offer high-resolution, locally validated observations. Combining these datasets enhances both the spatial coverage and ecological accuracy of the modelling framework. These species were selected based on the reported presence of the species within the area and crossing the road, but also because some species migrate through the region but have limited speed (pangolins). Among the species, the African savannah elephant was the species with the largest dispersal capacity (nearly 100 km), while the ground pangolin was the species with the lowest dispersal capacity (with 10 km).

Even though only mammals were considered, the results are still useful under the concept of umbrella species and the characteristics of the landscape within the study area. After running the analysis six species were removed from further analysis due to the lower suitability presented within the focal study area: *A. melampus*, *C. natalensis*, *Conochaetus taurinos*, *Equus quagga*, *Taurotragus orix* and *Tragelaphus strepsiceros*.

Table Error! No text of specified style in document.**-1: List of mammals included in habitat suitability assessment**

n	Common name	Scientific name
1	Hartebeest	*Alcephalus buselaphus*
2	Impala	*Aepyceros melampus*
3	Spotted hyena	*Crocuta crocuta*
4	Red forest duiker	*Cephalophus natalensis*
5	Blue wildebeest	*Connochaetes taurinus*
6	Plains zebra	*Equus quagga*
7	Sable antelope	*Hippotragus niger*
8	Waterbuck	*Kobus ellipsiprymnus*
9	African savannah elephant	*Loxodonta africana*

10	African wild dog	*Lycaon pictus*
11	Ground pangolin	*Smutsia temminckii*
12	Oribi	*Ourebia ourebi*
13	Common warthog	*Phacochoerus africanus*
14	Southern reedbuck	*Redunca arundinum*
15	Yellow baboon	*Papio cynocephalus*
16	Lion	*Panthera leo*
17	African buffalo	*Syncerus caffer*
18	Common duiker	*Sylvicapra grimmia*
19	Nyala	*Tragelaphus angasii*
20	Common eland	*Taurotragus oryx*
21	Greater kudu	*Tragelaphus strepsiceros*

Source: Biodiversity specialist elaboration targeting species noted to have crossed the N1 as per information from GNP authorities.

Species distribution models (SDMs) provide a robust framework to assess potential wildlife–road interactions because they predict the probability of species occurrence across a landscape by linking known occurrence records with environmental predictors (Elith & Leathwick, 2009). The central theoretical premise is that the likelihood of encountering a species in each location is structured by ecological gradients and habitat availability, rather than being randomly distributed. This makes SDMs particularly well suited for road ecology, where collision risk is a function of both traffic intensity and the probability of animals being present in or near the road corridor (Clevenger & Nielsen, 2012; van der Ree et al., 2015).

In Mozambique, wildlife monitoring relies heavily on aerial surveys, which face important limitations: they are costly, logistically demanding, and typically restricted to protected areas such as Gorongosa National Park. This means that large areas of adjacent landscapes, including the Gorongosa–Caia N1 corridor, lack systematic survey data. Moreover, aerial surveys are prone to detection biases, especially under dense canopy or for species occurring at low densities (Norton-Griffiths & McConville, 2007).

Under these premises, SDMs offer a defensible way to extend the ecological information embedded in aerial survey data beyond park boundaries, while also providing a framework to correct for sampling bias. Presence-only modelling approaches, such as MaxEnt, explicitly allow the use of bias files or target-group background sampling to ensure that background points are drawn from areas with equivalent survey effort (Phillips et al., 2009). In practice, this means that although the occurrence records originate inside Gorongosa NP, the ecological relationships they capture (e.g., elephants favouring wooded savannas near water, herbivores preferring floodplains and open grasslands) can be transferred across the broader landscape when background sampling and model validation procedures correct for the uneven distribution of effort (Fourcade et al., 2014).

By accounting for sampling bias in this way, the SDMs do not simply replicate the survey footprint of Gorongosa but generalise habitat–occurrence relationships across similar environments in the region. This is particularly valuable where direct monitoring is lacking, as is the case for the N1 corridor. Combining these corrected SDM outputs with traffic volume and speed data allows the identification of high-risk collision “hotspots” with greater confidence, thereby supporting evidence-based mitigation measures such as wildlife crossings, targeted signage, or speed reduction zones.

While raw aerial survey data are spatially limited, the integration of bias-correction methods within an SDM framework enables their ecological signal to be meaningfully extended to areas of conservation concern outside Gorongosa. This strengthens the predictive power of the EIA and aligns with international best practice, where SDMs are routinely applied in data-poor contexts to anticipate and mitigate biodiversity impacts (Franklin, 2010; Guisan & Zimmermann, 2000).

Environmental variables

Species distribution modelling (SDM) integrates species occurrence records with environmental and ecological predictors to estimate the potential geographic distribution of organisms under current or future conditions. This approach is grounded in ecological niche theory, which posits that species distributions are shaped by climatic and environmental constraints.

For this study, 19 bioclimatic variables (Figure 2) representing near-present climate conditions were retrieved from the WorldClim database (www.worldclim.com), either for near-current (historical) and near-future scenarios (2035). These variables are derived from monthly temperature and precipitation data and are designed to capture biologically meaningful aspects of climate, including:

- Annual trends (e.g., mean annual temperature, annual precipitation).
- Seasonality (e.g., temperature annual range, precipitation seasonality).
- Extreme or limiting factors (e.g., minimum temperature of the coldest month, precipitation of the driest quarter).

Together, these variables provide a comprehensive climatic profile that is widely used in ecological modelling and conservation planning. Prior to modelling, it is critical to address multicollinearity among predictor variables, as strong correlations can inflate model performance metrics and lead to biased estimates of species–environment relationships. To mitigate this, a Principal Components Analysis (PCA) was conducted. PCA reduces dimensionality by transforming correlated variables into a smaller set of uncorrelated components, thereby minimizing autocorrelation and avoiding over- or under-estimation of species distributions. This step ensures that the modelling framework captures the dominant climatic gradients while reducing redundancy in the predictor set.

By combining occurrence data with these processed bioclimatic predictors, SDMs can generate robust estimates of species' potential distributions, which are essential for applications such as landscape permeability analysis, habitat connectivity modelling, and conservation prioritization.

Figure 2: List of variables included for species distribution modelling.

Code	Description
v1	Annual Mean Temperature (°C)
v2	Mean Diurnal Temp Range (Mean of monthly (max temp—min temp)) (°C)
v3	Isothermality (v2/v7) (*100)
v4	Temperature Seasonality (standard deviation *100)
v5	Max Temperature of Warmest Month (°C)
v6	Min Temperature of Coldest Month (°C)
v7	Temperature Annual Range (v5–v6) (°C)
v8	Mean Temperature of Wettest Quarter (°C)
v9	Mean Temperature of Driest Quarter (°C)
v10	Mean Temperature of Warmest Quarter (°C)
v11	Mean Temperature of Coldest Quarter (°C)
v12	Annual Precipitation (mm)
v13	Precipitation of Wettest Month (mm)
v14	Precipitation of Driest Month (mm)
v15	Precipitation Seasonality (Coefficient of Variation)
v16	Precipitation of Wettest Quarter (mm)
v17	Precipitation of Driest Quarter (mm)
v18	Precipitation of Warmest Quarter (mm)
v19	Precipitation of Coldest Quarter (mm)

Habitat suitability modelling

The potential distribution of the species was predicted using the maximum entropy algorithm in Maxent v4.3.3. (Phillips et al., 2006). Maxent is a machine learning algorithm widely used for species distribution modelling. It operates on the principle of maximum entropy, estimating the probability distribution of a species' presence across a landscape based on environmental variables such as climate, elevation, and land cover. Maxent uses presence-only data, meaning it requires only the locations where the species have been observed, rather than both presence and absence data. The model works by finding the distribution that is closest to uniform (maximum entropy) while still being constrained by the environmental conditions at known species locations. It is particularly effective in handling complex, non-linear relationships between species and their environment, making it a powerful tool for predicting species distributions, assessing habitat suitability, and informing conservation strategies.

Species distribution models (SDMs) provide a robust framework to assess potential wildlife–road interactions because they predict the probability of species occurrence across a landscape by linking known occurrence records with environmental predictors (Elith & Leathwick, 2009). The central theoretical premise is that the likelihood of encountering a species in each location is not random but structured by ecological gradients and habitat availability. This makes SDMs particularly well suited for road ecology, where the risk of vehicle collisions is a function of both traffic intensity and the probability of animals being present in or near the road corridor (Clevenger & Nielsen, 2012; van der Ree et al., 2015).

Direct estimates of collision risk in African contexts face important limitations. Aerial wildlife surveys, which remain the main systematic source of data in Mozambique, are logistically demanding, costly, and spatially constrained. They often cover only protected areas such as Gorongosa National Park, leaving adjacent landscapes, including the Gorongosa–Caia N1 road corridor, poorly surveyed (Craigie et al., 2010). Even when available, aerial counts tend to underdetect species in dense vegetation or at small group sizes, and they provide only coarse spatial resolution, insufficient for road-level risk mapping (Norton-Griffiths & McConville, 2007).

In this context, SDMs offer a scientifically defensible way to extend the ecological signal beyond the boundaries of the aerial survey transects and the park itself. By integrating occurrence data from Gorongosa's aerial surveys with environmental predictors such as land cover, topography, water availability, and vegetation productivity, SDMs can identify suitable habitats across the broader landscape, including the road corridor. The assumption is not that Gorongosa aerial surveys capture all individuals dispersing toward the N1, but rather that the ecological relationships derived from these data (e.g., elephants favouring wooded savannas near water, large herbivores preferring floodplains or open grasslands) remain valid outside the park boundaries (Phillips et al., 2006). This transferability of habitat–occurrence relationships is widely recognized in species distribution modelling and underpins applications in conservation planning, climate adaptation, and impact assessment (Guisan & Zimmermann, 2000; Franklin, 2010).

Using SDMs in this way directly addresses two challenges: (i) the absence of systematic wildlife monitoring along the N1 corridor, and (ii) the need to generate spatially explicit, fine-scale predictions of animal presence where mitigation measures must be prioritized. Rather than relying exclusively on sparse carcass counts or extrapolating raw aerial survey numbers, the modelling framework provides a probabilistic surface of habitat use. When combined with traffic volume and speed data, this enables the identification of high-risk “collision hotspots” along the road, offering decision-makers evidence-based locations for mitigation such as signage, speed regulation, or wildlife crossings.

The use of SDMs in this study is theoretically justified and practically necessary. They allow the ecological information embedded in Gorongosa aerial surveys to inform risk assessments beyond park limits, overcoming the constraints of limited survey coverage and resolution. This approach is consistent with international best practice in environmental impact assessment, where predictive habitat models are increasingly used to anticipate and mitigate biodiversity impacts in data-poor contexts (Clevenger & Huijser, 2011; Mateo Sánchez et al., 2016).

As indicated in section 2.1, data was obtained through public repository and field constrained data. However, raw occurrence data often contain spatial biases due to uneven sampling effort, accessibility of sites, or clustering of records around research stations and roads. Such biases can artificially inflate model performance by over-representing certain environmental conditions while under-representing others. To address this, prior to modelling occurrence points were spatially filtered using the spThin package in R, which applies a thinning algorithm to reduce spatial autocorrelation among records.

Filtering was conducted to ensure that the occurrence data matched the spatial resolution of the climate predictors (bioclimatic variables from WorldClim). Climate data are typically available at resolutions such as 1 km^2 or 5 km^2, meaning that multiple occurrence records within a single grid cell would not provide additional independent information. By thinning records to one per grid cell, the dataset avoids pseudo-replication and ensures that each occurrence contributes unique information to the model. This step is essential for producing robust SDMs because:

- Reduces sampling bias and spatial autocorrelation.

- Aligns the scale of biological data (species occurrences) with the scale of environmental predictors (climate variables).
- Prevents overfitting, which can occur when clustered points exaggerate species–environment relationships.
- Improves the transferability of models to new areas or future climate scenarios, as the relationships are based on independent, representative data.

By harmonizing occurrence records with the resolution of climate variables, the resulting models provide more reliable estimates of species' potential distributions and landscape permeability, supporting conservation planning and ecological inference.

Preparation of the resistance surface

Prior to assessing landscape permeability, it was necessary to prepare a resistance surface[1], which represents the relative difficulty for species to move across the landscape. To construct this layer, two types of spatial data were initially compiled: vector and raster. All vector datasets were converted into raster format to ensure compatibility, after which all raster layers were reclassified into dimensionless values to allow direct comparison and integration. Resistance values were categorized using a standardized scale: 0 = not suitable; 2 = very low resistance; 4 = low resistance; 6 = medium resistance; 8 = high resistance; 10 = very high resistance.

This classification scheme provides a consistent framework for quantifying landscape features in terms of their permeability to species movement. Except for land cover, all variables were classified into five categories using the Jenks natural breaks method, which optimizes class intervals by minimizing variance within classes and maximizing variance between classes. This approach is widely used in ecological modelling to capture natural groupings in environmental data. The reclassified raster layers were then combined in ArcGIS 16.0.1 through a weighted summation. The following weights were applied, reflecting the relative importance of each variable in shaping resistance: Land cover = 0.20; Habitat suitability = 0.20; Topography = 0.28;

[1] Resistance layers represent the degree to which some landscape feature impedes or facilitates species movement (Adriaensen et al., 2003), typically represented as a cell (pixel) value in a grid (raster) within a Geographic Information System (GIS).

Population density = 0.10; Species richness = 0.07; Human Footprint = 0.15, as indicated in Equation 1. For each $species_i$:

$$Index_i = 0.20Cover + 0.28Topo - 0.10PopDens + 0.07Richness - 0.15HFP + 0.20Species_i$$

These weights were derived from a regression analysis of all variables, following established approaches in landscape ecology (e.g., Zhang et al., 2018; Kott, 2022). The resulting resistance surface integrates multiple ecological and anthropogenic factors, providing a robust basis for evaluating landscape permeability and identifying potential movement corridors. To aid calculations, all variables were normalized to range from 0-1, using the Equation 1:

$$r_{norm} = \frac{r - \min(r)}{\max(r) - \min(r)} \qquad \text{(Eq. 1)}$$

The decision to combine reclassified raster layers through a weighted summation reflects both methodological rigor and practical considerations in landscape ecology. This approach is widely adopted because it allows multiple ecological and anthropogenic variables to be integrated into a single resistance surface while maintaining transparency and interpretability. As such, this method ensures transparency and interpretability, flexibility in incorporating diverse data, avoidance of overfitting and comparability across studies.

Each of the variables represents a distinct ecological or anthropogenic factor influencing movement. The weighting scheme balances biophysical constraints (land cover, topography, slope) with anthropogenic pressures (roads, population density) and ecological relevance (habitat suitability, species richness) to provide a multidimensional resistance surface that realistically captures landscape permeability.

- Land cover is one of the most influential determinants of species movement. Different land cover types (e.g., forest, grassland, cropland, urban areas) vary in permeability: natural habitats typically facilitate movement, while urban or agricultural areas often act as barriers. Assigning a high weight reflects its central role in defining habitat continuity and fragmentation.

- Habitat suitability, derived from species distribution models, indicates how favourable a location is for a species. Areas of low suitability represent higher resistance to movement. Including this variable ensures that the resistance surface reflects species-specific ecological requirements, aligning connectivity modelling with biological realism.

- Topographic features such as elevation and terrain ruggedness influence dispersal. Steep or complex terrain can hinder movement, while flat areas are generally more permeable. This variable captures the physical constraints imposed by the landscape itself. Topography (represented by elevation) was treated as a cost surface, as steeper and higher terrain tends to reduce animal movement and habitat accessibility and was therefore assigned a negative weight.

- Human population density reflects the intensity of human presence and associated pressures (settlements, agriculture, infrastructure). High-density areas typically correspond to reduced permeability due to disturbance, habitat loss, and increased risk of conflict. Including this variable ensures anthropogenic impacts are explicitly represented.

- Areas of high species richness often indicate ecologically valuable and diverse habitats. Incorporating species richness helps prioritize regions that support multiple species simultaneously. Although weighted lower, it adds an important biodiversity dimension, ensuring that connectivity planning benefits broader ecological communities rather than single species alone.

- Human footprint – it was included as a measure of cumulative anthropogenic pressure on the landscape, integrating the effects of infrastructure, settlements, agriculture, and accessibility. Higher values of the Human Footprint indicate greater levels of human disturbance, habitat modification, and fragmentation, which are widely documented to reduce habitat quality, restrict animal movement, and increase mortality and conflict risk for wildlife. Accordingly, the Human Footprint was treated as a cost variable and assigned a negative weight in the composite index, such that increasing anthropogenic pressure reduces the overall suitability or priority value of a given location."

Connectivity assessment

A connectivity model[2] was developed using Circuitscape v4.0.5 (McRae et al., 2016), a widely applied tool in landscape ecology. Circuitscape is grounded in circuit theory (CT), which conceptualizes population connectivity as analogous to the flow of electrical current across a network (McRae, 2006; McRae et al., 2008). In this framework, landscapes are represented as resistive surfaces, and species movement is modelled as current flow, allowing for the identification of multiple pathways and the quantification of connectivity across heterogeneous environments.

The model employs a graph-theoretical approach to predict movement patterns and evaluate how landscape features influence species dispersal (Cushman et al., 2013). This approach is particularly effective because it accounts for both direct and indirect pathways, thereby capturing the redundancy and complexity of ecological networks that traditional least-cost path methods may overlook.

The resistance surface used in the model was constructed by integrating several ecological and anthropogenic variables. Specifically, the inverse of individual habitat suitability maps (1 – ENM) (Sunny et al., 2022) was combined with species richness maps, as well as environmental and human-related factors including elevation, slope, distance to roads (Euclidean distance), land cover, and population density. The inverse of habitat suitability reflects the relative difficulty of movement within a given location, with lower suitability corresponding to higher resistance (Mateo-Sánchez et al., 2014).

Connectivity calculations were performed using focal points in pairwise modelling mode, which estimates current flow between pairs of habitat patches or species occurrence points. This approach allows for the identification of critical corridors, bottlenecks, and areas of high

[2] Ecological connectivity can be defined as the degree of connection between the various natural environments present within a landscape.

resistance that may impede movement. By modelling connectivity for each species individually, the analysis provides species-specific information into landscape permeability, while also highlighting areas of potential multi-species overlap that are important for conservation planning.

Results

Landscape permeability refers to the levels or degrees to which a landscape allows for the movement of organisms, species, and ecological processes across it. These scales are often used in environmental and conservation studies to assess how well different species can move through a landscape that has been affected by human development, infrastructure, or other changes.

Landscape permeability in the study region was generally low, with most species exhibiting permeability values below 0.5 on a scale from 0 (completely impermeable) to 1 (fully permeable). Across all species and the entire landscape, permeability values ranged from 0.0625 to 0.3120, indicating that large portions of the region present limited permeability for animal movement.

When permeability was examined at the species level, substantial variation among species was observed. The highest permeability values were recorded for M. temminckii, with values ranging from 0.5333 to 0.9380, indicating that this species experiences comparatively high landscape permeability and encounters fewer spatial constraints to movement. In contrast, most other species showed more restricted permeability patterns and reached considerably lower maximum values. Specifically, the maximum permeability values for the remaining species were 0.516 for *Crocuta crocuta*, 0.7342 for *Hippotragus niger*, 0.5928 for *Kobus ellipsyprimnus*, 0.5291 for *Loxodonta africana*, 0.5566 for *Ourebia ourebi*, 0.6650 for both *Papio cynocephalus* and *Syncerus caffer*, and 0.6129 for *Redunca arundinum*. Although some species locally reached moderate to high permeability values, these were spatially limited and did not represent the dominant condition across the landscape.

Overall, the results indicate that permeability is spatially heterogeneous and species-specific, with only a small number of taxa experiencing high permeability over substantial areas. For most species, movement across the landscape appears to be constrained, resulting in generally low permeability values across much of the region. This pattern is consistent with the predominantly hilly and topographically complex nature of the Gorongosa ecosystem, which is characterized by pronounced elevational gradients, rugged terrain, and a mosaic of land cover types that may restrict or channel animal movement. Taken together, these results suggest that the study area does not function as a uniformly permeable landscape for large mammals, but rather as a patchwork of areas with varying degrees of permeability, where only certain species (notably *M. temminckii*) are able to move relatively freely across a broader portion of the region.

The generally low and spatially heterogeneous landscape permeability observed in the study area indicates that the region already imposes significant constraints on animal movement. This suggests that the rehabilitation of the N1 road is likely to have a disproportionate impact on ecological connectivity and wildlife movement, particularly for species with low permeability and limited movement alternatives. As a result, road impacts are expected to be spatially concentrated at specific corridors and pinch points, rather than uniformly distributed. These findings underscore the need for targeted, species-appropriate mitigation measures, including strategically placed wildlife crossing structures and carefully designed fencing, to reduce collision risk and maintain functional connectivity. The permeability maps developed in this study therefore provide a critical evidence base for identifying priority locations for mitigation and for guiding adaptive management throughout the project lifecycle.

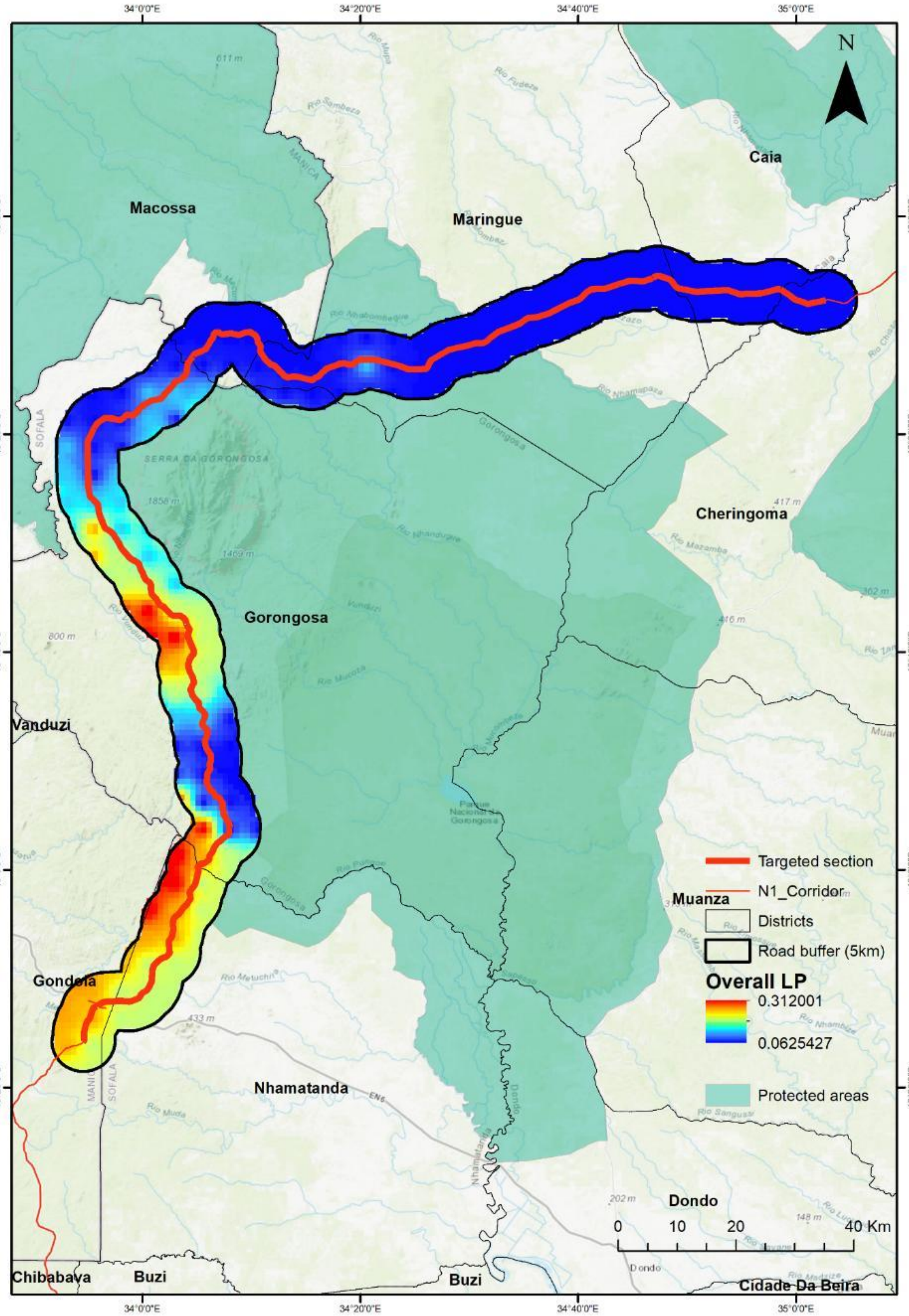

Figure 3: Landscape permeability across the Inchope-Caia road rehabilitation project. The scale should be considered between 0 and 1. A 5km buffer was considered.

The first section of the road (Inchope–Gorongosa, km 0–70) is characterised by the presence of significant human settlements and high traffic volumes, which together increase the risk of wildlife–vehicle collisions across all species. This risk is particularly pronounced where the road intersects the buffer zone of Gorongosa National Park (GNP). In these areas, the overlap between wildlife movement and intense human activity creates conditions conducive to conflict, especially for species such as hartebeest (*Alcelaphus buselaphus*), sable antelope (*Hippotragus niger*), waterbuck (*Kobus ellipsiprymnus*), pangolin (*Smutsia temminckii*), and oribi (*Ourebia ourebi*), which exhibit moderate to high permeability and are therefore more likely to encounter the road.

The second section of the road (Gorongosa–Caia, km 70–84) presents a comparatively lower risk for wildlife–vehicle interactions. This segment traverses a slightly elevated area extending from the Mount Gorongosa plateau, which appears to be less favourable for wildlife movement and crossings, likely due to increased energetic costs associated with traversing steeper or more rugged terrain. As a result, overall crossing probability in this section is reduced. Nevertheless, some risk remains, particularly for wide-ranging and mobile species such as elephants (*Loxodonta africana*), African wild dogs (*Lycaon pictus*), pangolins (*Smutsia temminckii*), oribi (*Ourebia ourebi*), warthogs (*Phacochoerus africanus*), and reedbuck (*Redunca arundinum*), although this risk is limited to a relatively small proportion of the landscape.

The third section of the road (Gorongosa–Caia, km 84–168) requires particular attention, as it largely coincides with the GNP buffer zone and therefore intersects areas of high ecological importance and wildlife use. Within this section, the first 10 km represent a priority zone where enhanced protection and mitigation measures are necessary to reduce the risk of wildlife–vehicle collisions. Moreover, even after the N1 corridor exits the buffer zone, elevated risk persists for approximately the subsequent 10 km, indicating that additional precautionary measures remain warranted beyond the formal boundary of the protected area to ensure continued safety for both wildlife and road users.

The spatially differentiated risk patterns identified along the N1 indicate that the ecological impacts of the road rehabilitation will not be uniform, but concentrated in specific segments, particularly where the road intersects the Gorongosa National Park buffer zone and adjacent high-permeability areas. These segments coincide with some active wildlife movement and involve species of high ecological and conservation importance, implying a non-negligible risk of increased wildlife mortality, disruption of movement, and functional fragmentation. Consequently, mitigation measures must be spatially targeted and species-appropriate, rather than uniformly applied along the corridor. The results support the prioritisation of precautionary measures and monitoring. Overall, the findings indicate that the road rehabilitation does not constitute an ecologically sensitive intervention that necessitates hard engineering but rather proactive, targeted, and adaptive mitigation to ensure that impacts on wildlife movement and survival are effectively minimised.

Conservation and construction implications

The existing N1 road within the Gorongosa ecosystem is currently in poor condition, which limits vehicle speeds and constrains traffic flow between southern and northern Mozambique. This low level of service has the incidental effect of reducing the frequency and severity of wildlife–vehicle collisions, as slower speeds allow drivers more time to react and reduce collision lethality. However, it also restricts economic and social connectivity along the corridor. The proposed rehabilitation aims to improve road surface quality, safety, and reliability, thereby enabling smoother and more efficient transport of people and goods.

As the road already exists, the rehabilitation will not introduce a new linear barrier into the landscape and therefore does not create new fragmentation in a structural sense. Nevertheless, rehabilitation is expected to alter the functional characteristics of the road by increasing average vehicle speeds, improving traffic flow, and potentially attracting higher traffic volumes. These changes may increase the probability of wildlife–vehicle collisions and elevate disturbance levels along the corridor, particularly in ecologically sensitive areas and where wildlife movement overlaps with the road. The primary ecological impact of the project is therefore not the creation of a new barrier, but the potential intensification of its barrier and mortality effects.

The permeability analysis indicates that the surrounding landscape is relatively flat and lacks strongly defined movement corridors that would concentrate animal crossings at specific, narrow locations. Instead, wildlife movement appears to be spatially diffuse, with multiple low-intensity crossing points rather than a small number of dominant corridors. In this context, the construction of large wildlife overpasses or underpasses is unlikely to be ecologically efficient or cost-effective, as such structures are most beneficial where animal movement is naturally channelled through predictable pinch points. Moreover, the installation of continuous fencing along the road could further restrict animal movement, exacerbate functional fragmentation, and interfere with natural ranging behaviour, particularly for wide-ranging species.

These findings suggest that the most appropriate mitigation strategy is not heavy structural intervention, but targeted, proportionate, and adaptive measures aimed at managing incremental risk. Such measures include locally reduced speed limits in high-risk sections, wildlife warning signage, driver awareness campaigns, improved night-time visibility, and the systematic monitoring of wildlife–vehicle collisions. These interventions address the principal mechanism of impact, increased collision risk due to higher vehicle speeds, while maintaining overall landscape permeability and avoiding unnecessary physical barriers.

Taken together, the results indicate that the rehabilitation of the N1 represents an ecologically sensitive modification of an existing infrastructure rather than a fundamentally new disturbance. While the project does not introduce new fragmentation, it may increase functional impacts on wildlife through changes in traffic dynamics. Accordingly, mitigation should focus on managing these incremental effects in a spatially targeted manner, particularly near the Gorongosa National Park buffer zone and other areas of elevated wildlife presence. This approach ensures that the rehabilitation achieves its socio-economic objectives while maintaining ecological safeguards and minimizing unintended impacts on wildlife movement and survival.

The rehabilitation of the N1 road through the Gorongosa ecosystem is expected to modify traffic dynamics, particularly by increasing vehicle speeds and improving traffic flow. While this will enhance transport efficiency, it may also increase the risk of wildlife–vehicle collisions and disturbance to wildlife, especially in ecologically sensitive areas and where wildlife movement intersects the road. To minimise these incremental impacts while maintaining landscape permeability, a set of targeted, non-structural and low-intrusion mitigation measures is proposed:

- Speed management and traffic calming - reducing vehicle speed in high-risk sections is one of the most effective measures to decrease both the likelihood and severity of wildlife–vehicle collisions. Locally reduced speed limits should be implemented in areas of elevated ecological sensitivity, particularly where the road intersects the Gorongosa National Park buffer zone and adjacent high-permeability areas. These speed limits should be supported by appropriate road signage, physical speed-calming elements where feasible (e.g. rumble strips or optical speed reduction markings), and enforcement measures to ensure compliance. Lower speeds not only reduce collision probability but also increase driver reaction time and significantly decrease wildlife mortality rates.

- Wildlife warning signage and driver awareness - Targeted wildlife warning signs should be installed in sections identified as having elevated collision risk. These signs should be species-specific where possible (e.g. elephant or antelope silhouettes) and placed strategically in advance of known or predicted crossing zones. In addition, driver awareness campaigns — including informational materials at toll points, service stations, or through transport operators — can further increase driver vigilance, particularly during peak wildlife movement periods such as dawn, dusk, and seasonal migration periods.

- Road design and visibility enhancements - Improving driver visibility reduces collision risk, especially at night and in areas with vegetation close to the road. Vegetation should be managed along the road verge to prevent tall grasses or shrubs from obscuring animals approaching the road. Where feasible, improved road lighting at critical crossing areas can enhance driver detection of animals without creating excessive disturbance to wildlife. Reflective road markings and delineators can also help drivers anticipate potential hazards.

- Monitoring and adaptive management - a structured wildlife–vehicle collision monitoring programme should be established before and after rehabilitation. This programme should include systematic carcass surveys, incident reporting by road maintenance staff, and collaboration with park authorities and local communities. Monitoring results should be reviewed regularly to assess the effectiveness of mitigation measures and to identify emerging hotspots. If collision rates increase or shift spatially, mitigation measures should be adapted accordingly, for example by extending speed-reduced zones or adding signage in newly identified risk areas.

- Avoidance of extensive fencing and major crossing structures - given the relatively flat terrain in most parts of the area and the absence of strongly concentrated wildlife movement corridors, large wildlife overpasses or underpasses are not considered necessary or cost-effective in this context. Similarly, continuous fencing along the road is not recommended, as it could further restrict animal movement, exacerbate functional fragmentation, and interfere with natural ranging behaviour. The proposed approach therefore prioritises maintaining landscape permeability while managing collision risk through behavioural and operational measures rather than physical barriers.

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Appendix 1

Landscape permeability for selected species in the entire targeted section of the road

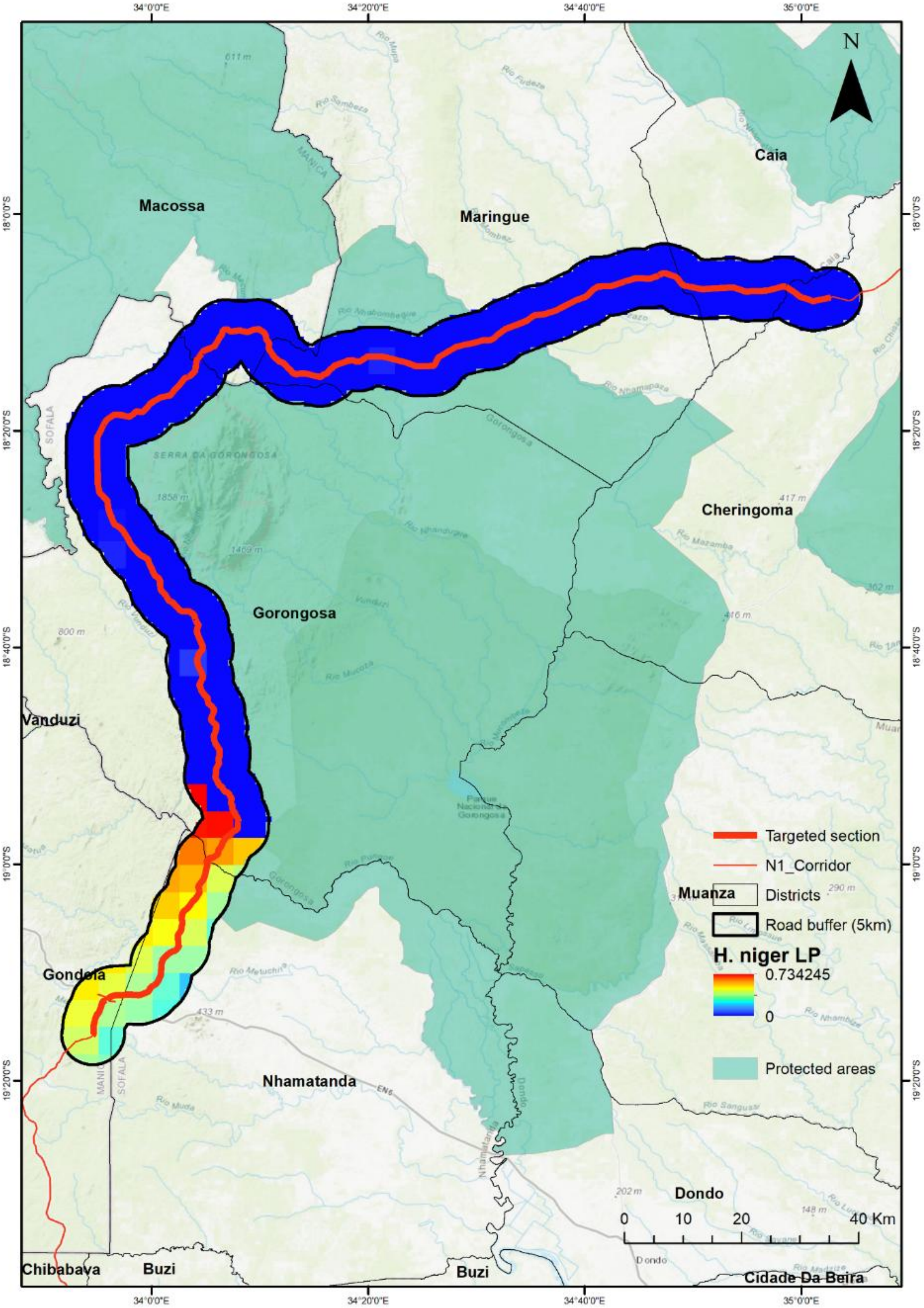


Figure A1: Landscape permeability across the Inchope-Caia road rehabilitation project for the sable antelope. The scale should be considered between 0 and 1.

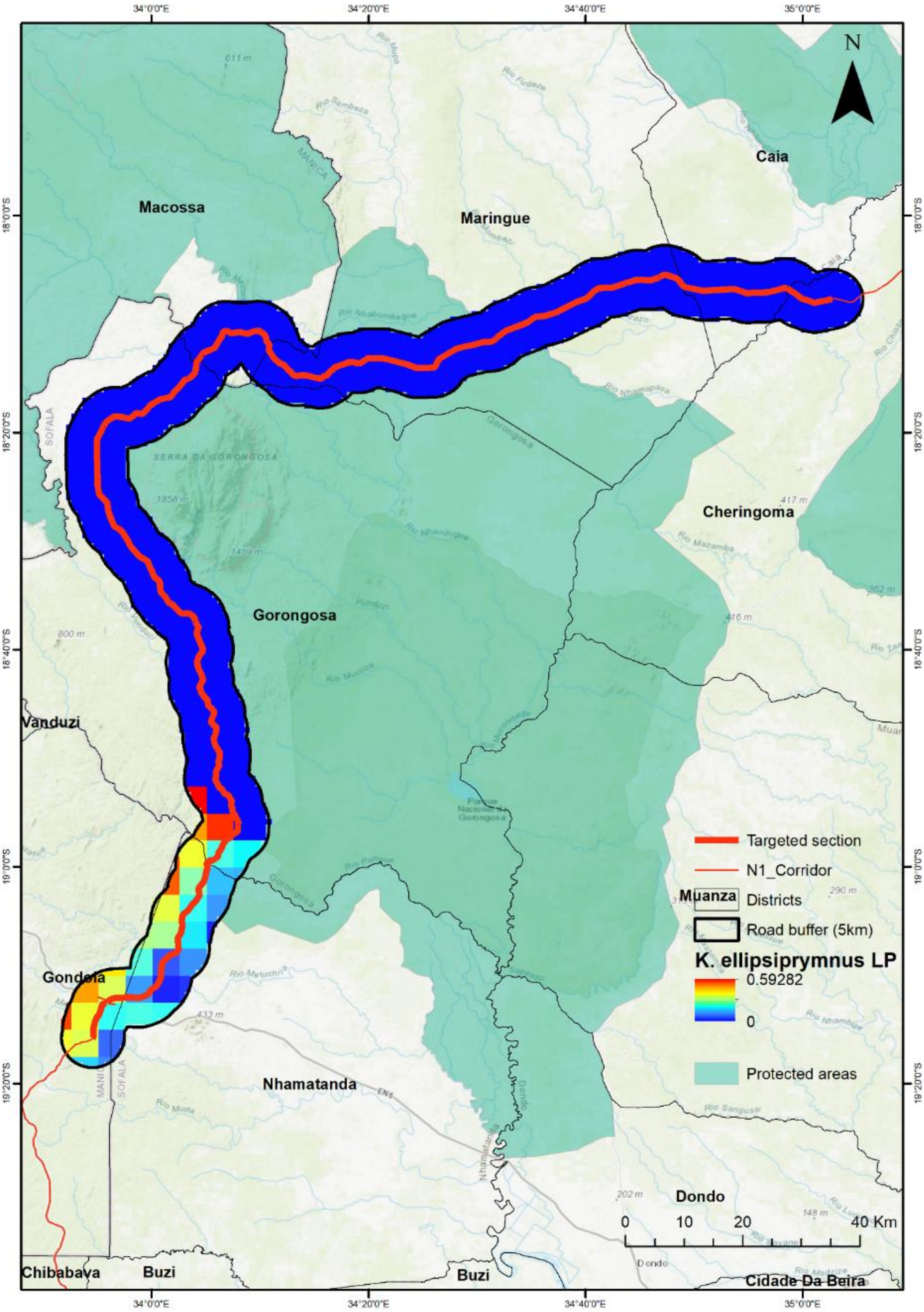


Figure A2: Landscape permeability across the Inchope-Caia road rehabilitation project for the waterbuck. The scale should be considered between 0 and 1.

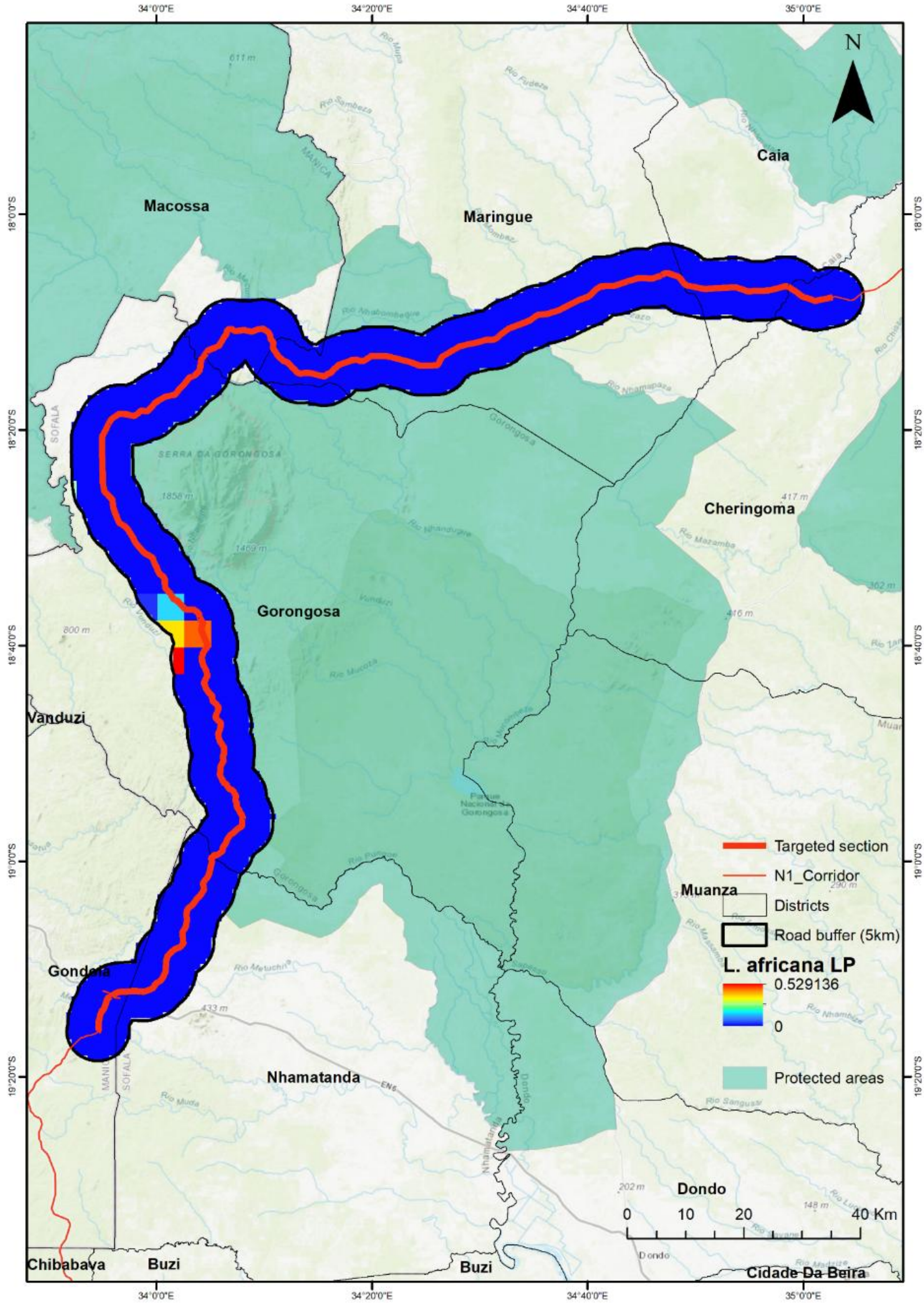


Figure A3: Landscape permeability across the Inchope-Caia road rehabilitation project for the savannah elephant. The scale should be considered between 0 and 1.

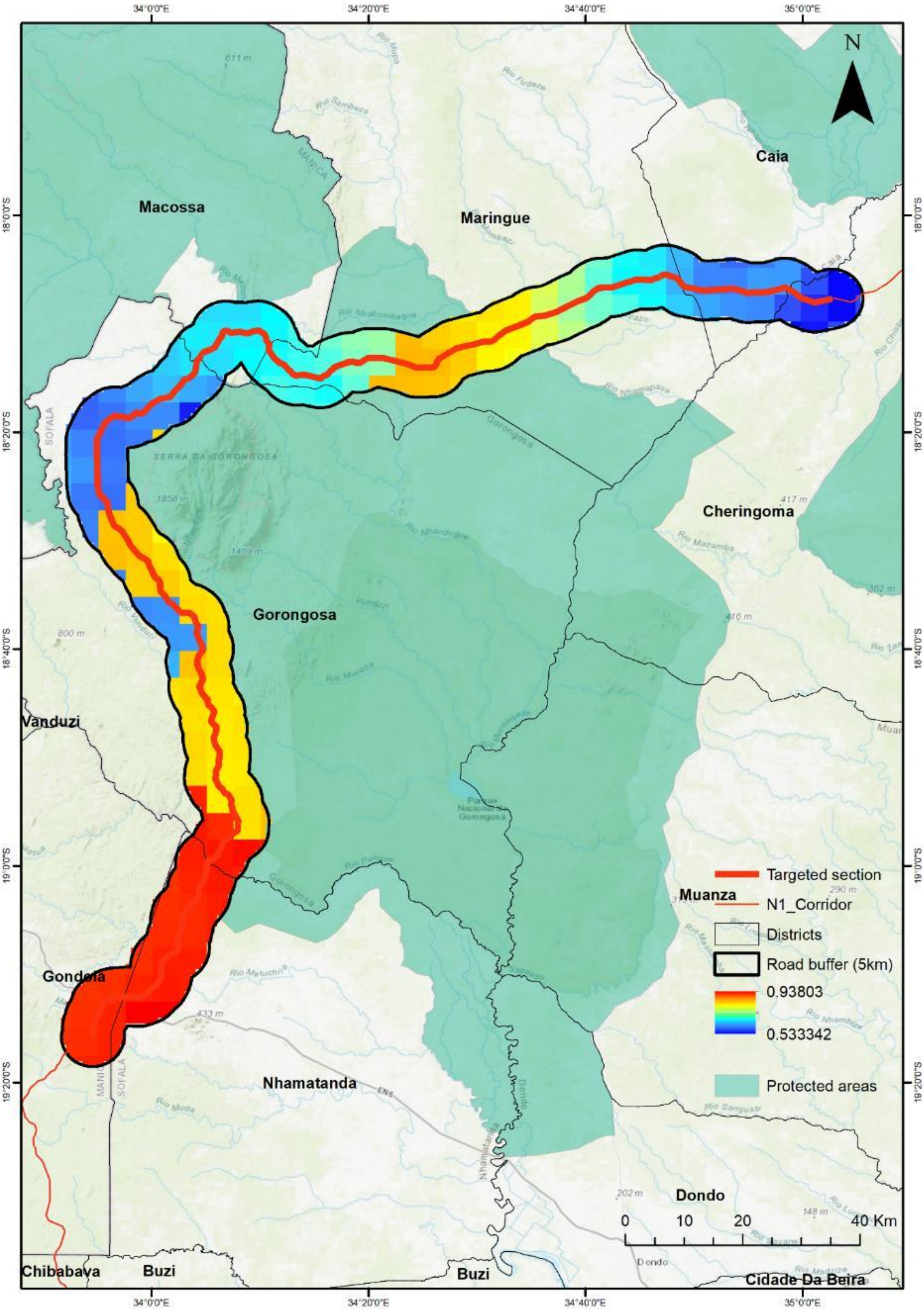


Figure A4: Landscape permeability across the Inchope-Caia road rehabilitation project for the ground pangolin. The scale should be considered between 0 and 1.

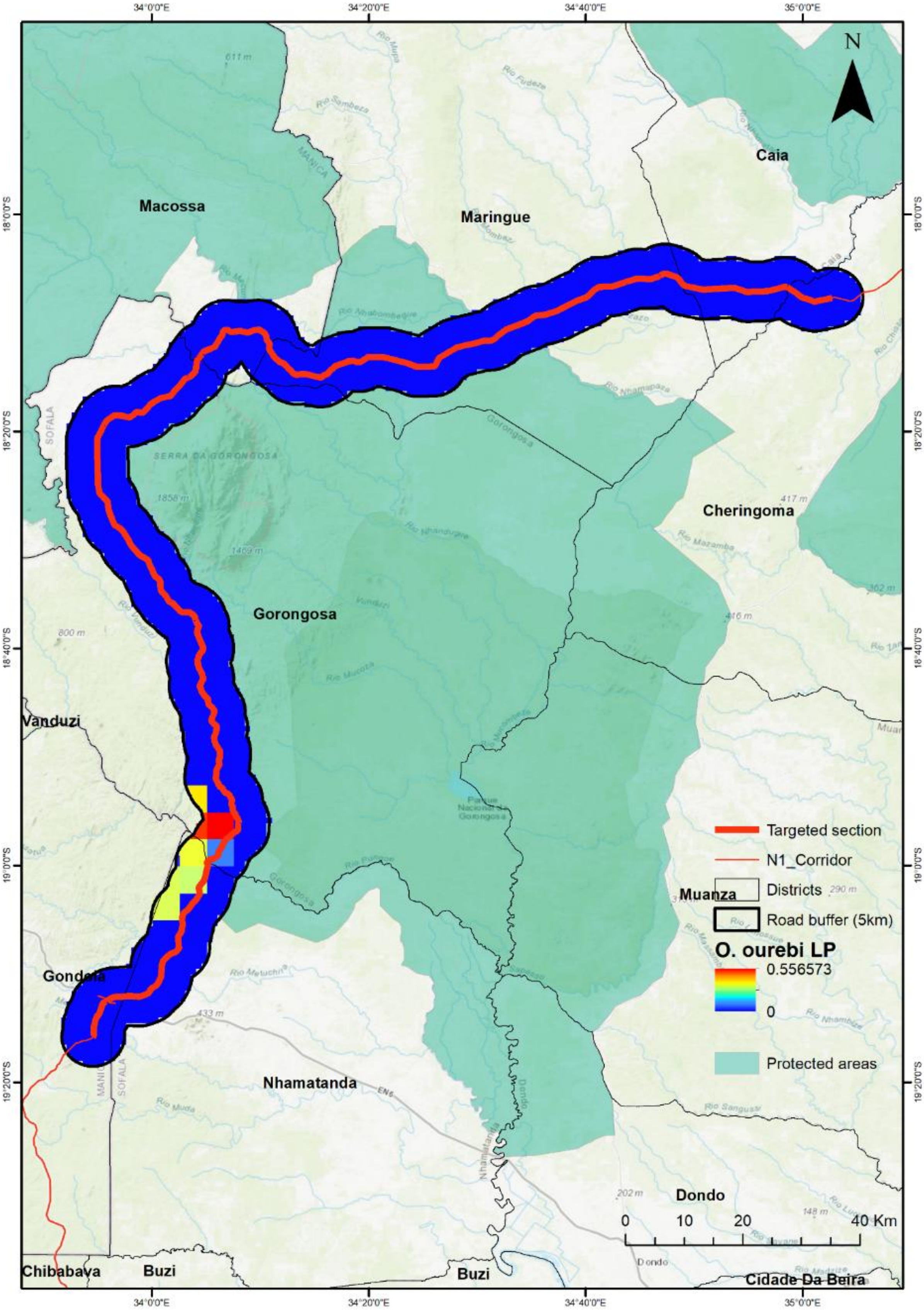


Figure A5: Landscape permeability across the Inchope-Caia road rehabilitation project for the oribi. The scale should be considered between 0 and 1.

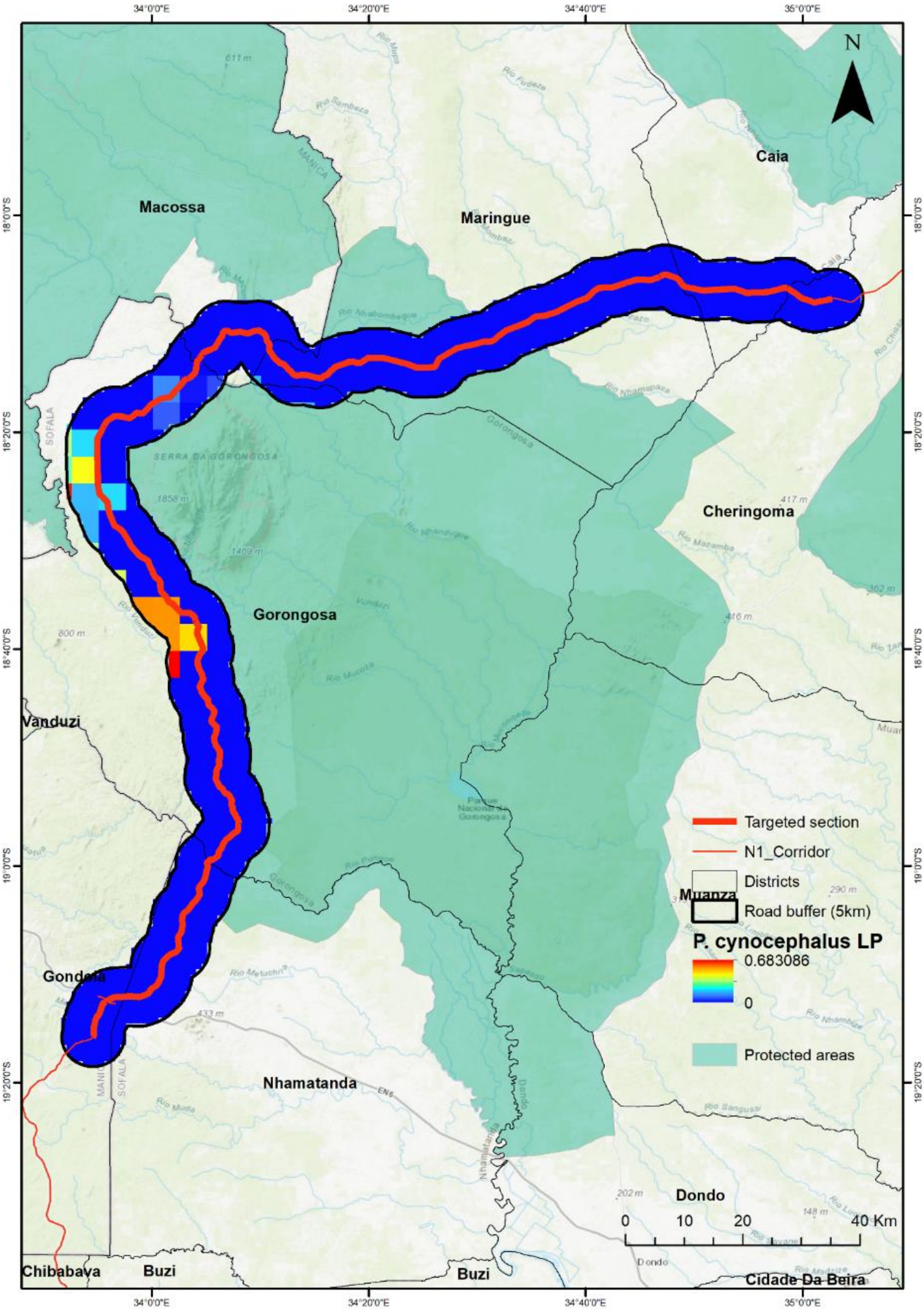


Figure A6: Landscape permeability across the Inchope-Caia road rehabilitation project for the yellow baboon. The scale should be considered between 0 and 1.

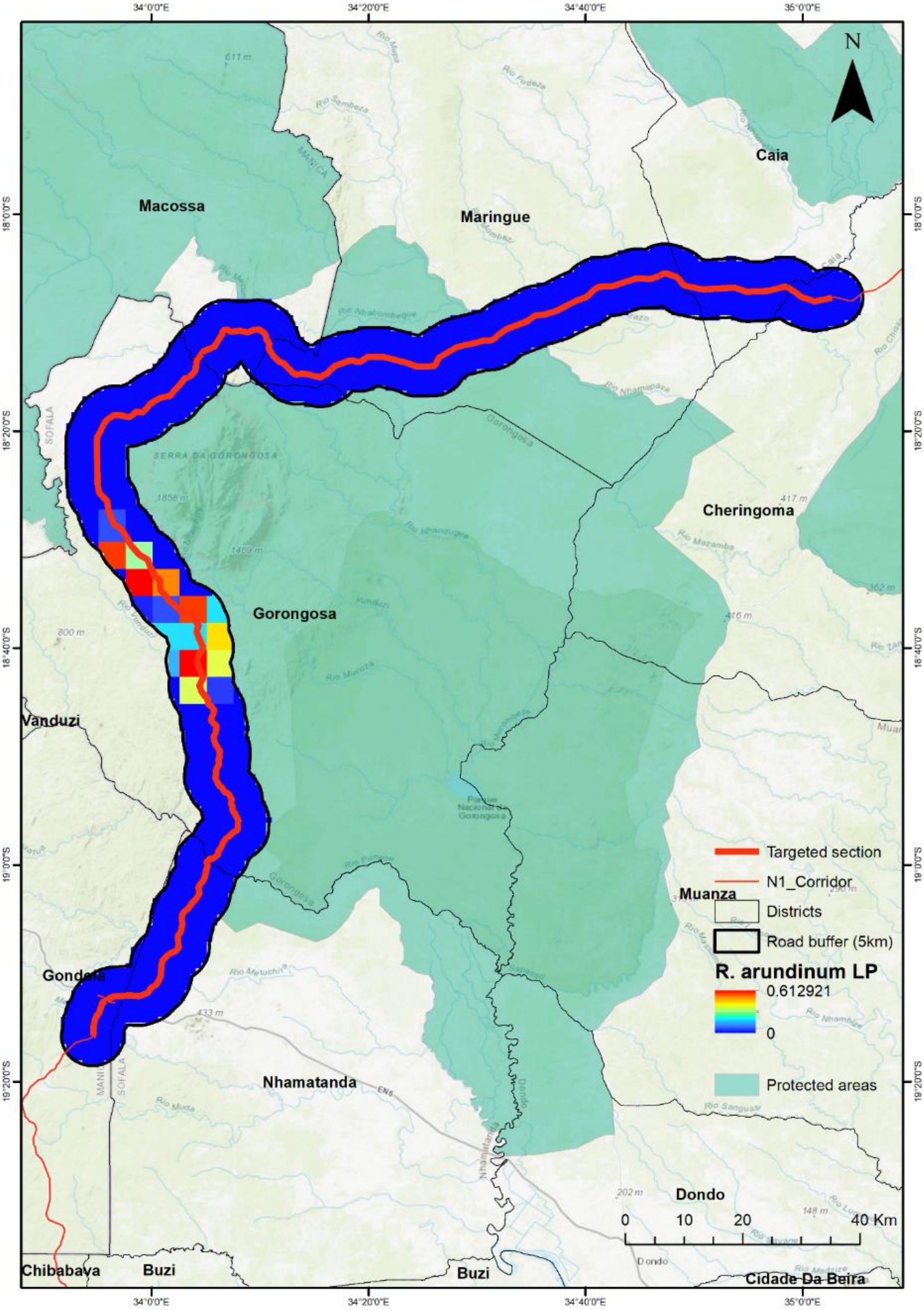


Figure A6: Landscape permeability across the Inchope-Caia road rehabilitation project for the southern reedbuck. The scale should be considered between 0 and 1.

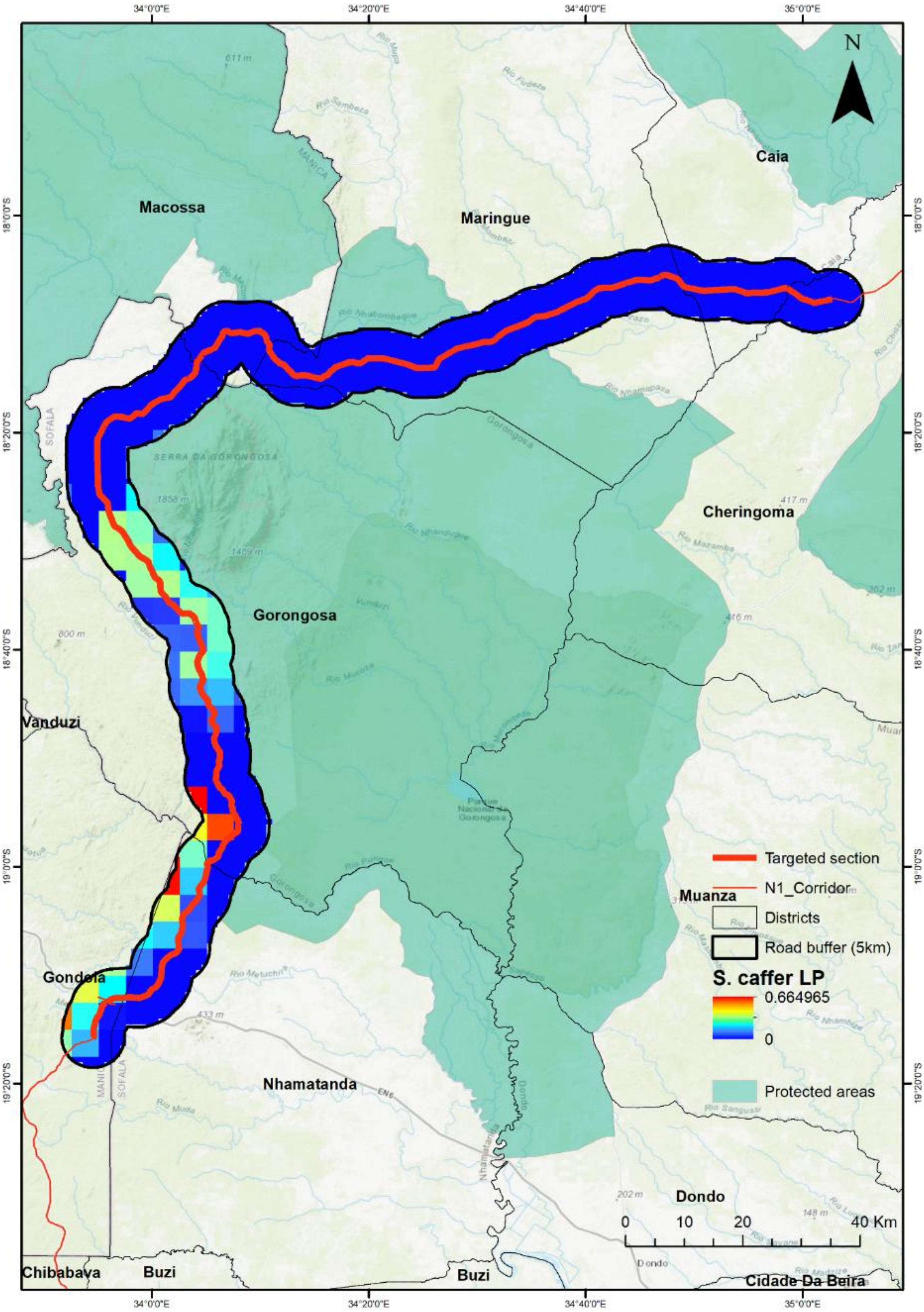


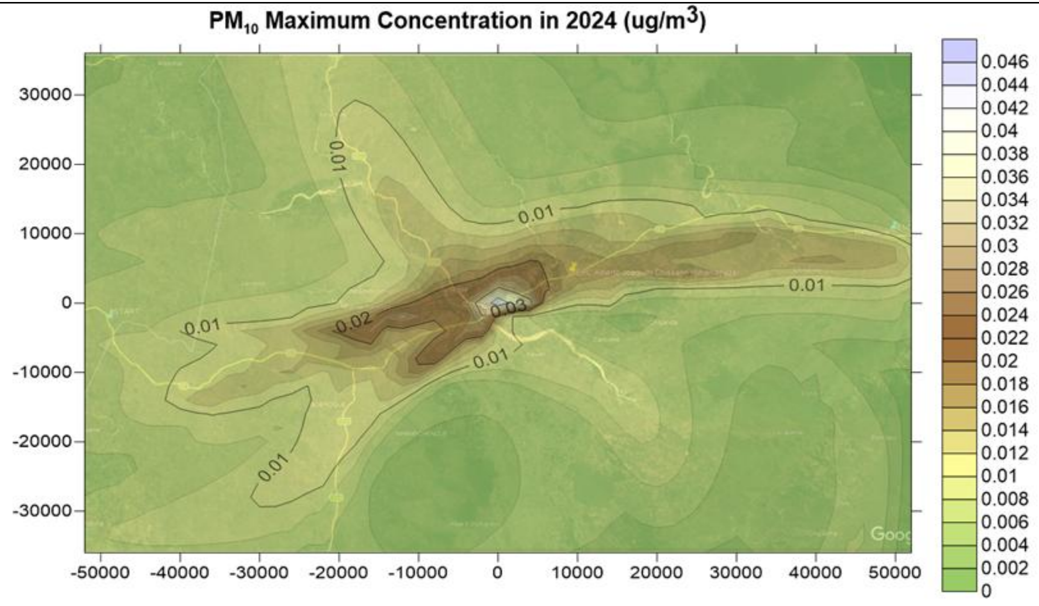
Figure A7: Landscape permeability across the Inchope-Caia road rehabilitation project for the African savannah buffalo. The scale should be considered between 0 and 1.

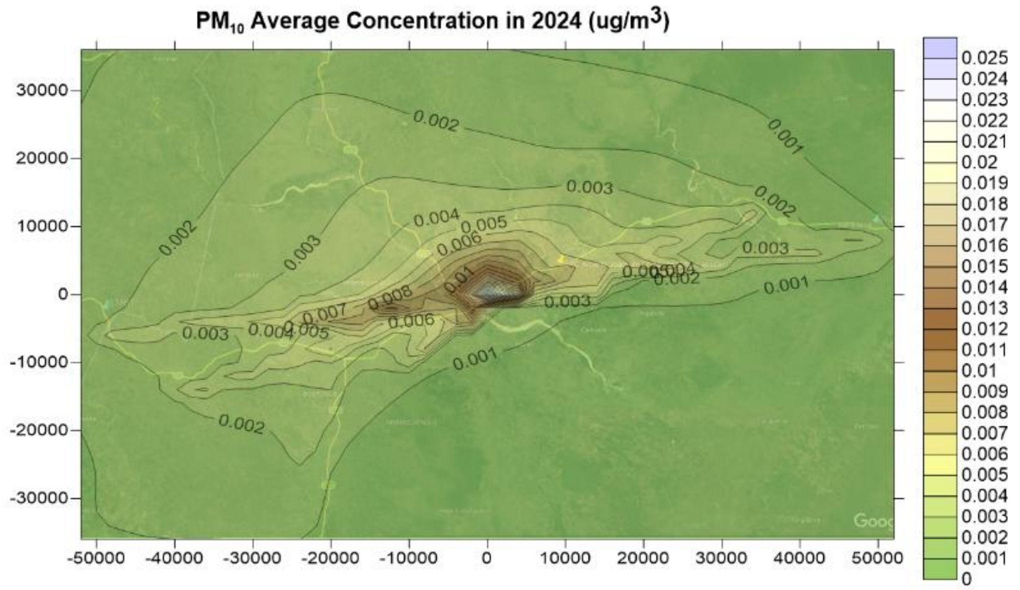
ANNEX 2

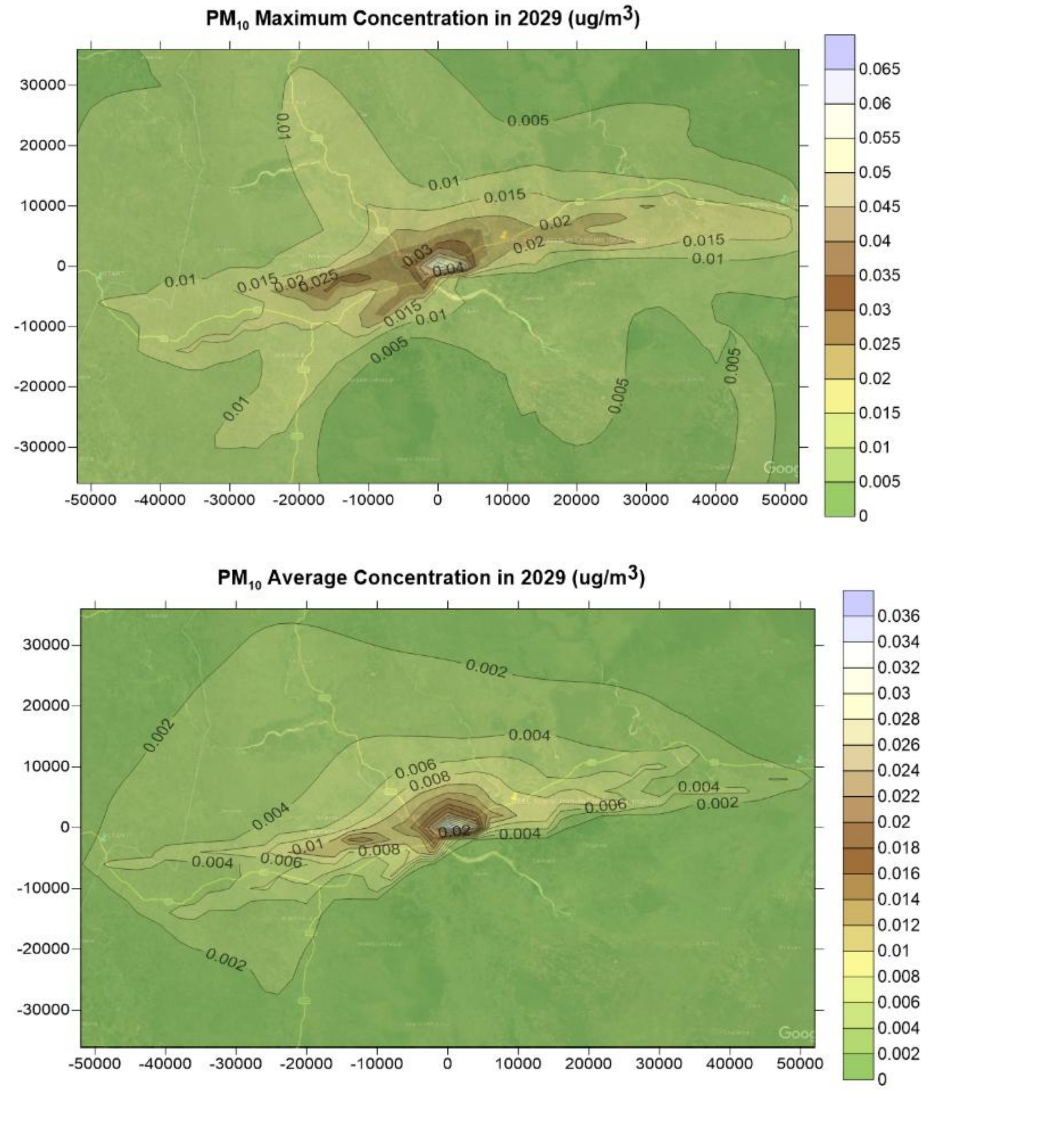
Air quality modeling spatial dispersion maps:

Air quality modeling spatial dispersion maps:

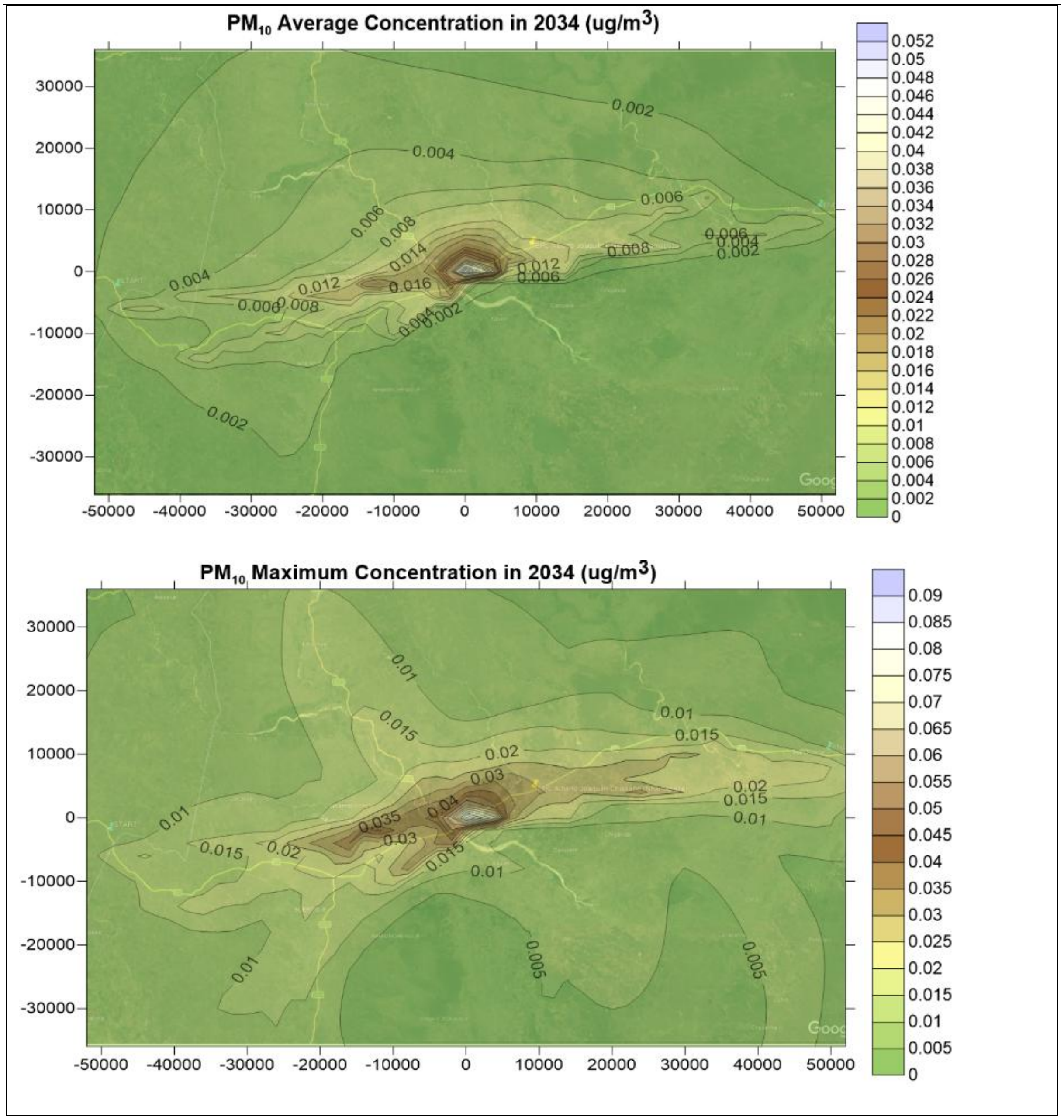
Dispersion maps for PM_{10}

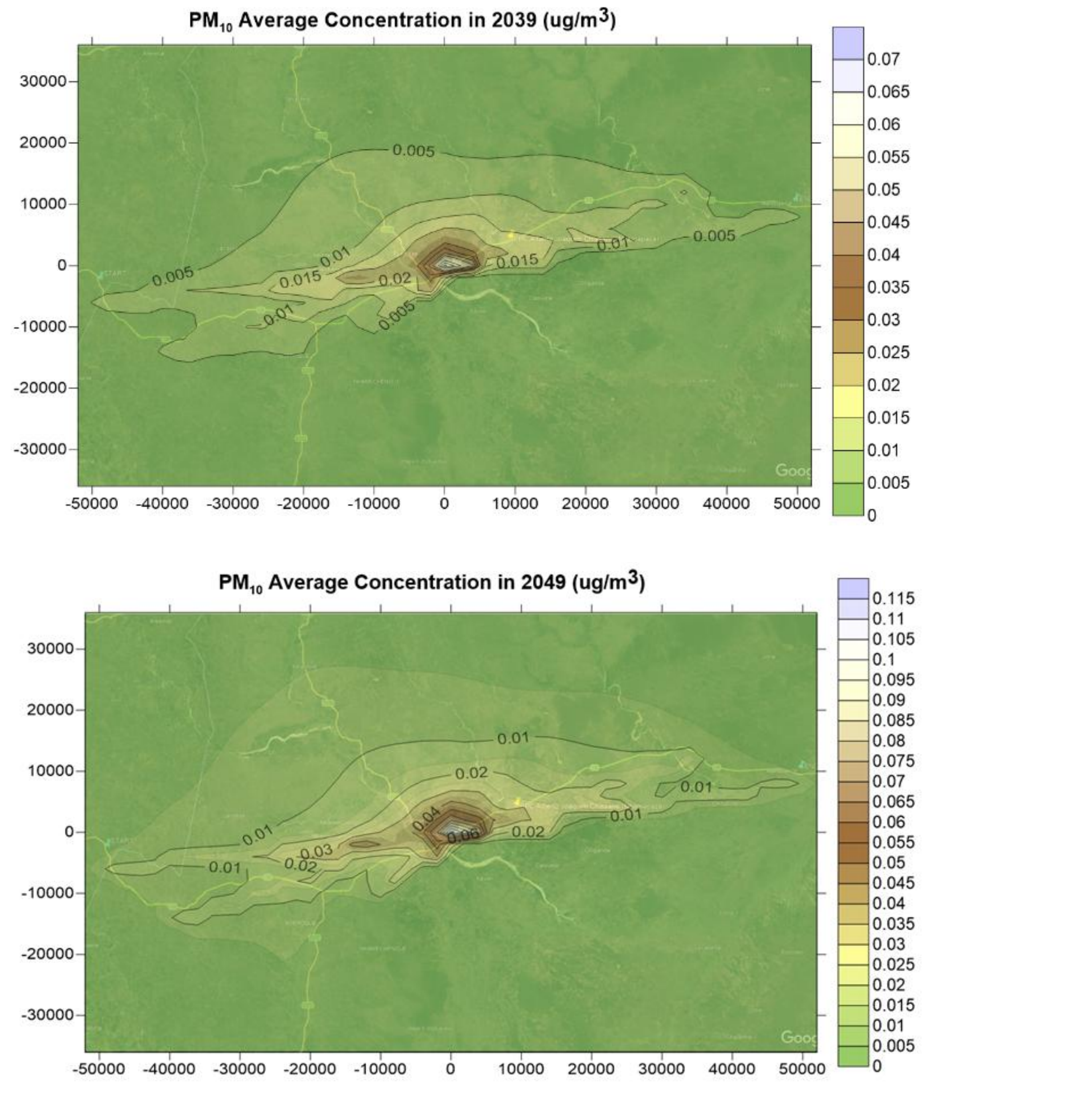





PM10 Maximum Concentration in 2029 (ug/m3)
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
PM10 Average Concentration in 2029 (ug/m3)
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0

Environmental and Social Impact Assessment: VOLUME 2B - MAIN REPORT

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0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
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0.11
0.105
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
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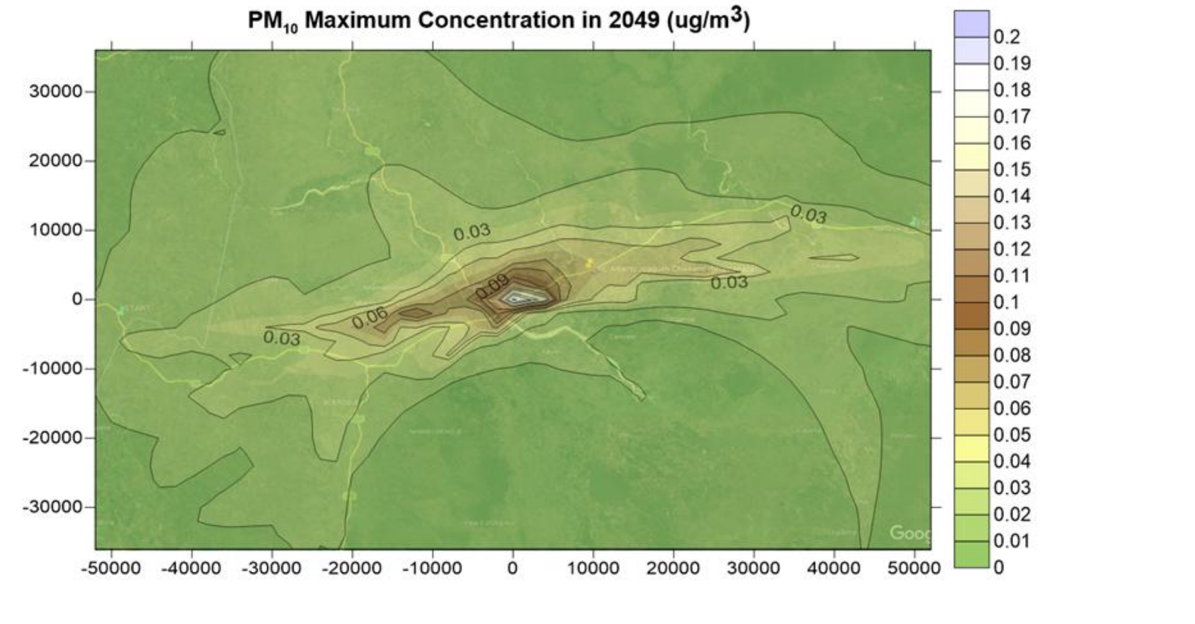
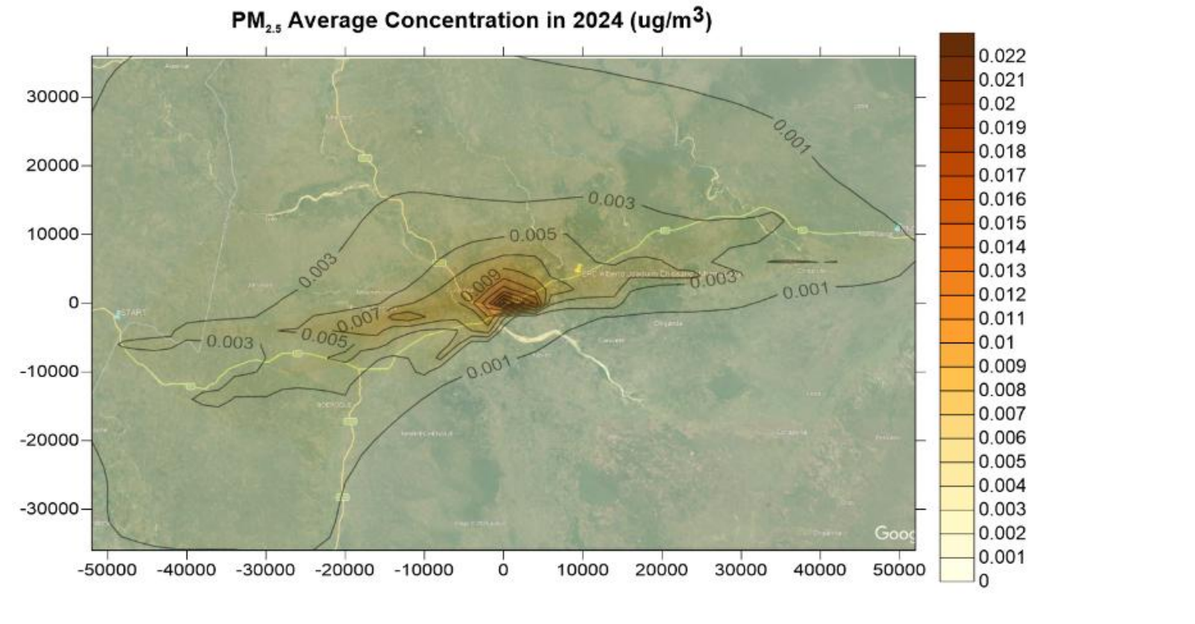
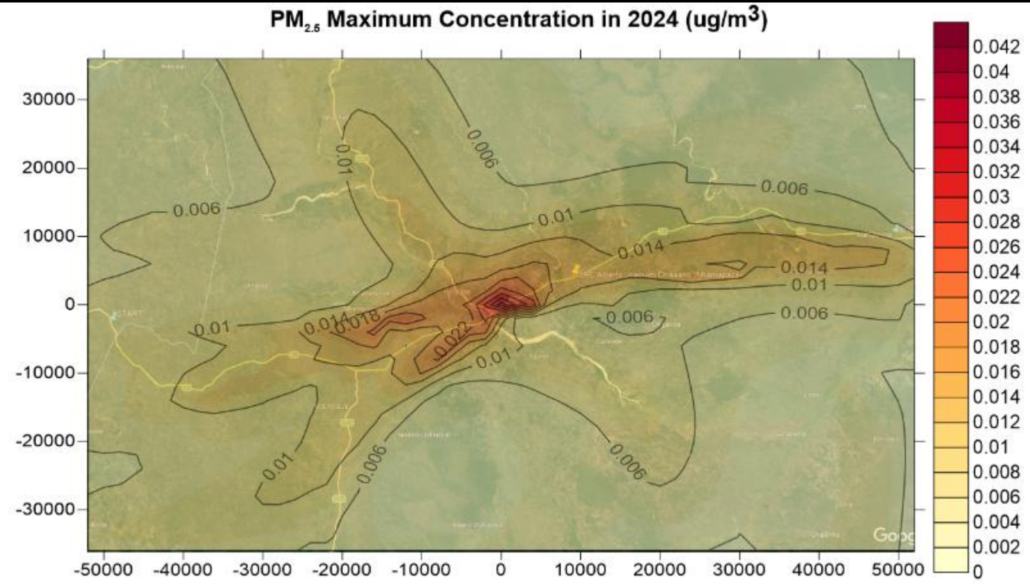


Dispersion maps for $PM_{2.5}$

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-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.006
0.01
0.014
0.018
0.022
0.042
0.04
0.038
0.036
0.034
0.032
0.03
0.028
0.026
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0.008
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0.002
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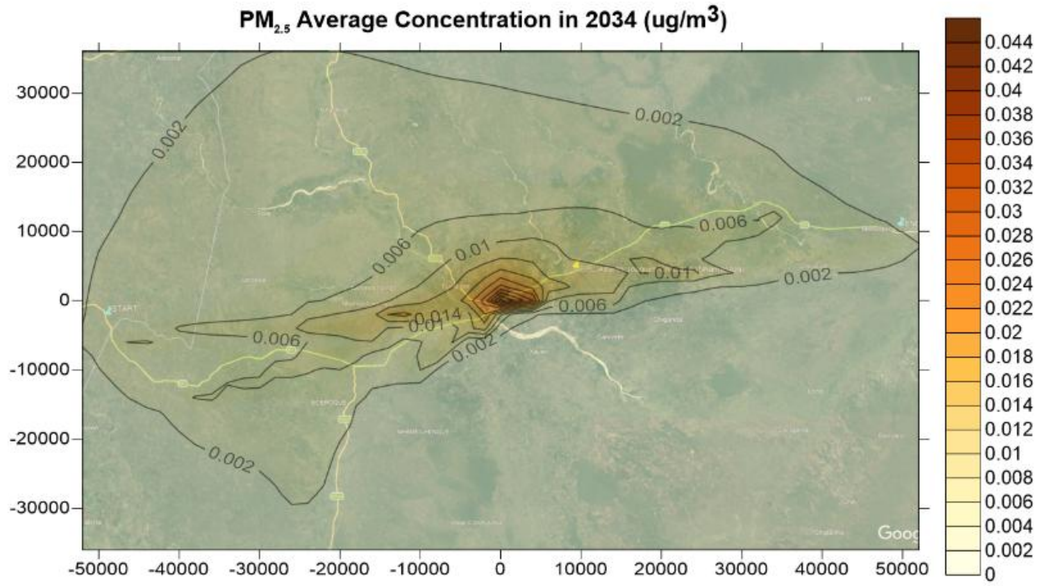
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-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
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50000
0.002
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0.042
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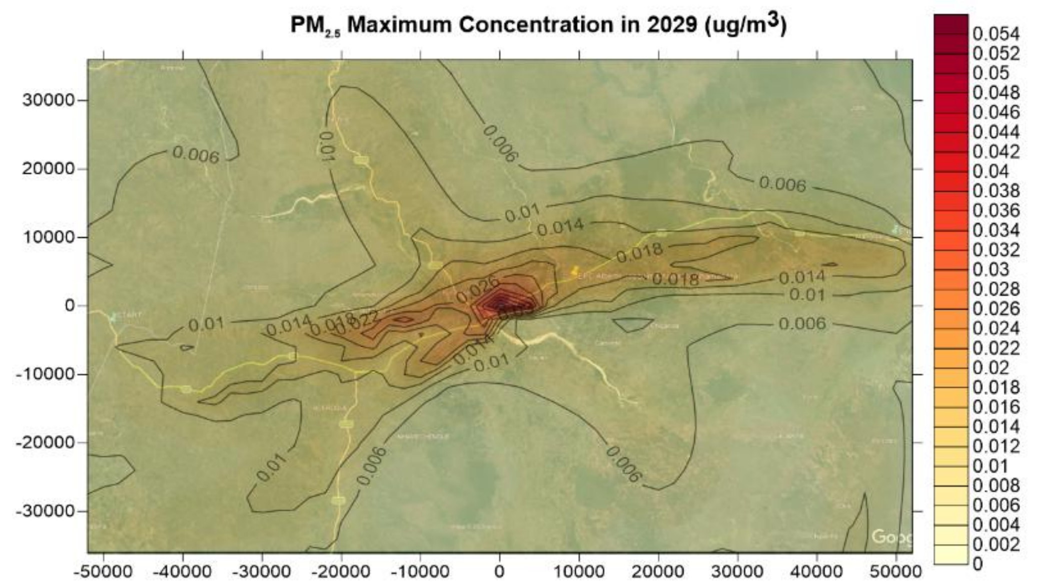
PM2.5 Maximum Concentration in 2029 (ug/m3)
30000
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-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.006
0.01
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0.026
0.054
0.052
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0.048
0.046
0.044
0.042
0.04
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0.036
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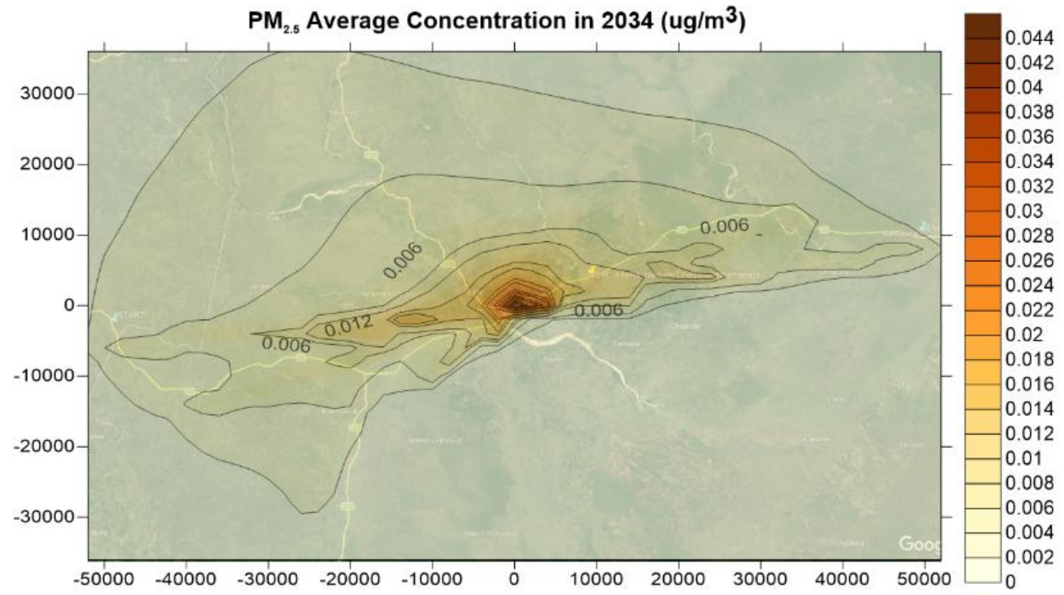
PM2.5 Average Concentration in 2034 (ug/m3)
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20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.006
0.012
0.044
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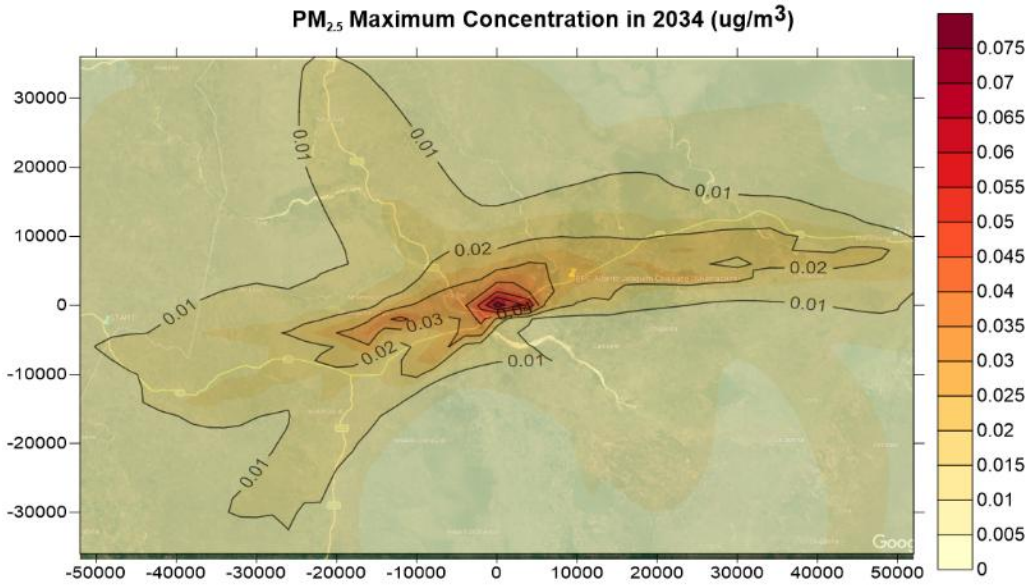
PM2.5 Maximum Concentration in 2034 (ug/m3)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.01
0.02
0.03
0.075
0.07
0.065
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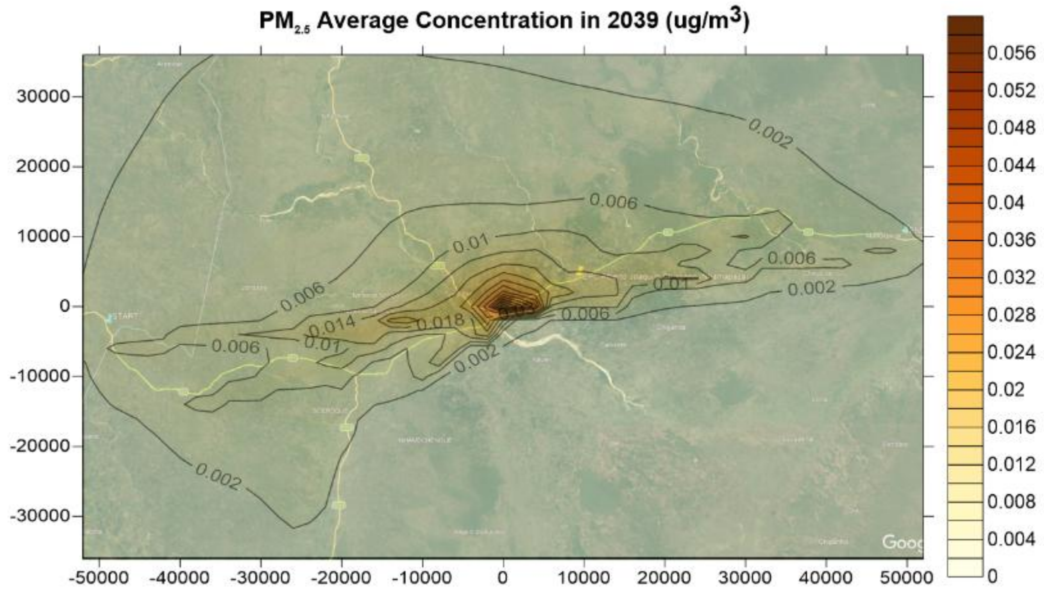
PM2.5 Average Concentration in 2039 (ug/m3)
30000
20000
10000
0
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-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.002
0.006
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0.014
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0.056
0.052
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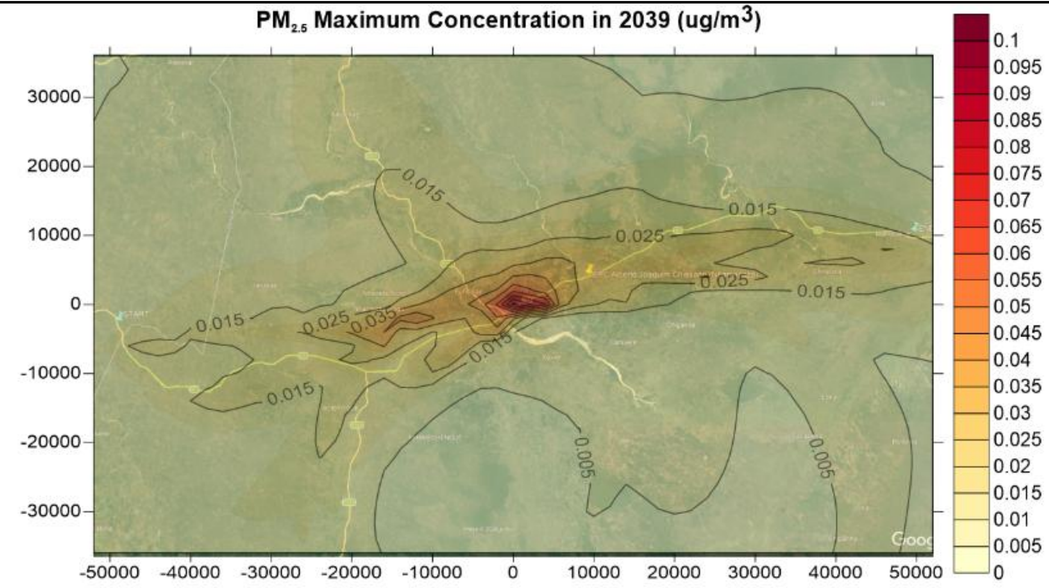
PM2.5 Maximum Concentration in 2039 (ug/m3)
30000
20000
10000
0
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-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.015
0.025
0.035
0.005
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
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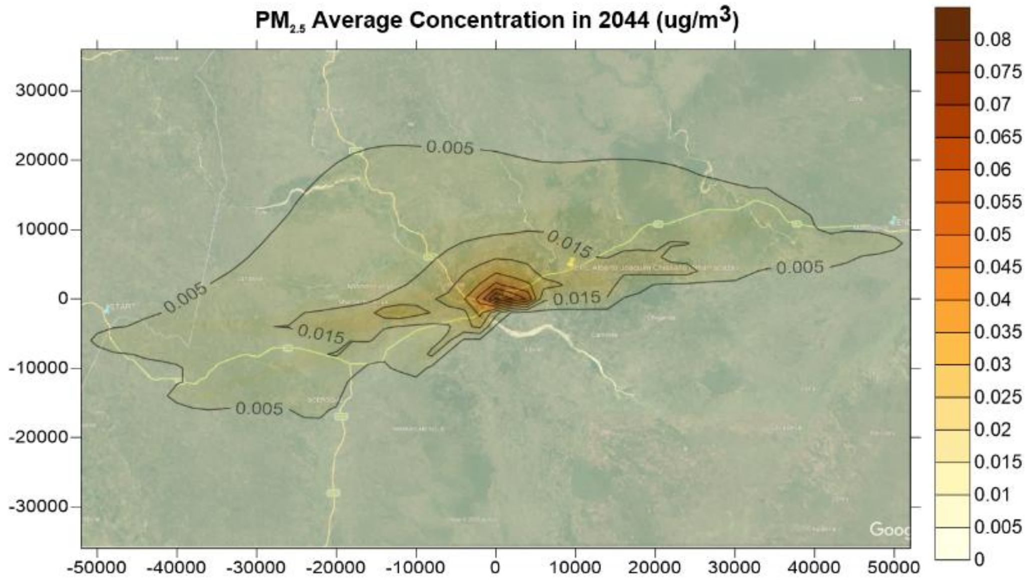
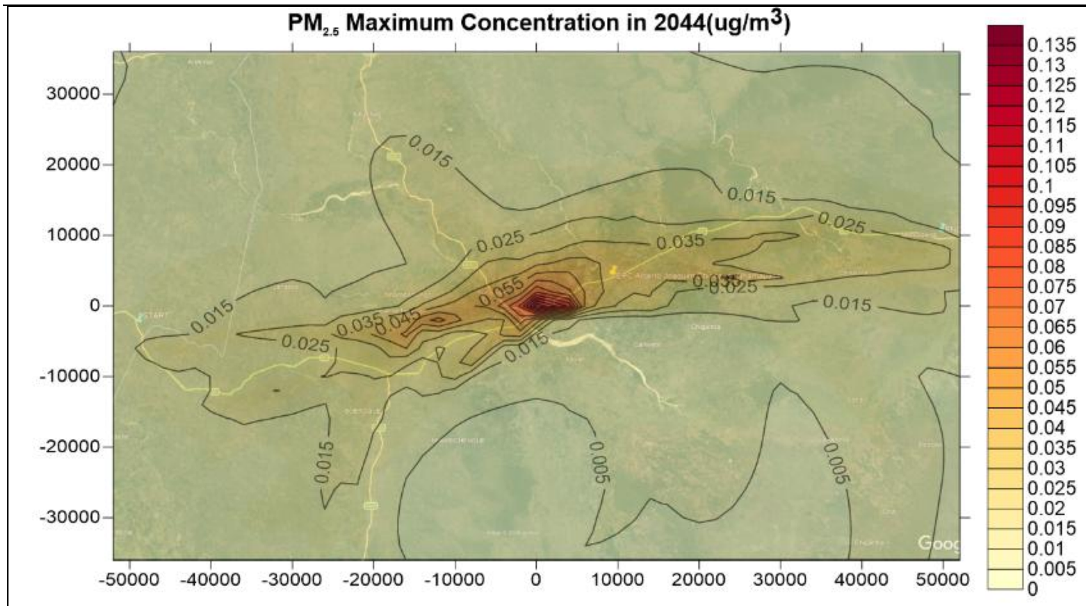
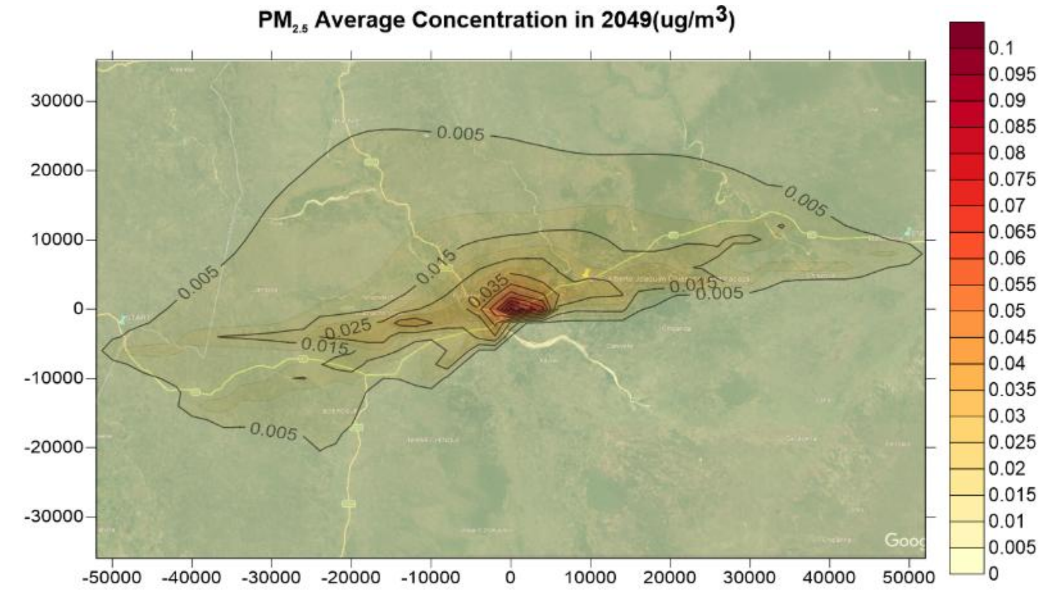
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0


PM2.5 Average Concentration in 2044 (ug/m3)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.005
0.015
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0


PM2.5 Maximum Concentration in 2044(ug/m3)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.015
0.025
0.035
0.045
0.055
0.005
0.135
0.13
0.125
0.12
0.115
0.11
0.105
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0


PM2.5 Average Concentration in 2049(ug/m3)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.005
0.015
0.025
0.035
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
0.055
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0.02
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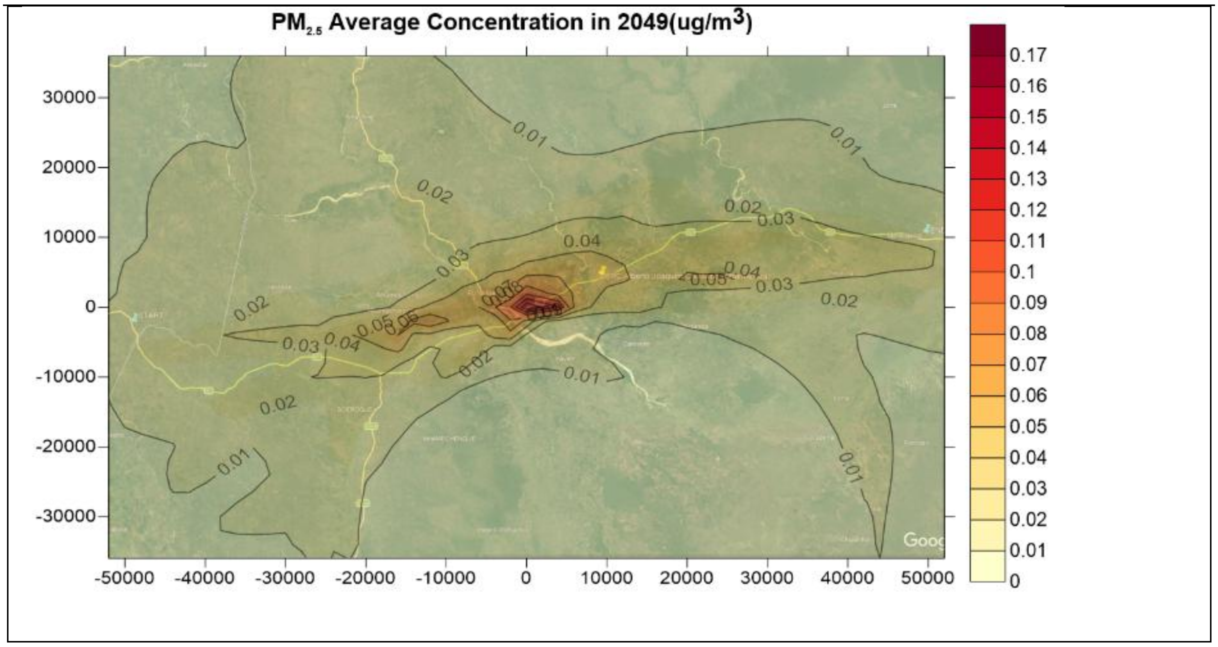
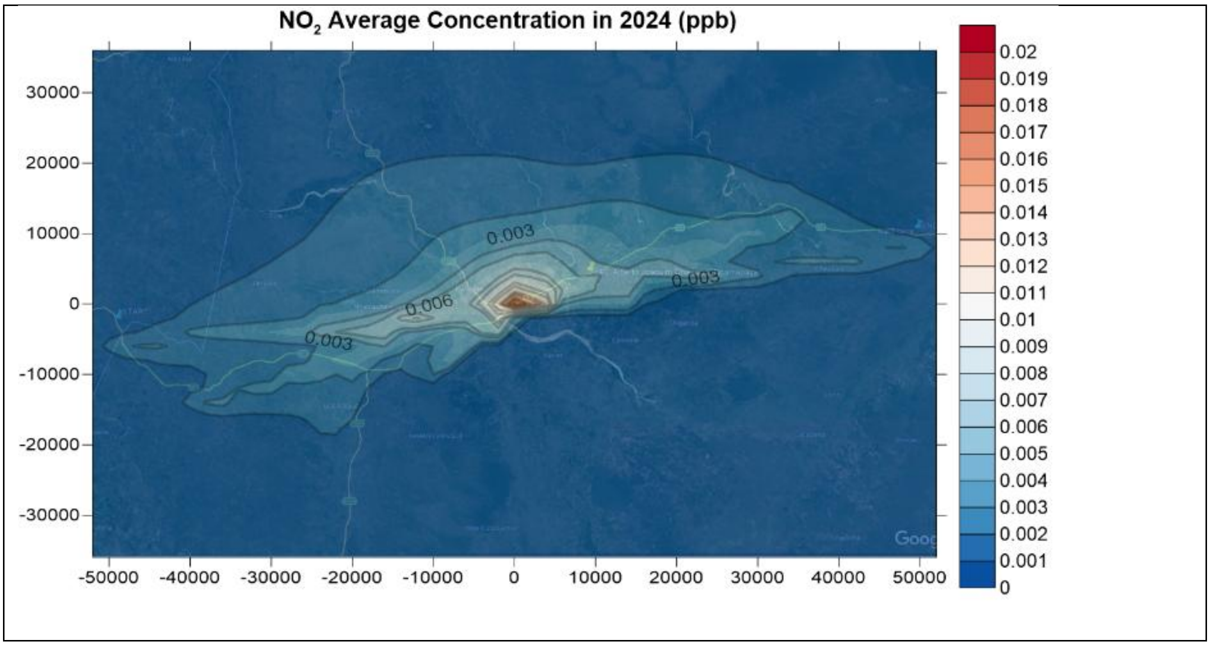
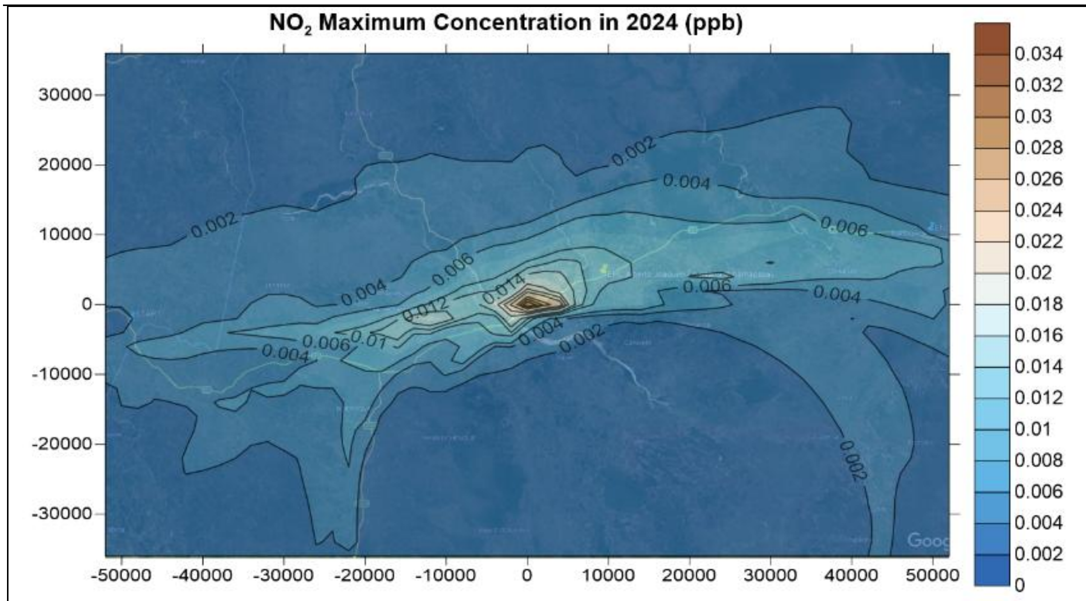
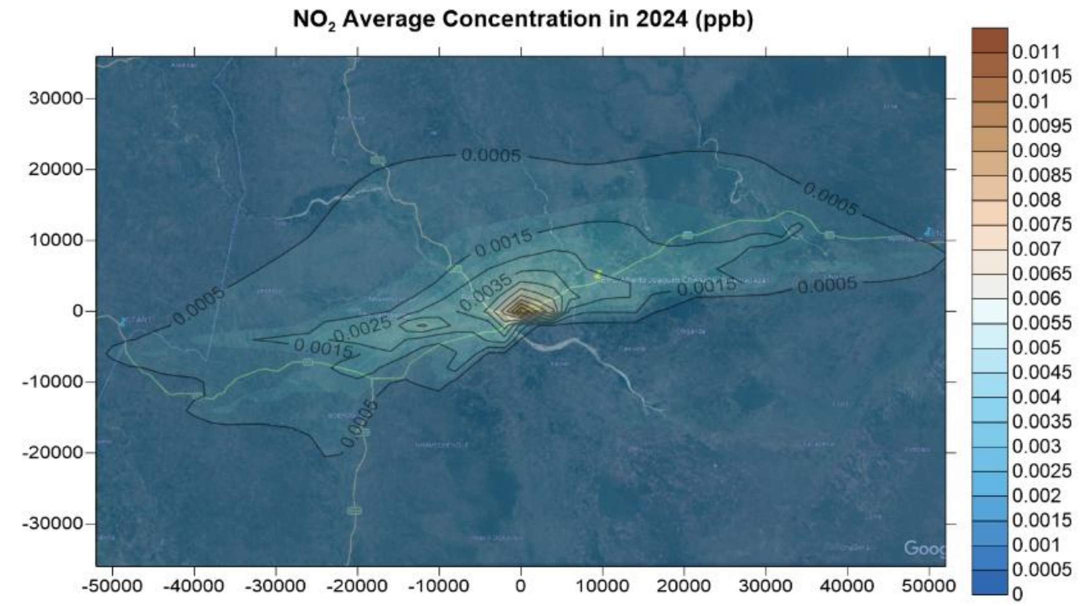
0.01
0.005
0

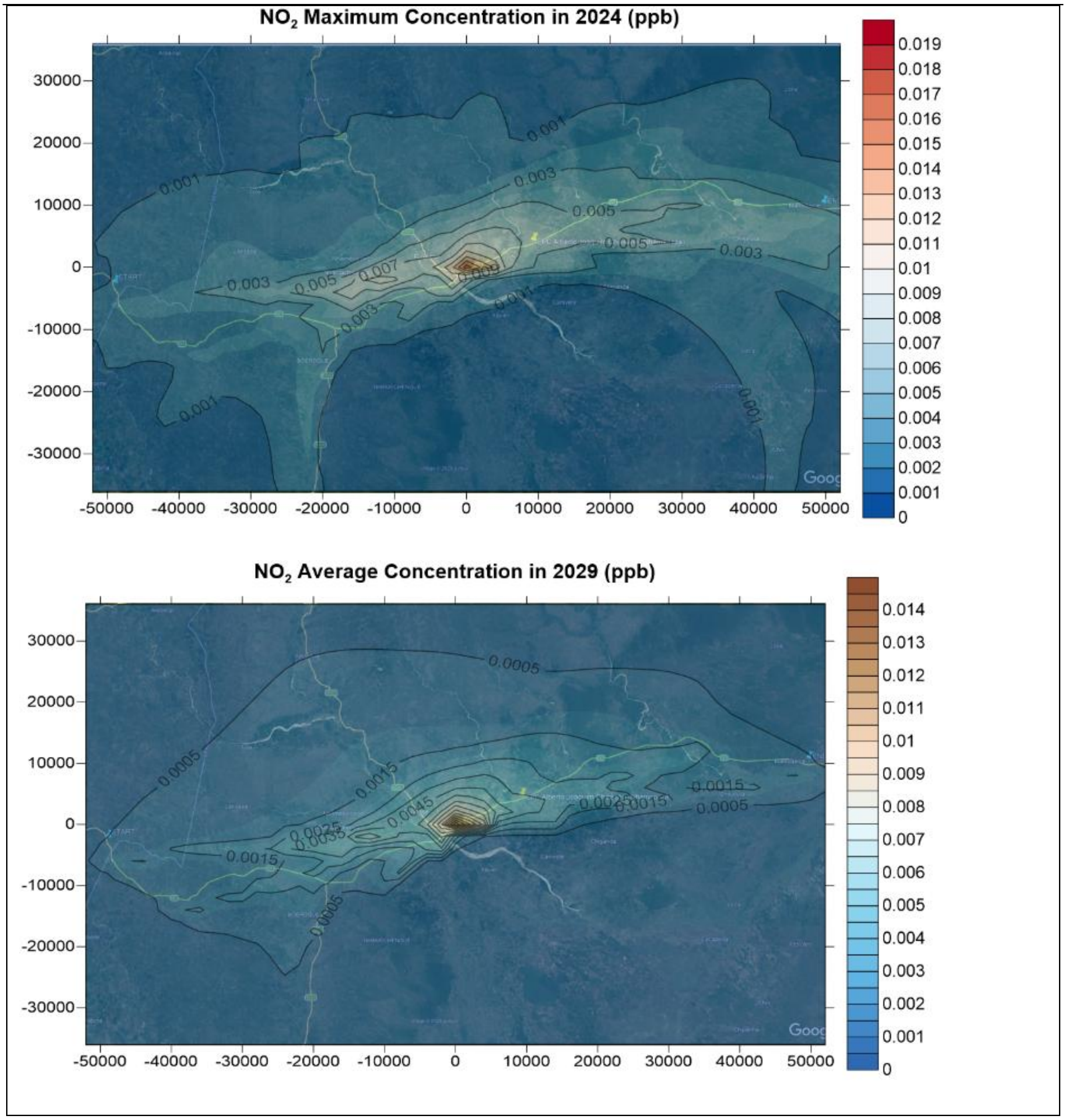


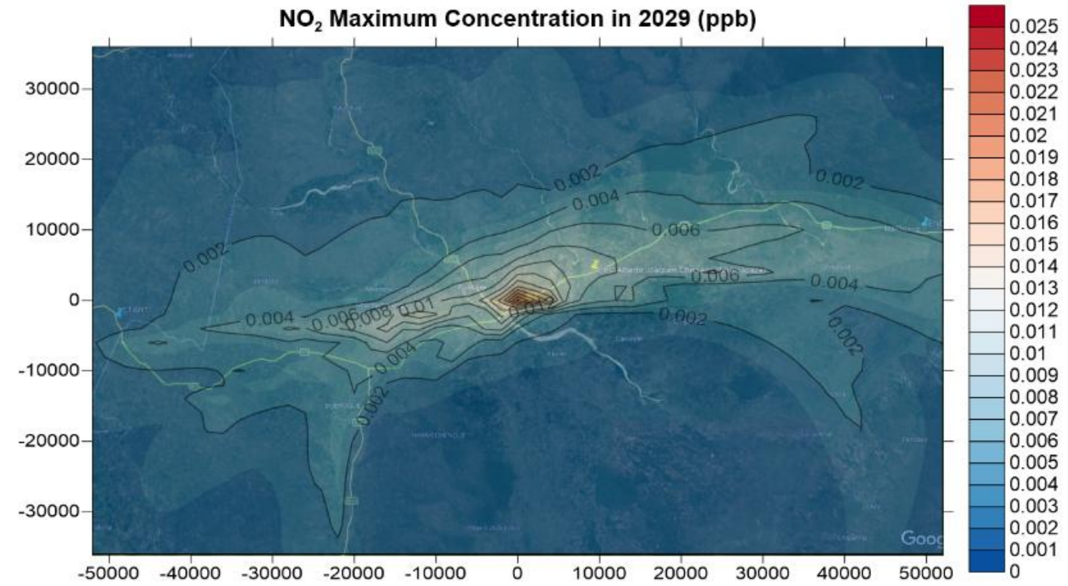
Dispersion maps for NO_2

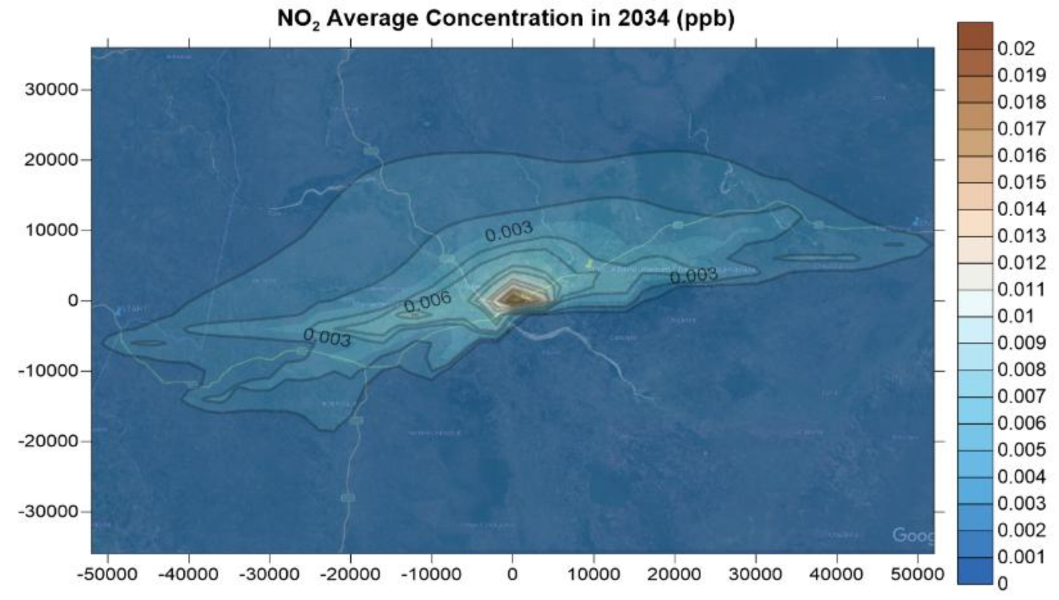


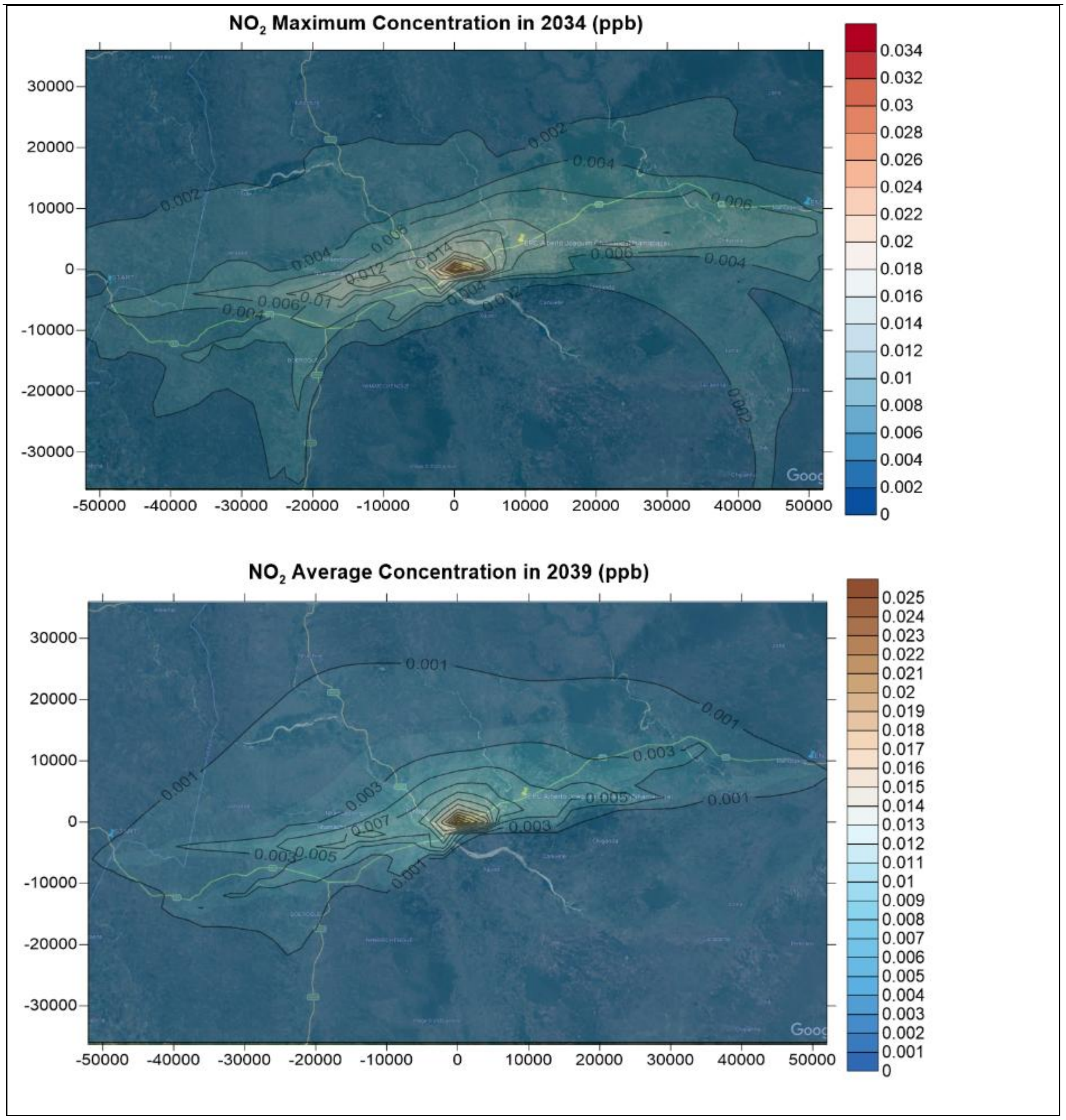

NO2 Maximum Concentration in 2024 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0

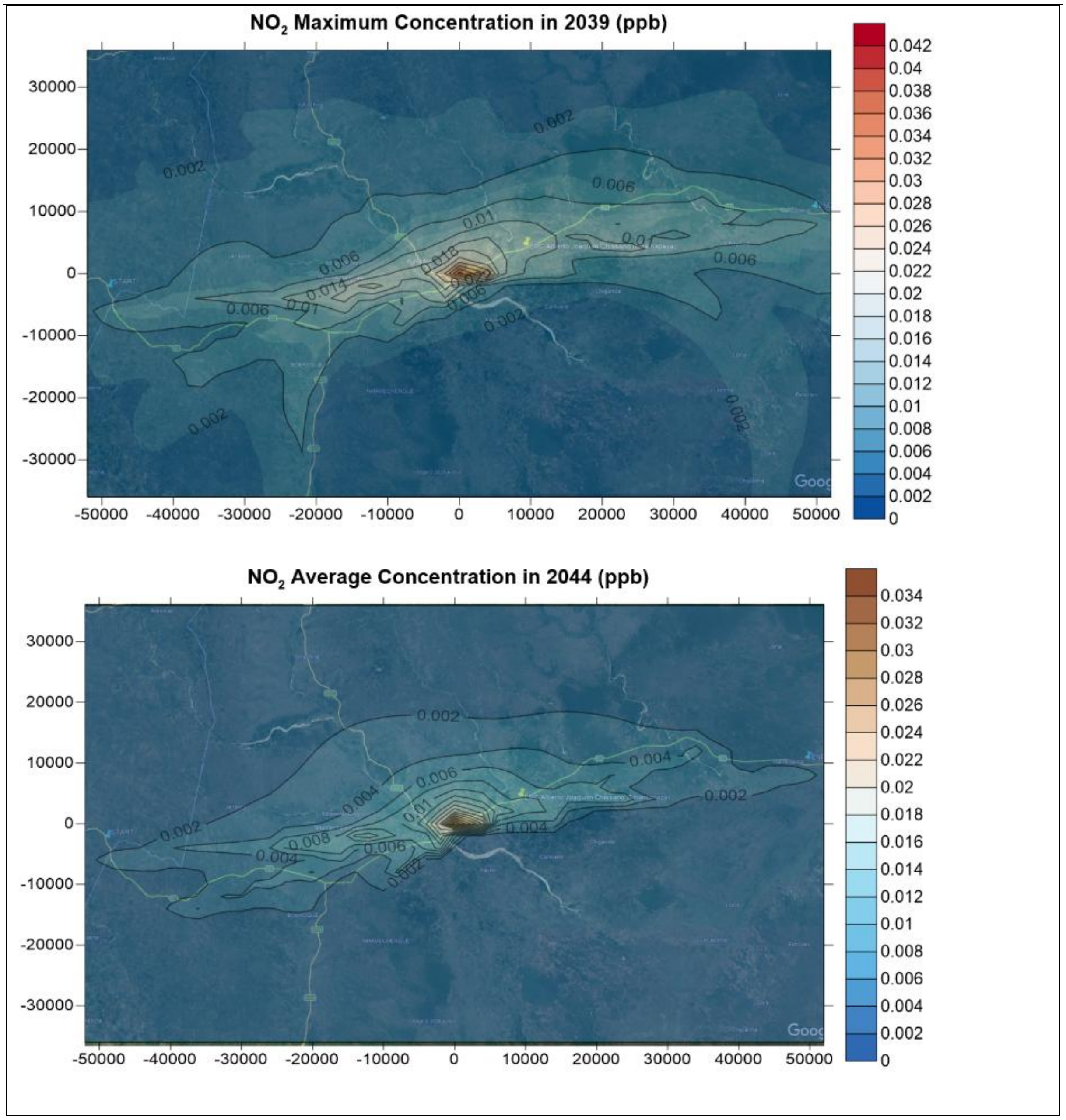

NO2 Average Concentration in 2024 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.011
0.0105
0.01
0.0095
0.009
0.0085
0.008
0.0075
0.007
0.0065
0.006
0.0055
0.005
0.0045
0.004
0.0035
0.003
0.0025
0.002
0.0015
0.001
0.0005
0

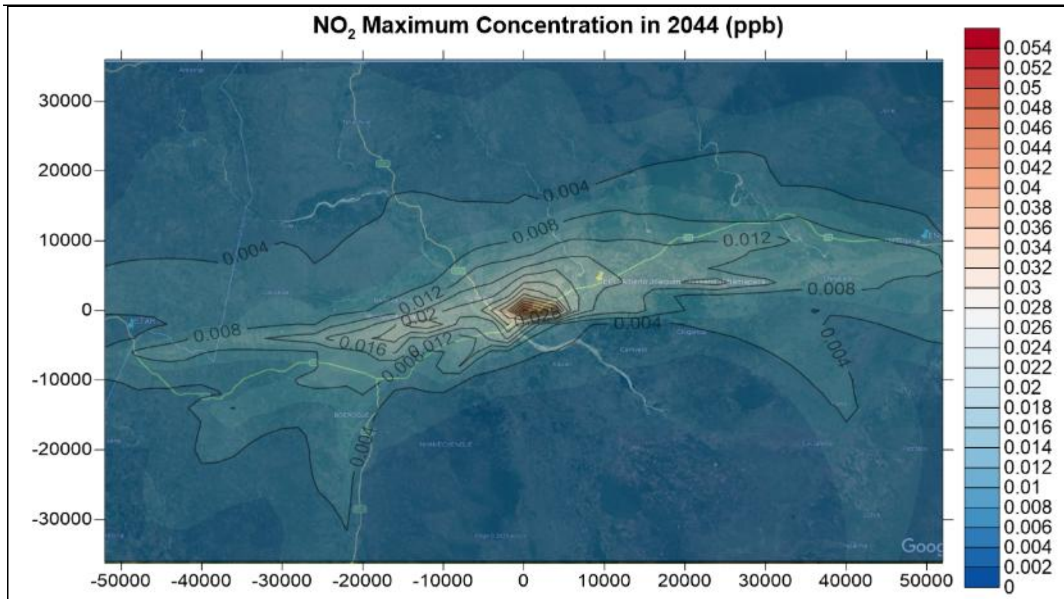

NO2 Maximum Concentration in 2024 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0
NO2 Average Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0

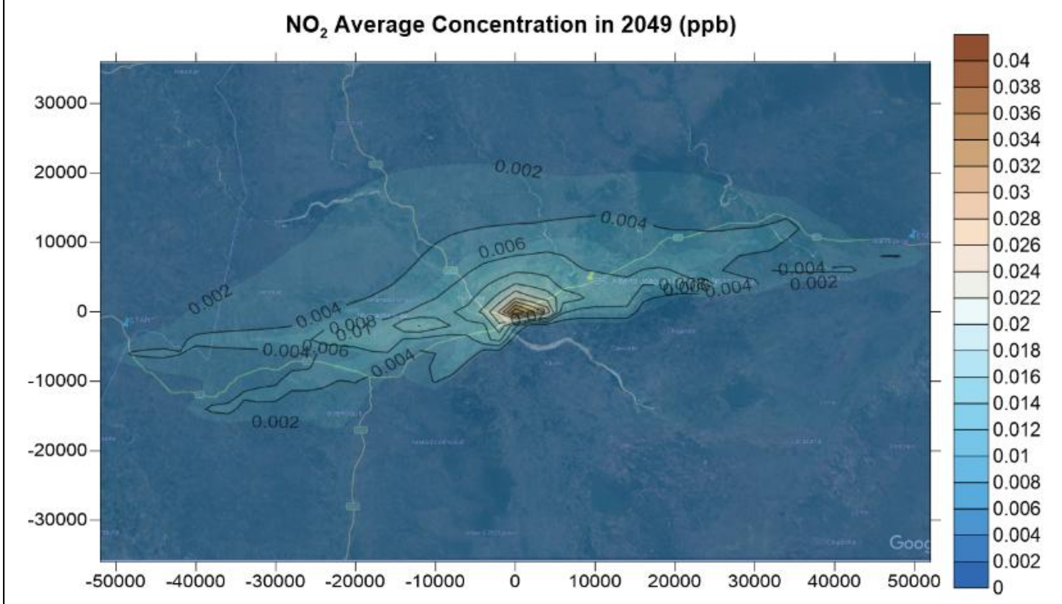

NO_2 Maximum Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.002
0.004
0.006
0.008
0.01
0.012
0.025
0.024
0.023
0.022
0.021
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0

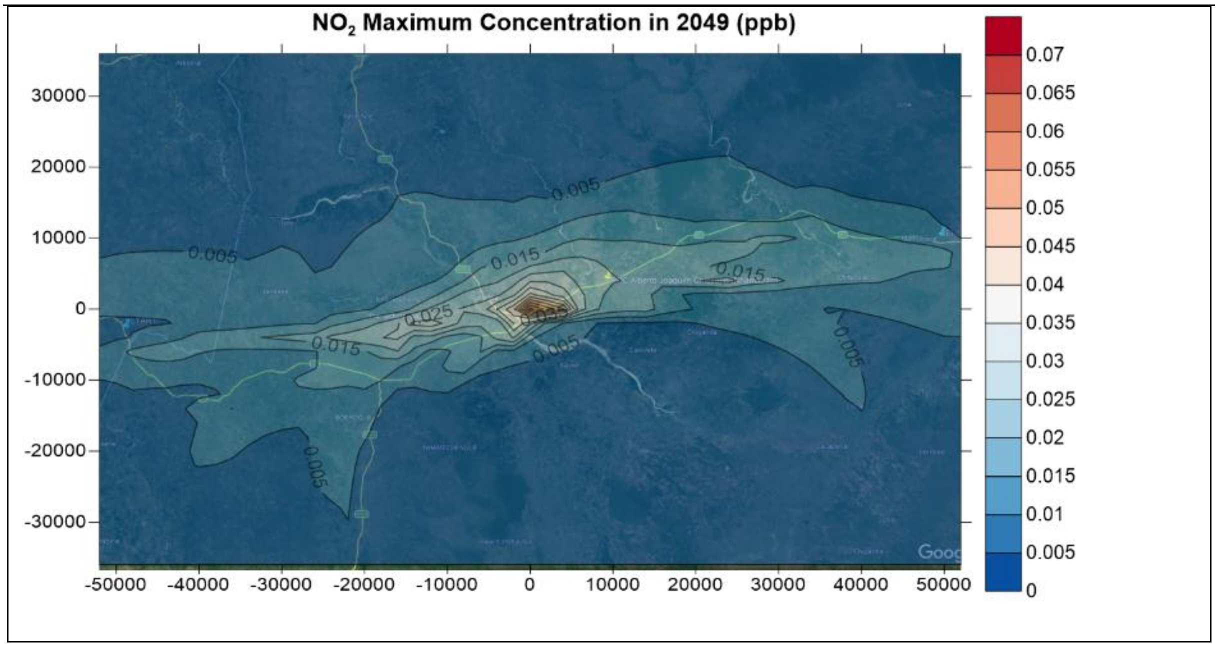

NO_2 Average Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.003
0.006
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0


NO_2 Maximum Concentration in 2034 (ppb)
NO_2 Average Concentration in 2039 (ppb)

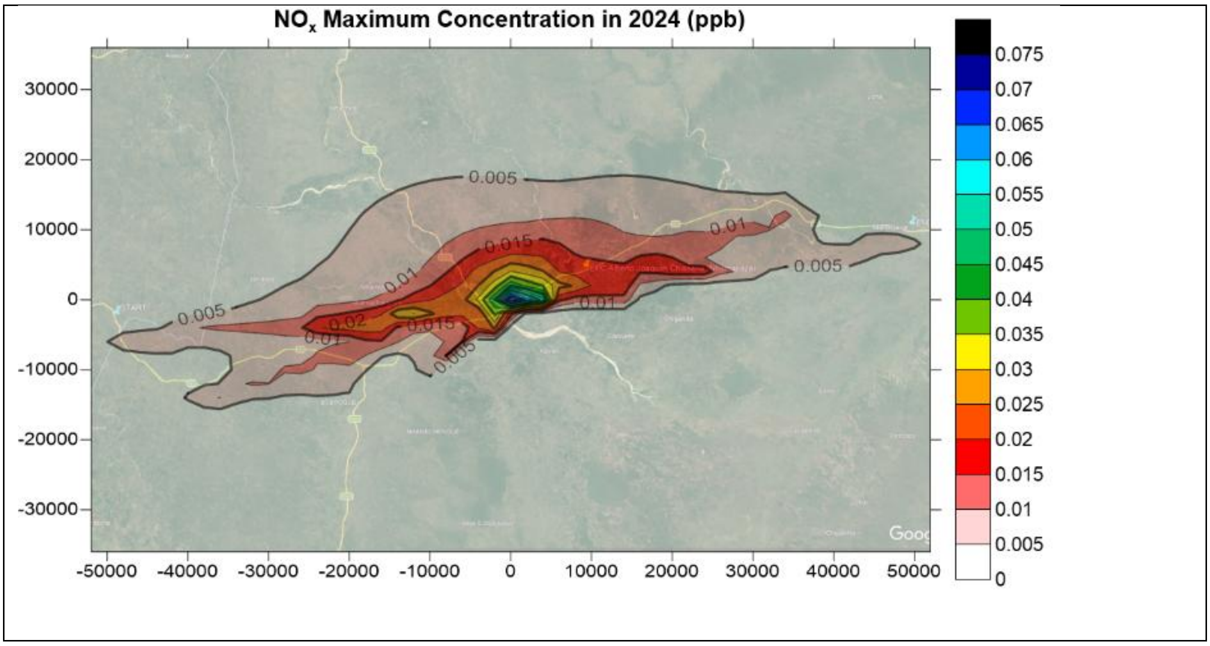

NO2 Maximum Concentration in 2039 (ppb)
NO2 Average Concentration in 2044 (ppb)

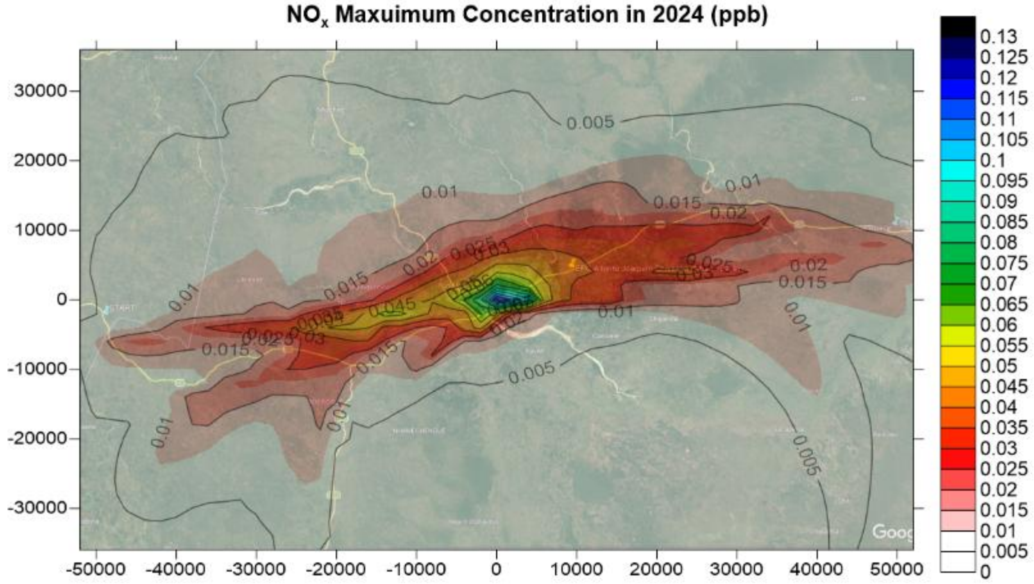

NO_2 Maximum Concentration in 2044 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.054 0.052 0.05 0.048 0.046 0.044 0.042 0.04 0.038 0.036 0.034 0.032 0.03 0.028 0.026 0.024 0.022 0.02 0.018 0.016 0.014 0.012 0.01 0.008 0.006 0.004 0.002 0

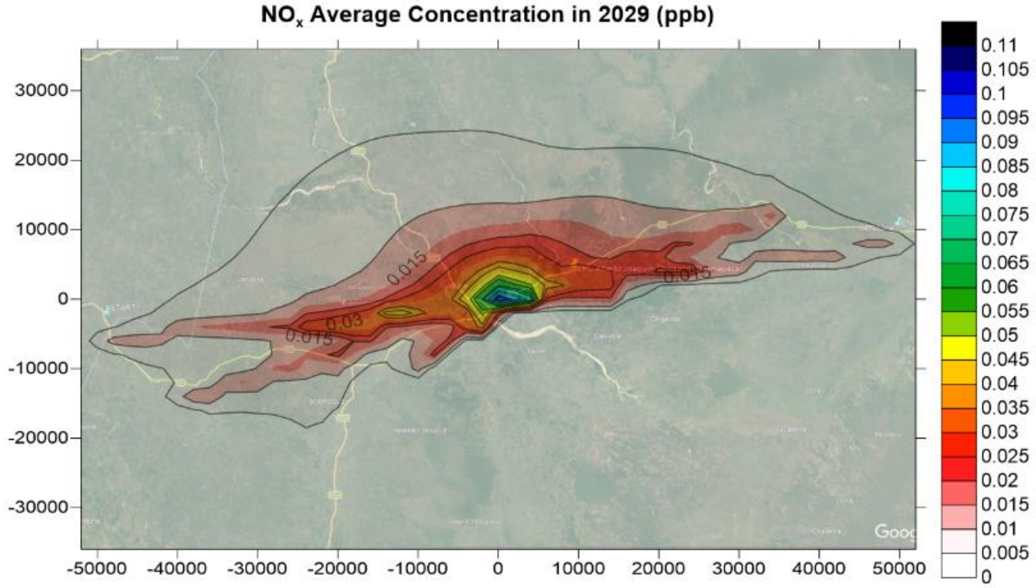

NO_2 Average Concentration in 2049 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.04 0.038 0.036 0.034 0.032 0.03 0.028 0.026 0.024 0.022 0.02 0.018 0.016 0.014 0.012 0.01 0.008 0.006 0.004 0.002 0

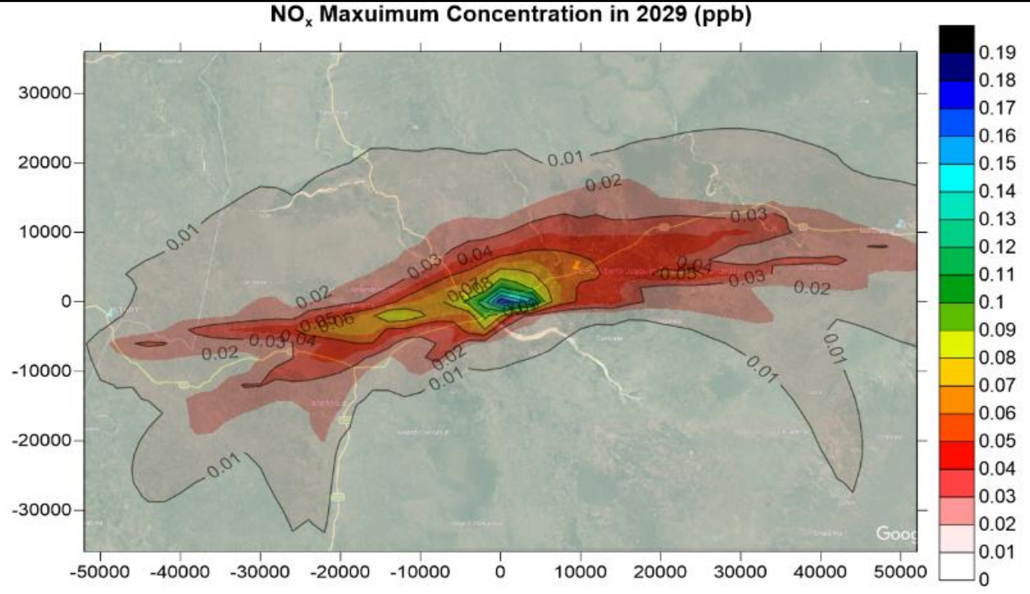


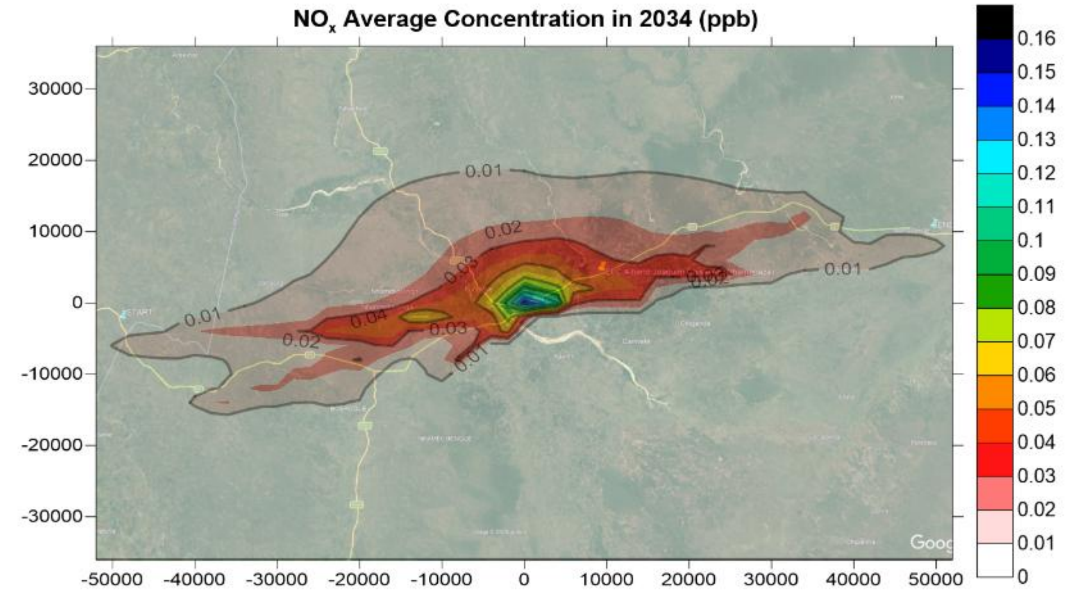
Dispersion maps for NO_x

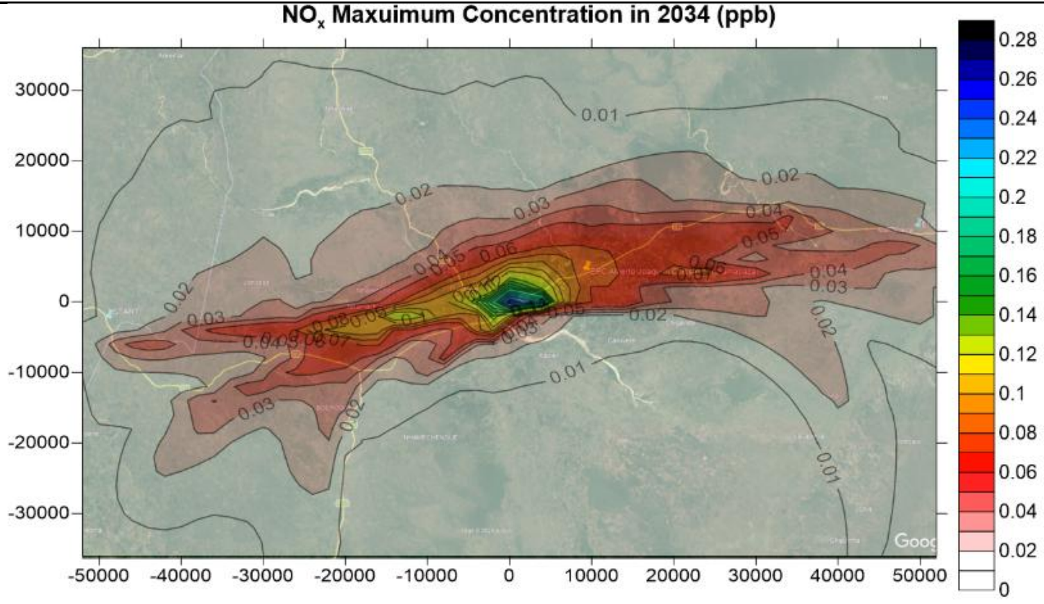


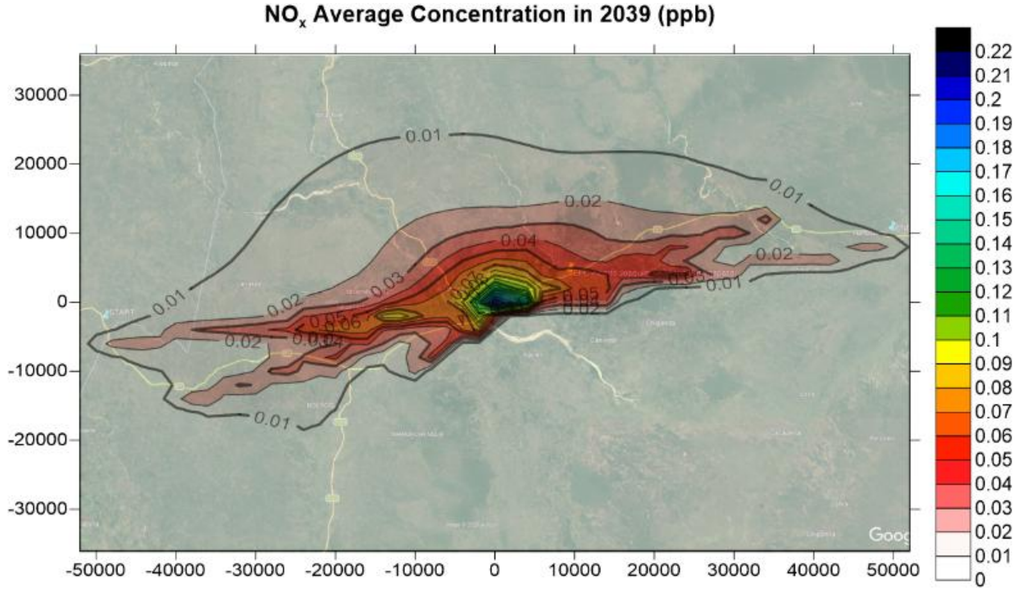

NOx Maxuimum Concentration in 2024 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.13
0.125
0.12
0.115
0.11
0.105
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0

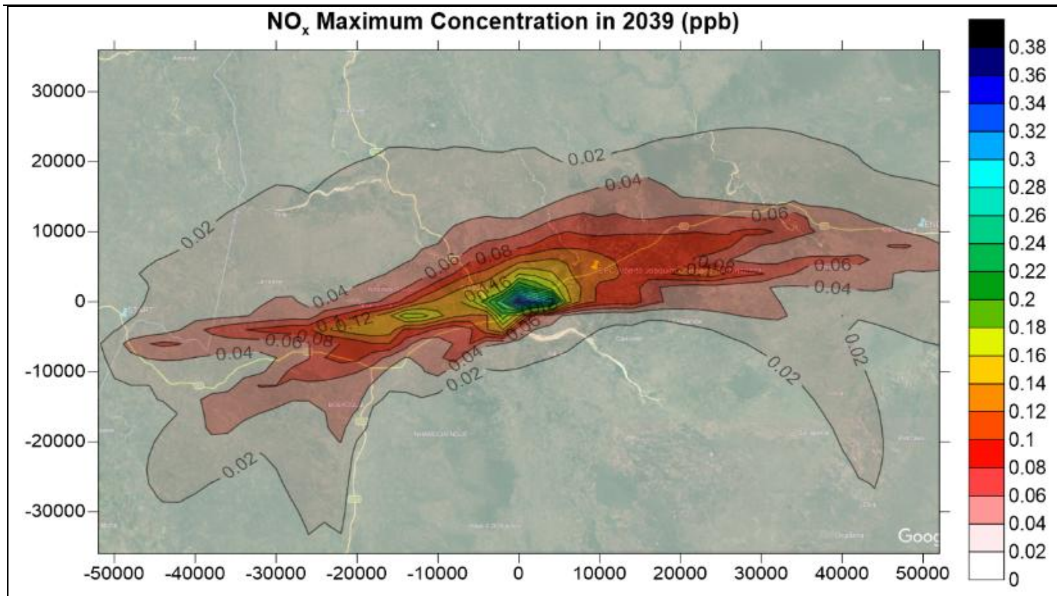

NOx Average Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.11
0.105
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0

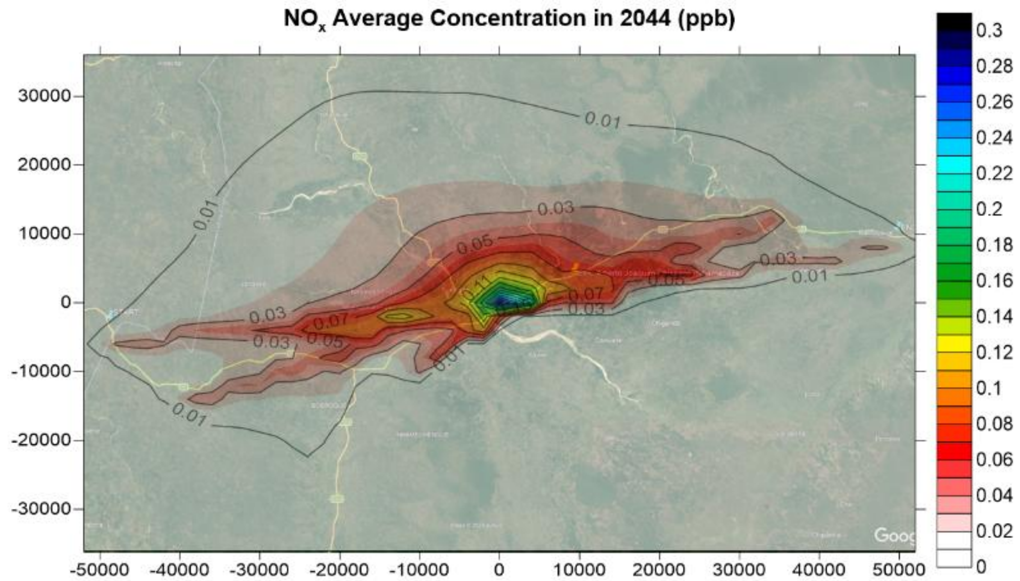

NOx Maxuimum Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0

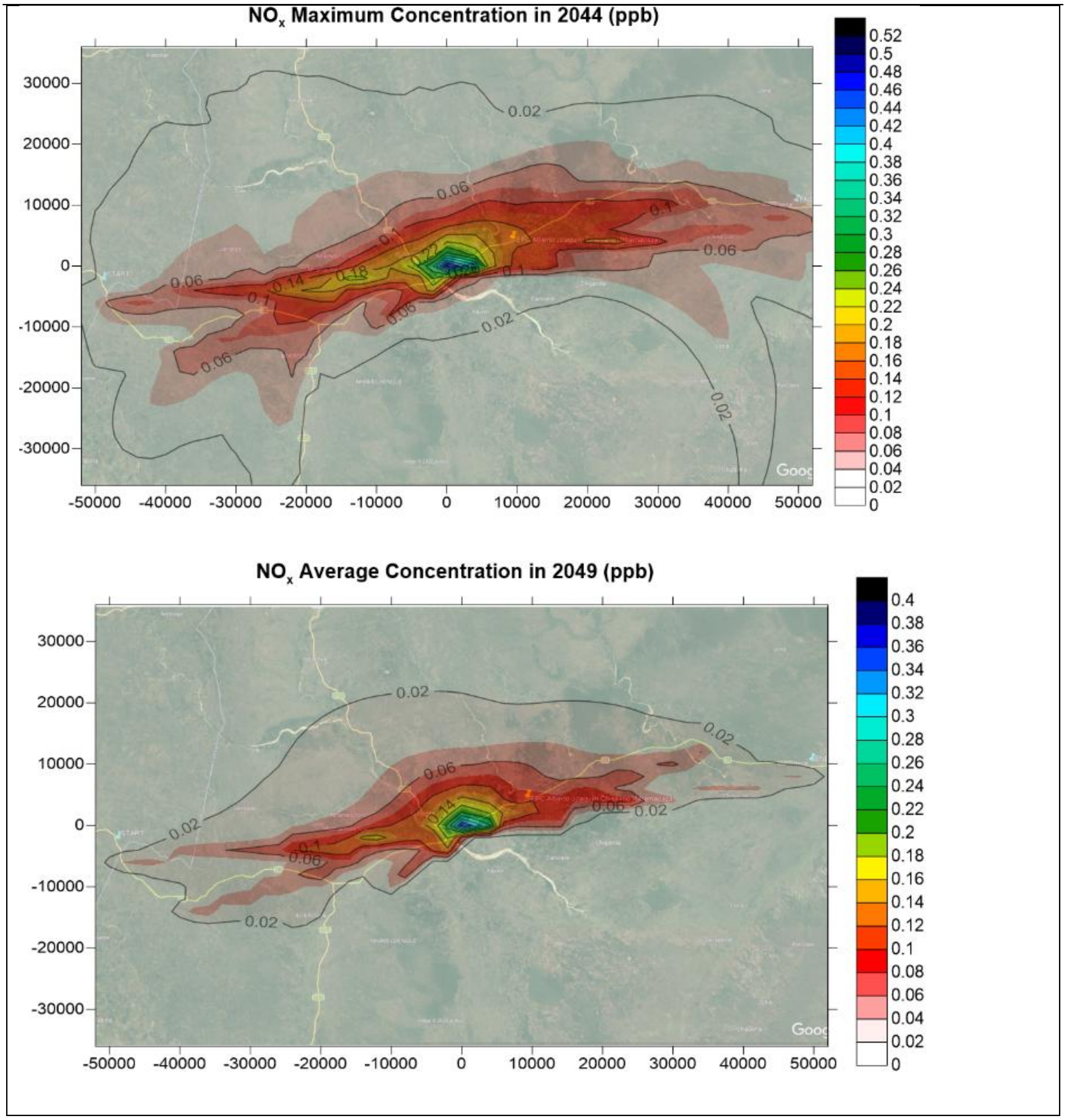

NOx Average Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0

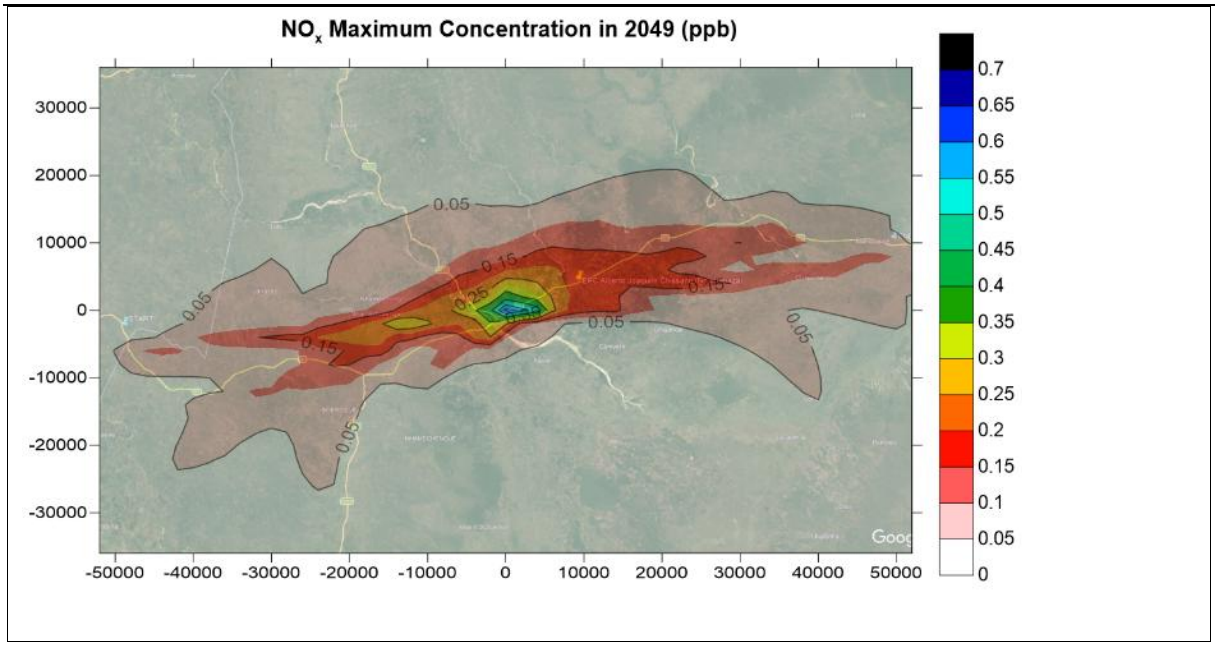

NOx Maxuimum Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.28
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0


NOx Average Concentration in 2039 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0

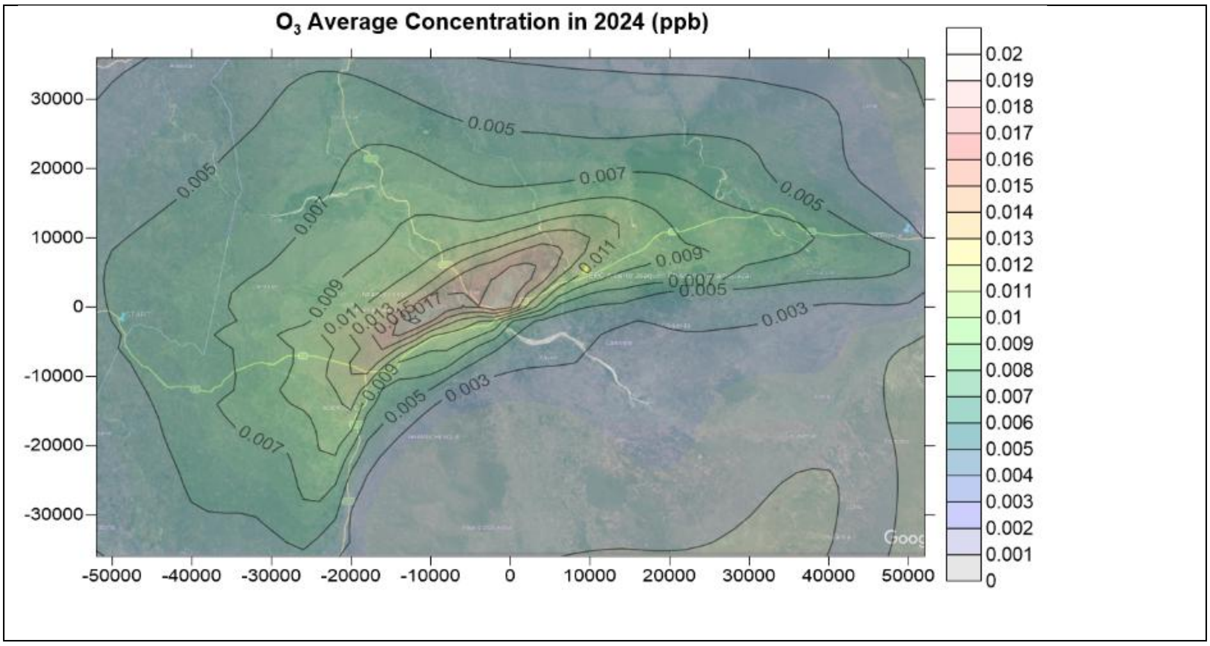

NO_x Maximum Concentration in 2039 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.38
0.36
0.34
0.32
0.3
0.28
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0

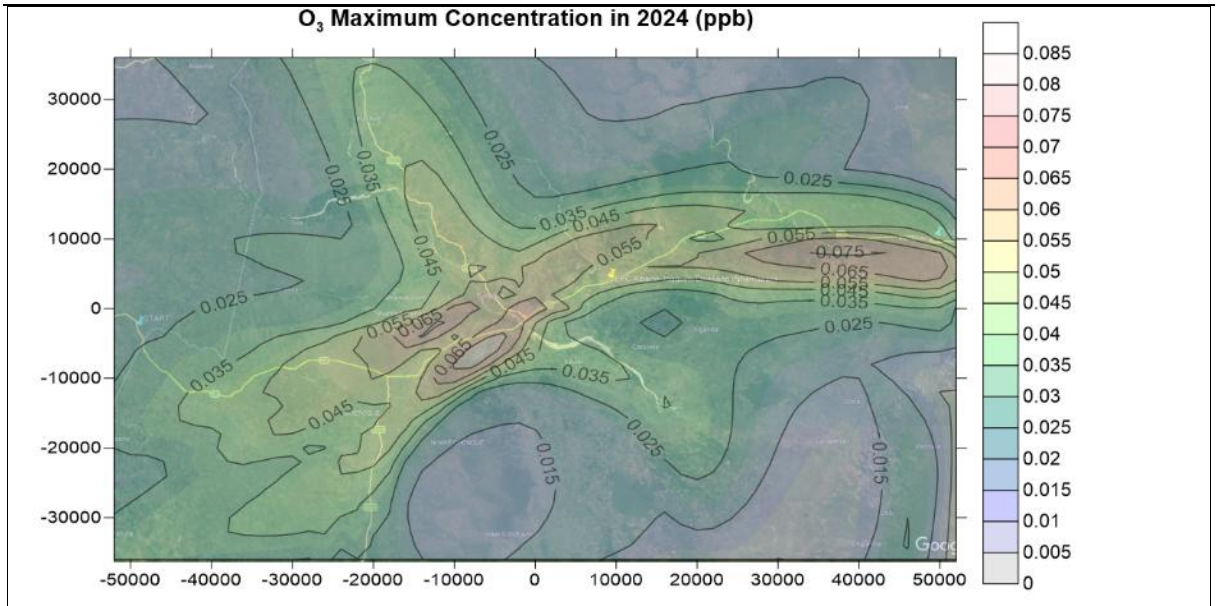

NO_x Average Concentration in 2044 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.3
0.28
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0

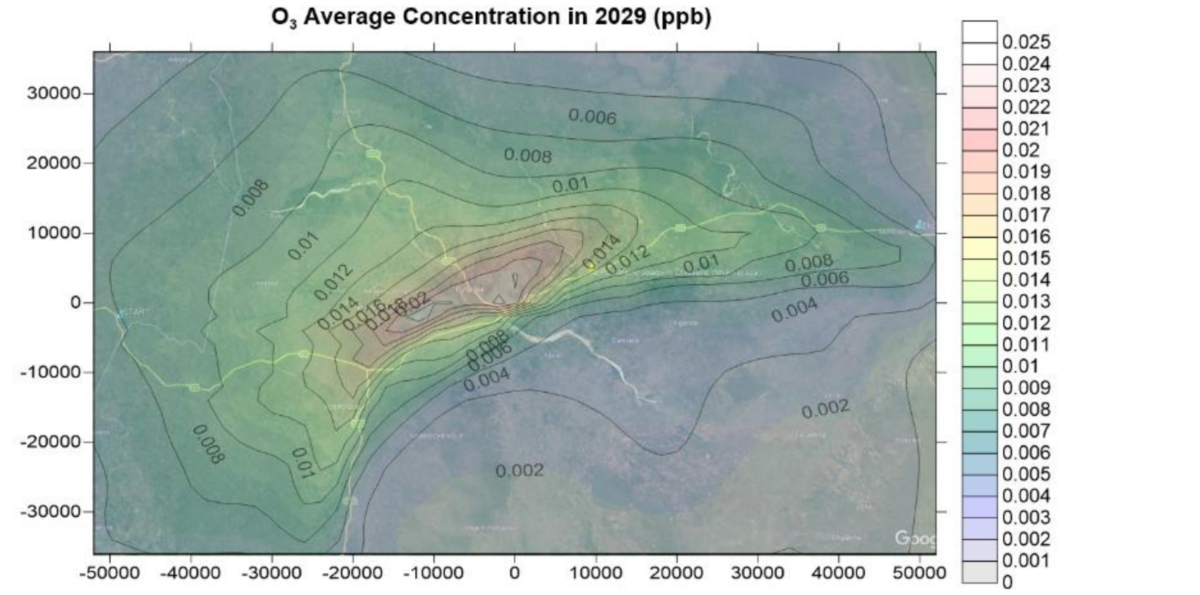

NOx Maximum Concentration in 2044 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.02
0.06
0.1
0.14
0.18
0.22
0.52 0.5 0.48 0.46 0.44 0.42 0.4 0.38 0.36 0.34 0.32 0.3 0.28 0.26 0.24 0.22 0.2 0.18 0.16 0.14 0.12 0.1 0.08 0.06 0.04 0.02 0
NOx Average Concentration in 2049 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.02
0.06
0.1
0.14
0.4 0.38 0.36 0.34 0.32 0.3 0.28 0.26 0.24 0.22 0.2 0.18 0.16 0.14 0.12 0.1 0.08 0.06 0.04 0.02 0

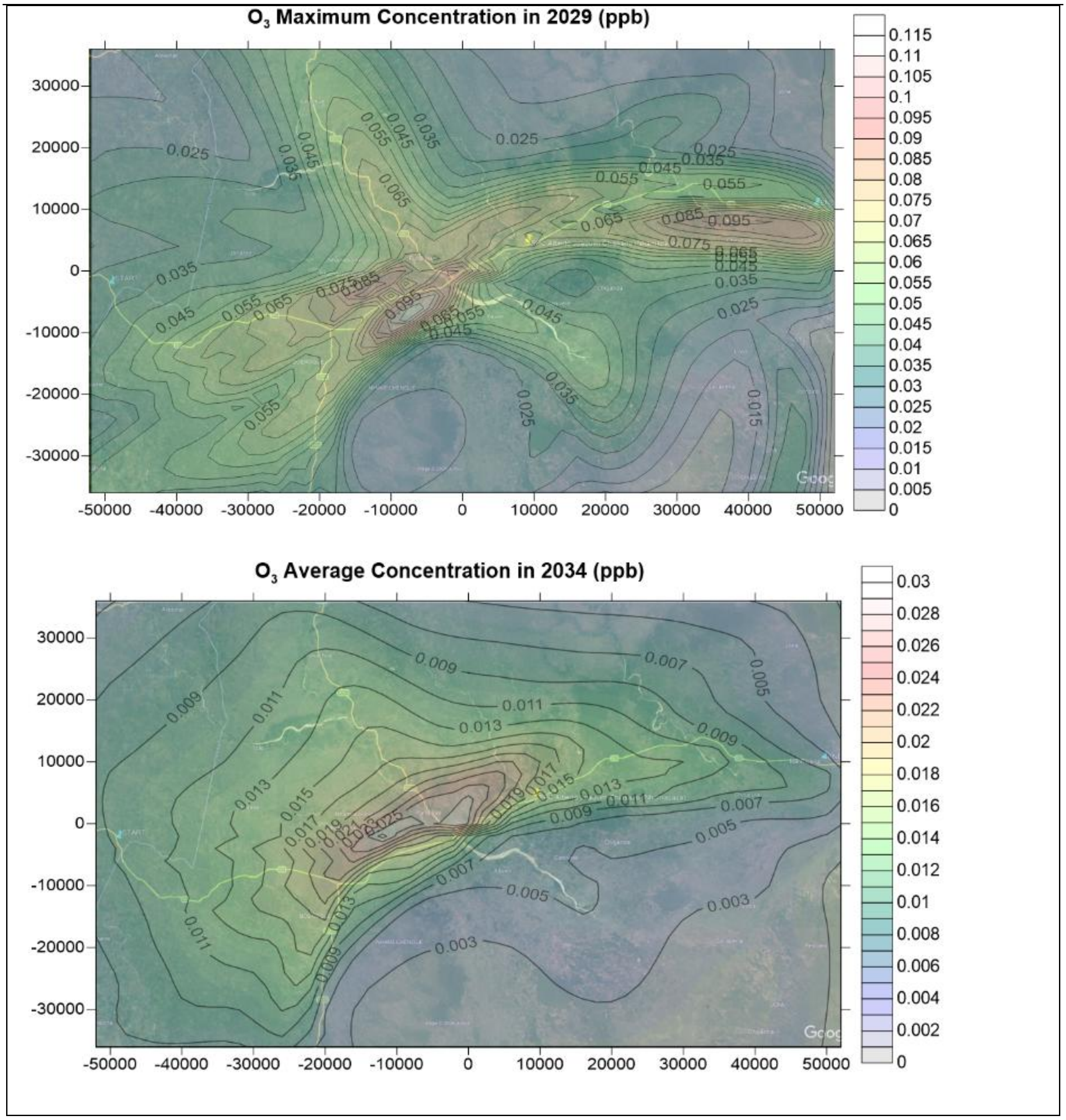


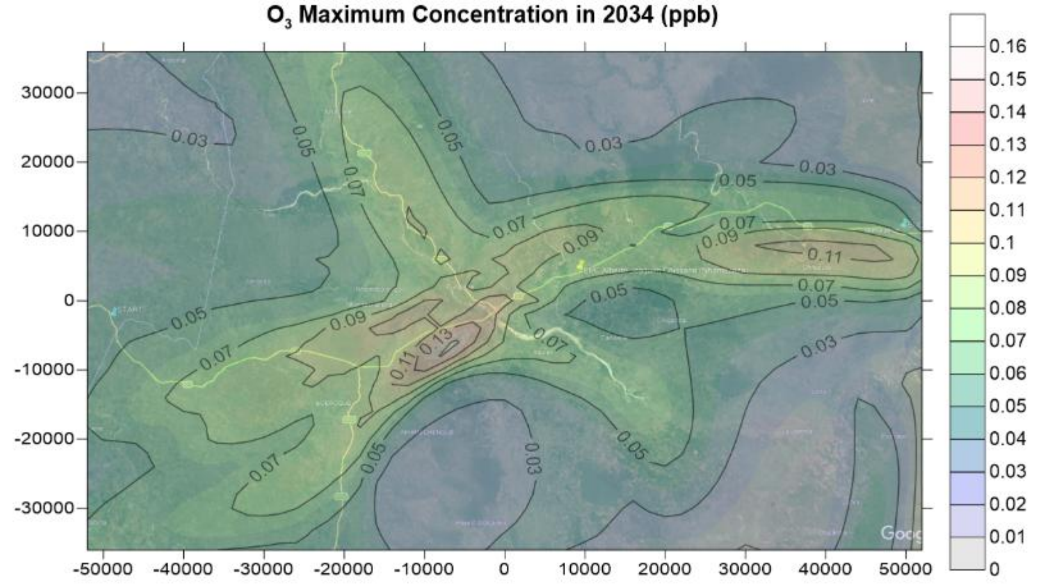
Dispersion maps for Ozone

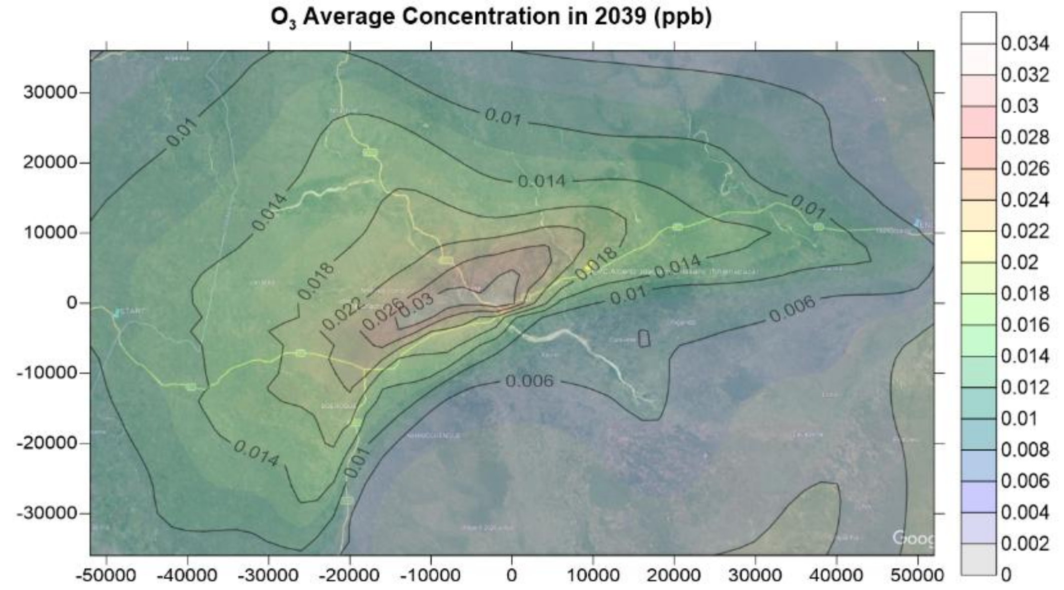


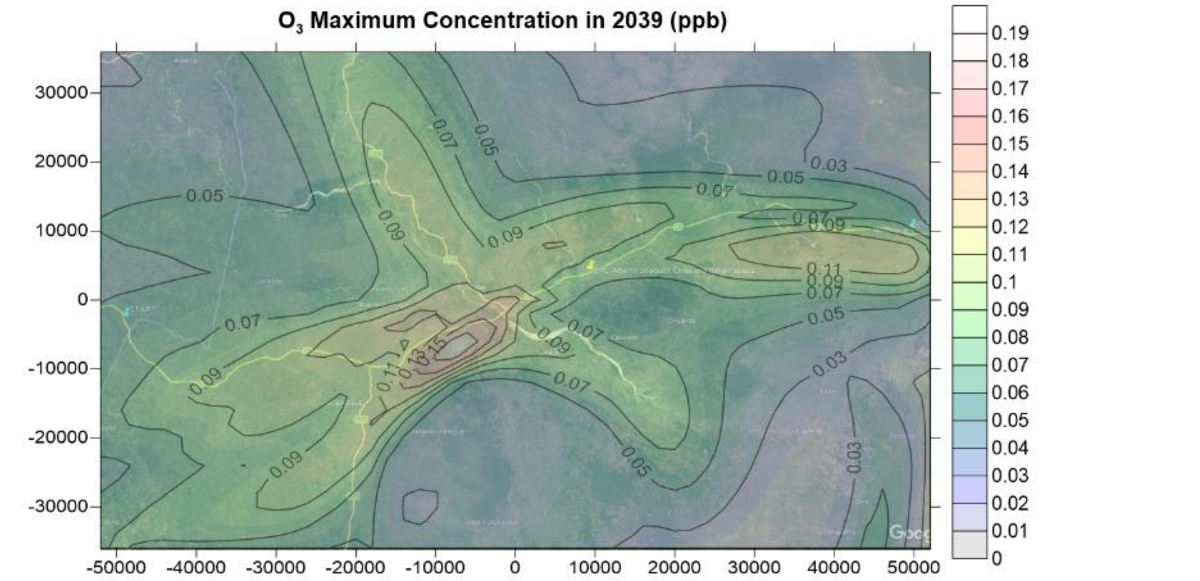

O3 Maximum Concentration in 2024 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.085
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0.025
0.035
0.045
0.055
0.065
0.075
0.015

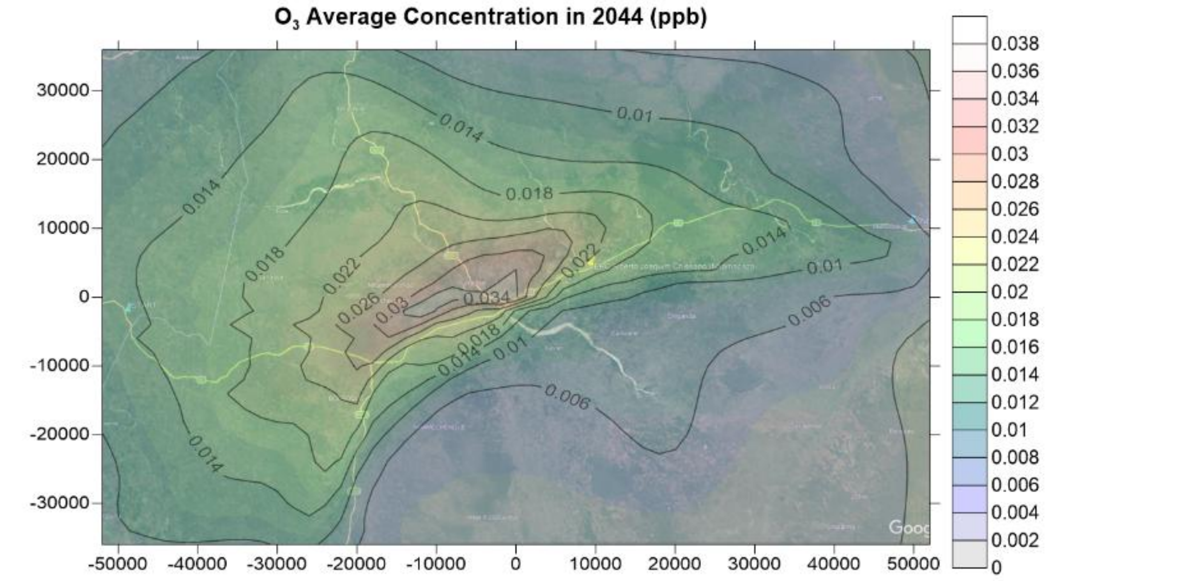

O3 Average Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.025
0.024
0.023
0.022
0.021
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0
0.006
0.008
0.01
0.012
0.014
0.004
0.002


O_3 Maximum Concentration in 2029 (ppb)
O_3 Average Concentration in 2034 (ppb)


O_3 Maximum Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0


O_3 Average Concentration in 2039 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0


O3 Maximum Concentration in 2039 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0


O3 Average Concentration in 2044 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
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0.008
0.006
0.004
0.002
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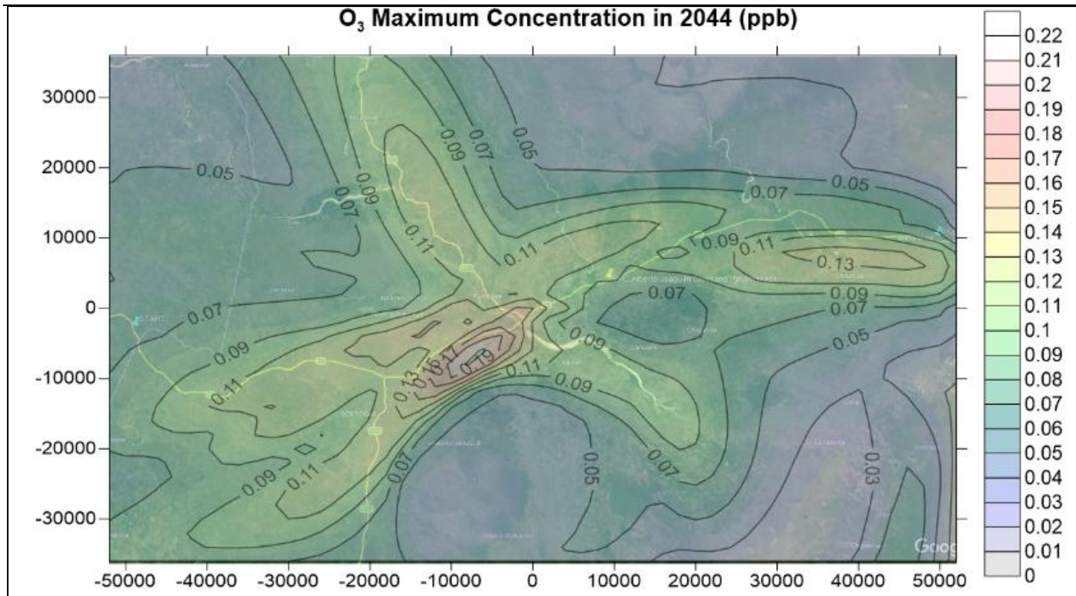
O3 Maximum Concentration in 2044 (ppb)
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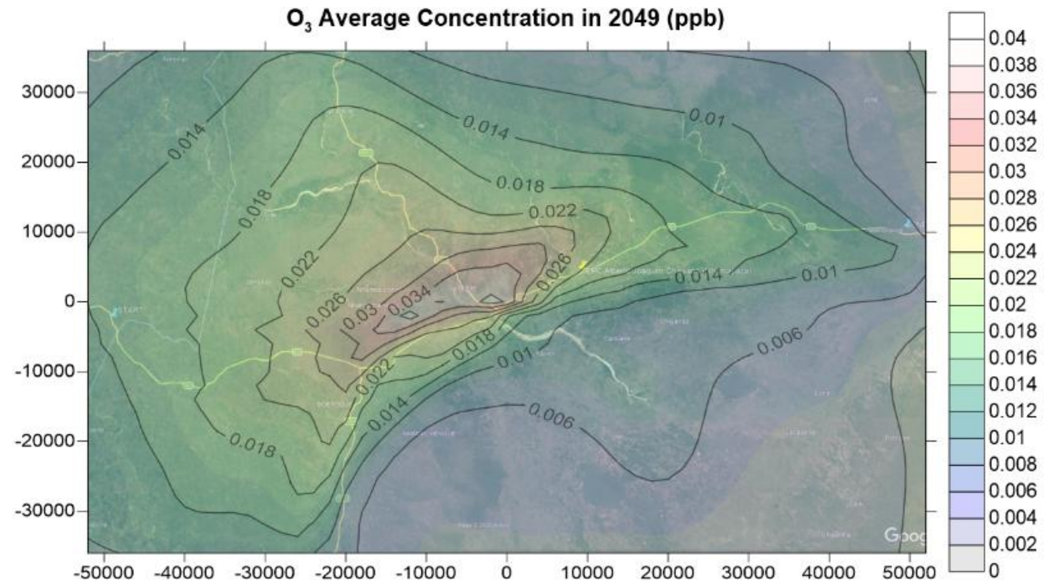
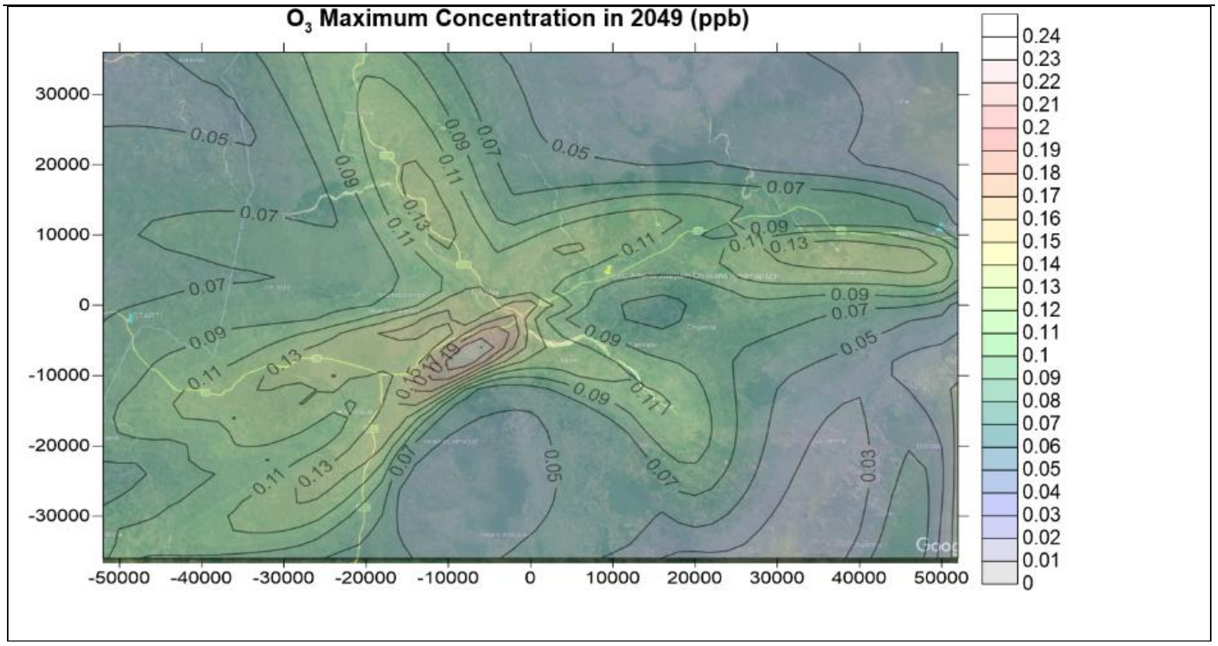
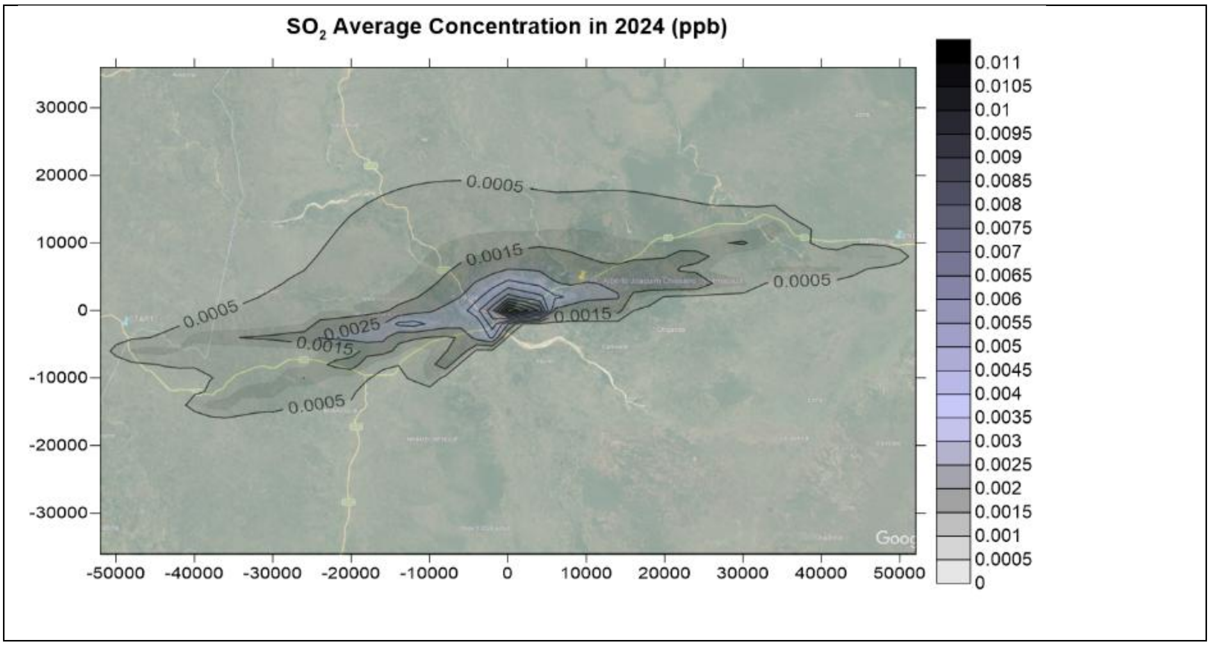
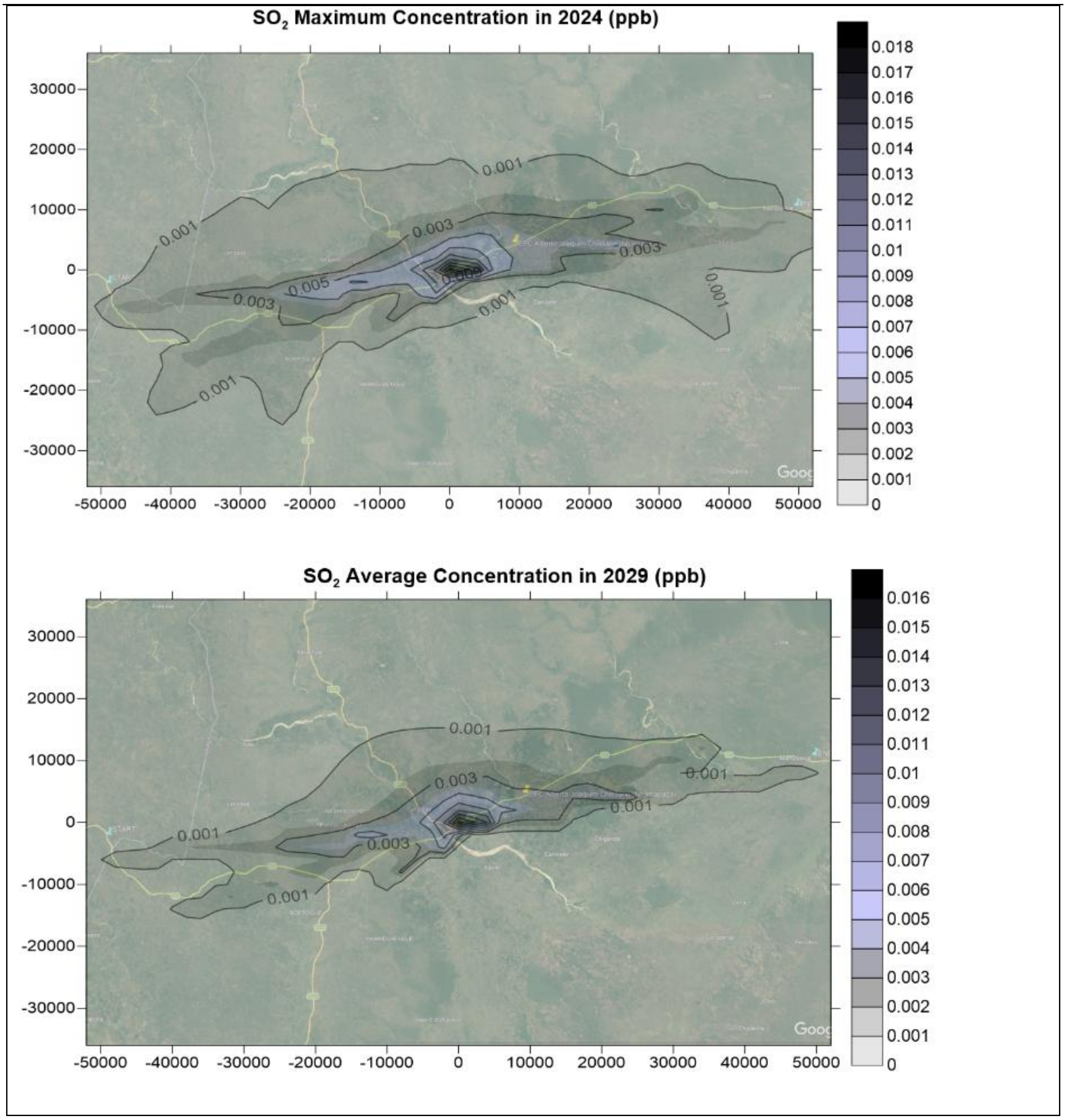
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0


O3 Average Concentration in 2049 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.04
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0



Dispersion maps for SO_2




SO₂ Maximum Concentration in 2024 (ppb)
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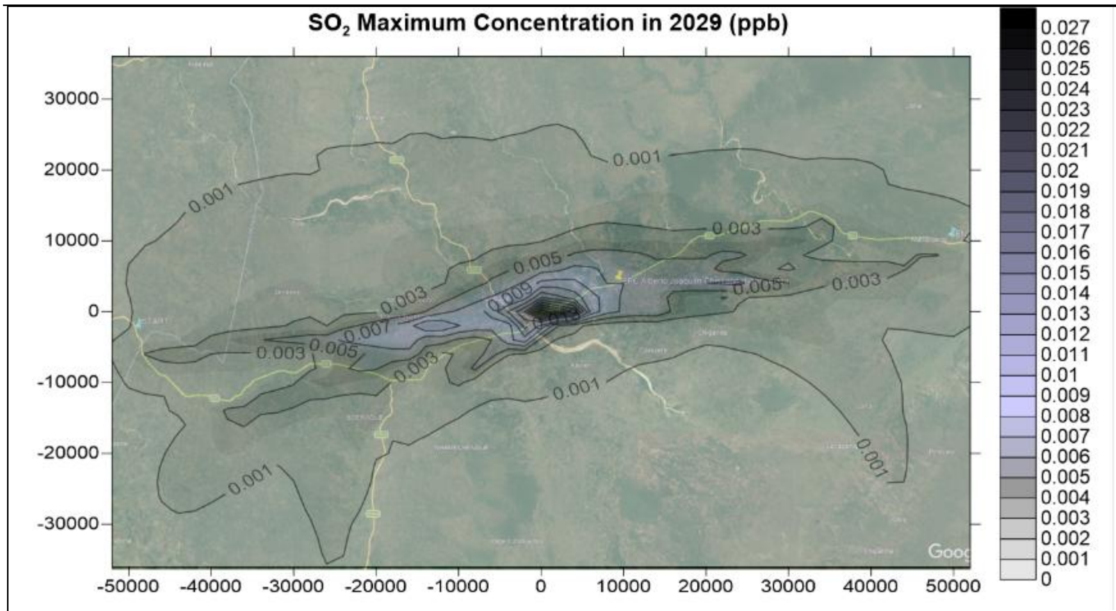
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.001
0.003
0.005
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0
SO₂ Average Concentration in 2029 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.001
0.003
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0


SO_2 Maximum Concentration in 2029 (ppb)
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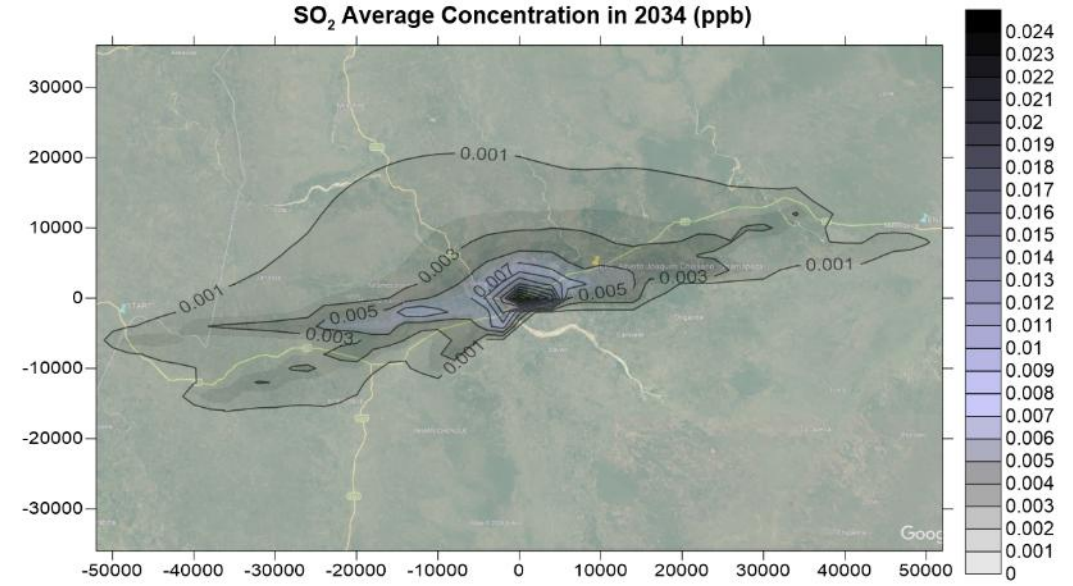
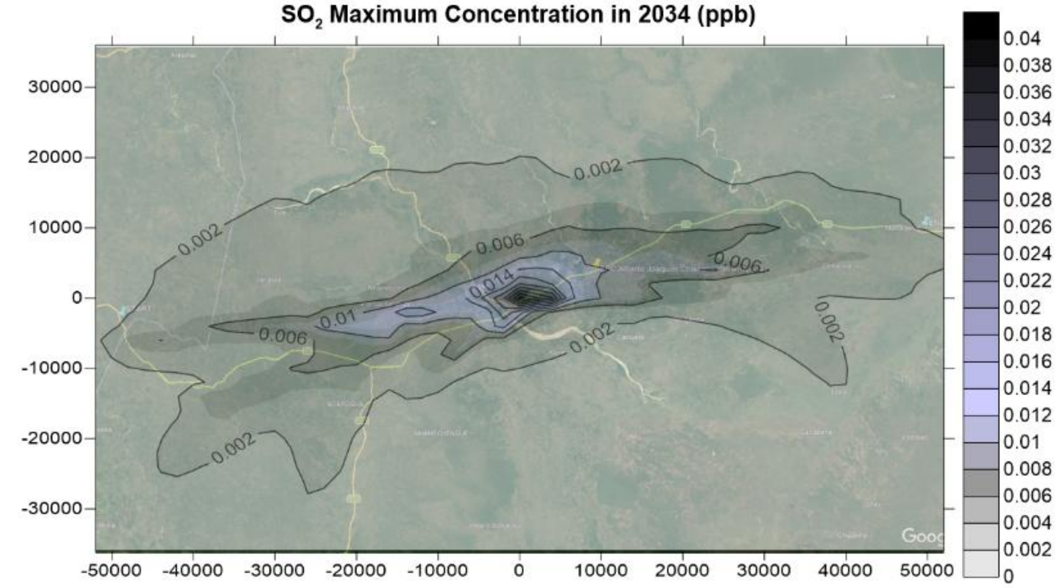
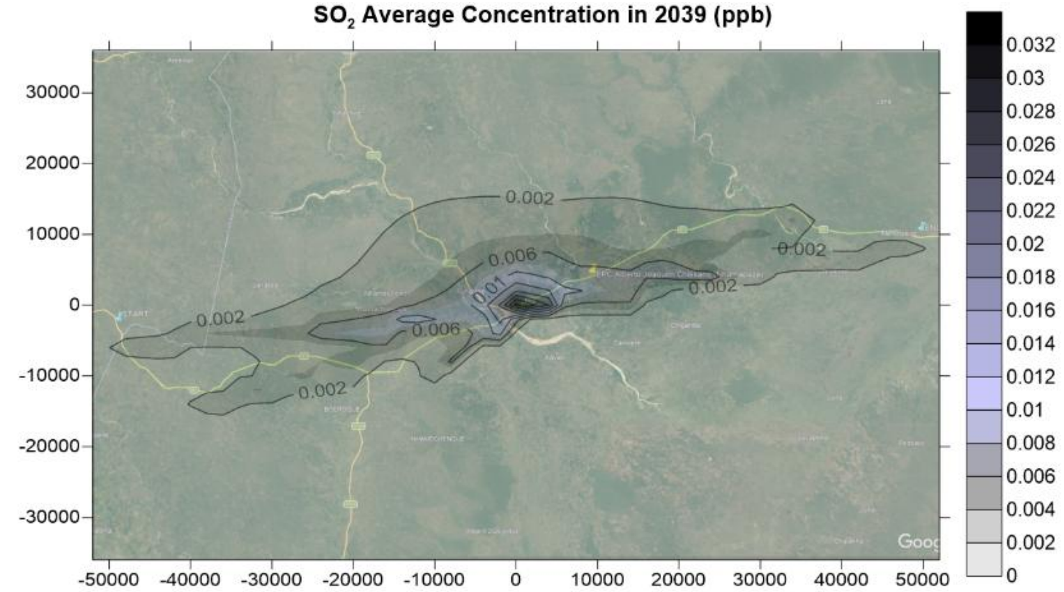
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.001
0.003
0.005
0.007
0.009
0.027
0.026
0.025
0.024
0.023
0.022
0.021
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0


SO_2 Average Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.001
0.003
0.005
0.007
0.024
0.023
0.022
0.021
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0


SO2 Maximum Concentration in 2034 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.002
0.006
0.01
0.014
0.04
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0


SO2 Average Concentration in 2039 (ppb)
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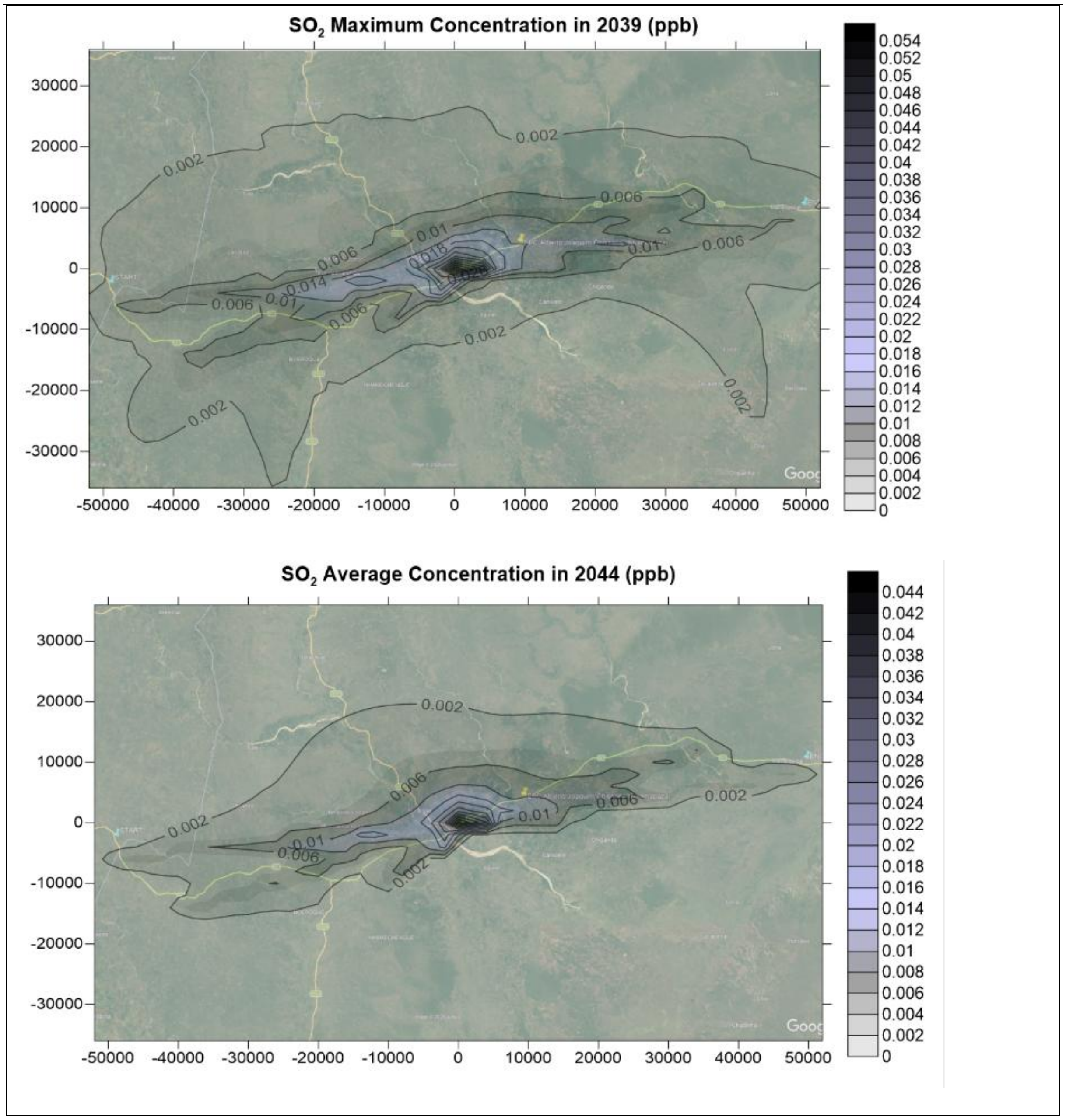
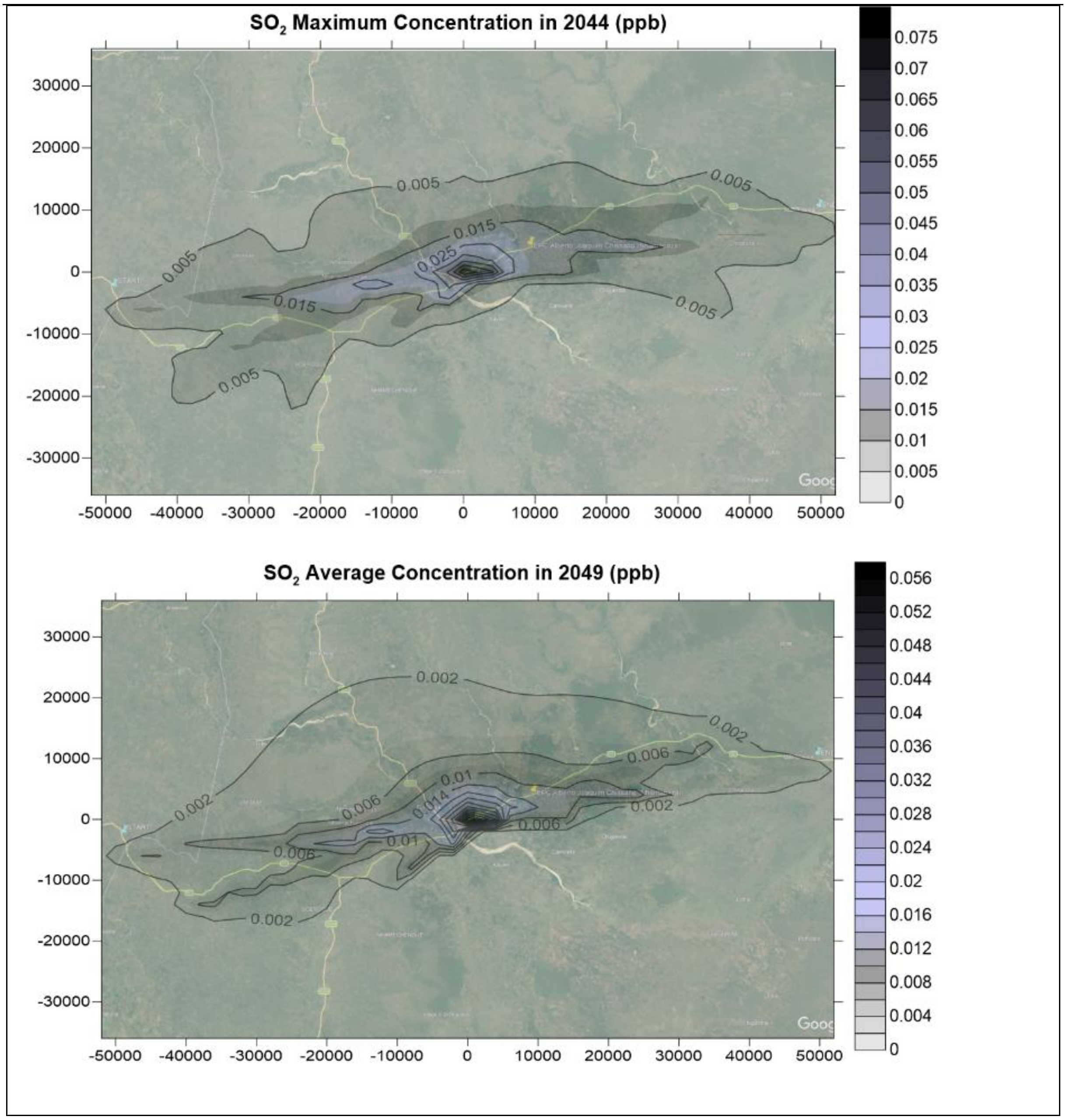
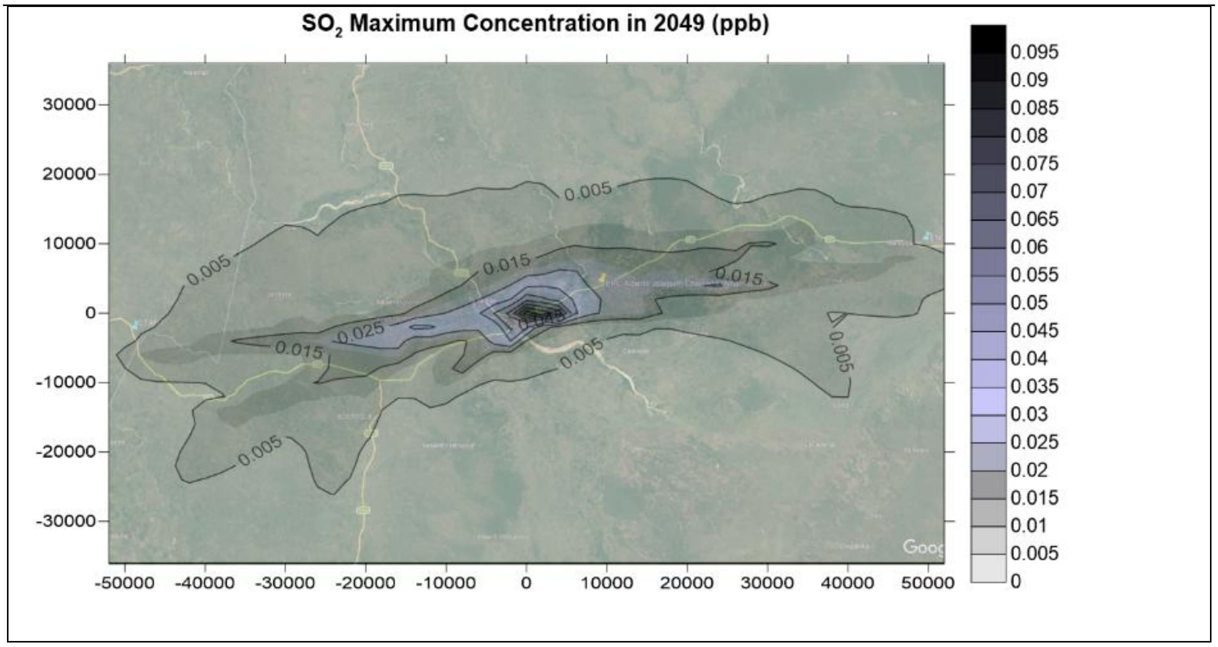
20000
10000
0
-10000
-20000
-30000
-50000 -40000 -30000 -20000 -10000 0 10000 20000 30000 40000 50000
0.002
0.006
0.01
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0


SO2 Maximum Concentration in 2039 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.002
0.006
0.01
0.014
0.018
0.026
0.054
0.052
0.05
0.048
0.046
0.044
0.042
0.04
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
SO2 Average Concentration in 2044 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.002
0.006
0.01
0.044
0.042
0.04
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0


SO2 Maximum Concentration in 2044 (ppb)
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
SO2 Average Concentration in 2049 (ppb)
0.056
0.052
0.048
0.044
0.04
0.036
0.032
0.028
0.024
0.02
0.016
0.012
0.008
0.004
0


SO2 Maximum Concentration in 2049 (ppb)
30000
20000
10000
0
-10000
-20000
-30000
-50000
-40000
-30000
-20000
-10000
0
10000
20000
30000
40000
50000
0.005
0.015
0.025
0.045
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0

Annex 3

TORs for noise modelling

TERMS OF REFERENCE (ToR)

Noise and Vibration Modelling

1. Objective

The objective of this assignment is to assess the current and future noise and vibration impacts associated with the upgrading/rehabilitation of the EN1 corridor, over a 25-year design horizon, in accordance with:

- Applicable Mozambican legislation, and
- The World Bank Group Environmental, Health and Safety (EHS) Guidelines.

The study shall:

- Establish baseline acoustic conditions;
- Predict future noise and vibration levels due to traffic growth;
- Assess compliance at sensitive receptors;
- Support the Environmental and Social Impact Assessment (ESIA) with robust, transparent, and verifiable results.

2. Scope of Work

2.1 Baseline Characterisation

- Compile and review existing noise measurement data;
- Validate representativeness (time period, meteorology, duration);
- Conduct additional measurements if required to ensure:
    - Daytime and night time coverage;
    - Representative conditions.

Parameters shall include:

- LAeq, Lmax, Lmin;
- Statistical indicators (L10, L50, L90);
- Meteorological conditions.

2.2 Identification of Noise and Vibration Sources

- Road traffic (primary source);
- Construction activities (where applicable);
- Local anthropogenic sources.

2.3 Sensitive Receptors

- Identify and map all sensitive receptors, including:
    - Residential areas;

  - Schools;
  - Health facilities;
  - Religious buildings;
- Ensure full spatial representation in GIS, addressing gaps noted in previous studies.

3. Noise Modelling Methodology

3.1 General Approach

The modelling shall:

- Use measured baseline equivalent to safest natural conditions as calibration reference;
- Represent the EN1 as a segmented linear source;
- Predict noise levels for:
  - Baseline scenario
  - Future scenarios (up to 25 years)

3.2 Calculation Method

Two-tier approach is required:

(A) Core Approach (Mandatory)

- Application of ISO 9613-2 principles:
  - Geometrical spreading;
  - Atmospheric absorption;
  - Ground effects.
- Traffic inputs (using traffic count study data from concept designs):
  - AADT/TMDA;
  - Vehicle composition (light/heavy);
  - Speeds.
- Conversion of traffic data into sound power levels, explicitly documented.
- Application of logarithmic relationships for traffic growth:
  - Avoid simplistic +3 dB assumptions unless justified.

(B) Enhanced Approach (Strongly Recommended)

To address World Bank concerns, the Consultant should consider use of dedicated road traffic noise models, such as:

- CadnaA;
- SoundPLAN;
- CNOSSOS-EU or NMPB methodologies.

These allow:

- Vehicle class differentiation;

- Speed-dependent emissions;
- Reflection, barriers, and terrain effects.

Availability of the particular software used will have to be verified by the consultant undertaking the study at that time as licence fees are only valid for certain periods of time.

4. Vibration Assessment

- Measurement and/or estimation of Peak Particle Velocity (PPV);
- Assessment at sensitive structures;
- Projection over the 25-year horizon where applicable.

5. Traffic Growth and Scenarios

- Use traffic projections consistent with air quality modelling;
- Define:
    - Baseline year;
    - Intermediate scenarios (optional but recommended);
    - Design year (25 years).

6. GIS Mapping and Spatial Analysis

6.1 Requirements

- Integration of results into GIS (e.g. ArcGIS or QGIS);
- Production of:
    - Noise contour maps (isophones);
    - Receptor location maps.

6.2 Important Clarification

- Maps are illustrative tools only;
- Compliance assessment shall be based on receptor-specific results, not interpolations.

7. Software and Tools

7.1 Minimum Tools

- Excel-based calculation model (fully transparent and auditable);
- GIS software for mapping.

8. Impact Assessment and Compliance

- Compare results against:
    - Mozambican standards;
    - IFC / WBG EHS noise limits;
- Assess:
    - Daytime and nighttime compliance;

- Incremental impacts;
- Significance of change.

9. Deliverables

The Consultant shall produce:

1. **Noise and Vibration Specialist Report**, including:
    - Introduction and objectives;
    - Methodology (fully transparent);
    - Assumptions and limitations;
    - Results and discussion.
2. **Receptor-Based Results Tables**
    - Baseline vs future levels;
    - Compliance assessment.
3. **Noise Maps**
    - Isophones;
    - Receptor overlays.
4. **Data and Tools**
    - Excel calculation sheets;
    - GIS software and files in raster or shapefile format.

10. Key Requirements

To address previous review comments, the study should:

- Explicitly document all assumptions;
- Clearly define metrics (e.g. LAeq, Lden, Lnight);
- Ensure traceability of calculations;
- Include all relevant sensitive receptors;
- Distinguish between:
    - Construction phase;
    - Operation phase.

11. Potential Timeline (to be confirmed by consultant)

- Baseline review and data validation: 4-8 weeks;
- Modelling and analysis: 8-12 weeks;
- Reporting: 4-8 weeks.