Spatial-Time Forecasting of dengue incidence in Ibagué, inclusion of spatial relation.

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Abstract

Heterogeneity in socio-economic and associated demographic conditions can interact with environmental variation in space and time. These factors create differential conditions across cities, which can modulate disease transmission at local spatial scales in large urban environments of the developing world. It is our general working hypothesis that the understanding, control, and prediction of the population dynamics of climate-sensitive infectious diseases such as dengue within cities require consideration of the pronounced spatial heterogeneity of urban environments. In concert, the environmental and socio-economic dimensions could define the relevant spatial scales at which to address malaria transmission dynamics. Thus, understanding and controlling transmission dynamics within cities will necessitate consideration of their pronounced spatial heterogeneity and of the relevant spatial scales at which to address temporal variation in incidence.

1. Introduction

Time series exhibiting spatial dependencies are present in many domains including ecology, meteorology, biology, medicine, economics, traffic, and vision. The observations can come from multiple sources e.g. GPS, satellite imagery, video cameras, etc. Two main difficulties when modeling spatio-temporal data come from their size - sensors can cover very large space and temporal lags - and from the complexity of the data generation process. Reducing the dimensionality and uncovering the underlying data generation process naturally leads to consider latent dynamic models. This has been exploited both in statistics and in machine learning (ML).

Despite an increasing interest in the role of spatial heterogeneity, the population dynamics of vector-transmitted diseases has typically been addressed with temporal surveillance records aggregated at the level of whole towns, cities, or regions, including the development of recent statistical inference methods for confronting process-based models to time series data. Such coarse resolutions have been the norm in part because climate variability is thought to operate at relatively large, regional scales, synchronizing dynamics in space (The Moran effect). These (mean-feld) models assume for the most part that host populations are well mixed , so that that each individual is equally susceptible. In particular, they do not take into account how spatial variation in socio-economic , environmental and structural conditions affect vector habitat, biting rates, vector control, contact rates and host susceptibility.

2. Related Work

2.1. State of Art

It has been showed that infectious disease may vary in both spatio-temporal dimension which suggest that in large urban environments of the developing world an aggregated approach may not explain the dynamics of the disease, they showed that interactions of both environmental and socio-economic factor drives the spread of the disease [1]. Then accounting for the local variation in highly heterogeneous environments such as cities it is pivotal to understand diseases transmission and ultimately prioritize control and surveillance effort. It is therefore important to identify and quantify the processes responsible for observed epidemiological microscopic patterns: the result of individual interactions in changing social and ecological landscapes. The recent advance in Deep Learning has lead to huge research in including street and satellite's imagery to quantify demographic and environmental factors, inequality [3, 4, 2].

2.2. Data-sets

Using raw incidence data from Ibagué from 2013-2019 we have in epidemic weeks each case represented by directions. Directions allow to locate information spatially by both comunas and barrios in Ibagué. Data in time is shown in figures below as well as in comuna resolution.

3. Approach

Our approach then first wants to use STNN [**?**].

References

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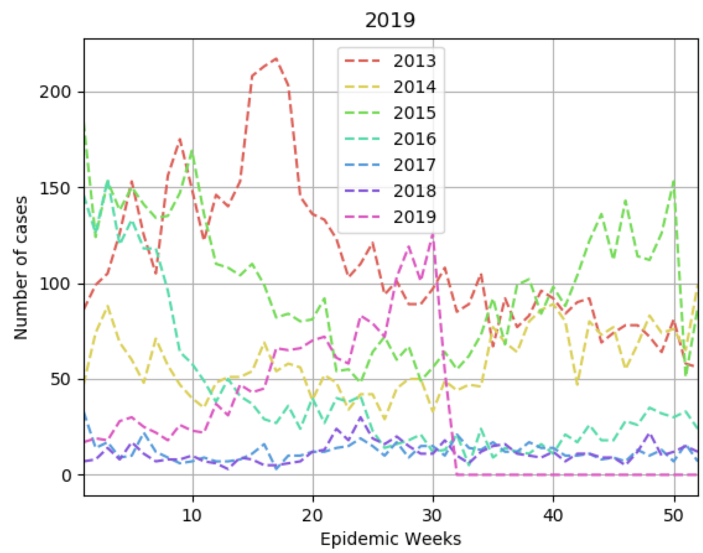
[2] Esra Suel, Marthe Boulleau, Majid Ezzati, and Seth Flaxman. Combining street imagery and spatial information for measuring socioeconomic status. (NeurIPS):1–5, 2018.

[3] Esra Suel, John W. Polak, James E. Bennett, and Majid Ezzati. Measuring social, environmental and health inequalities using deep learning and street imagery. *Scientific Reports*, 9(1):1–10, 2019.

[4] Scott Weichenthal, Marianne Hatzopoulou, and Michael Brauer. A picture tells a thousand…exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology. *Environment International*, 122(November 2018):3–10, 2019.



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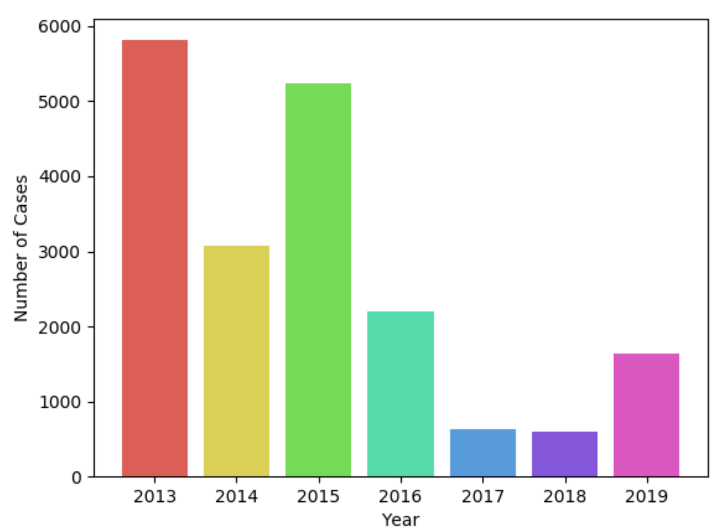

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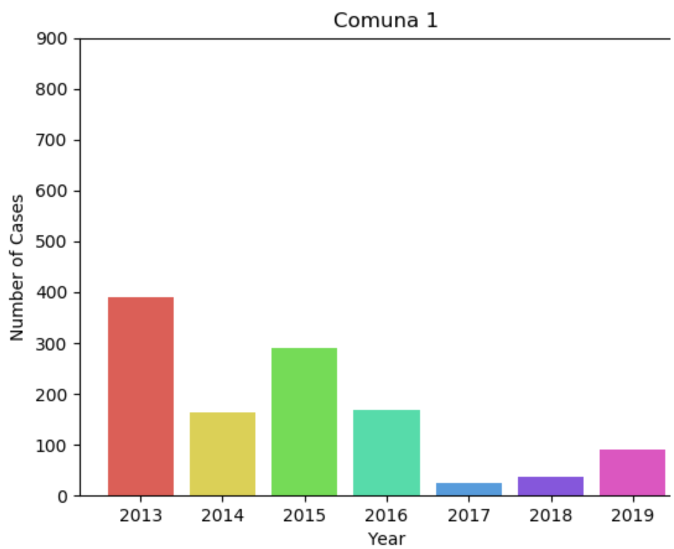

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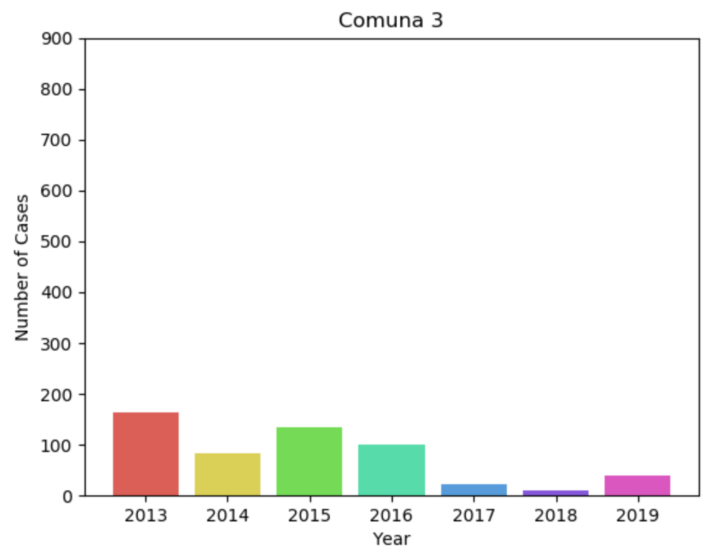

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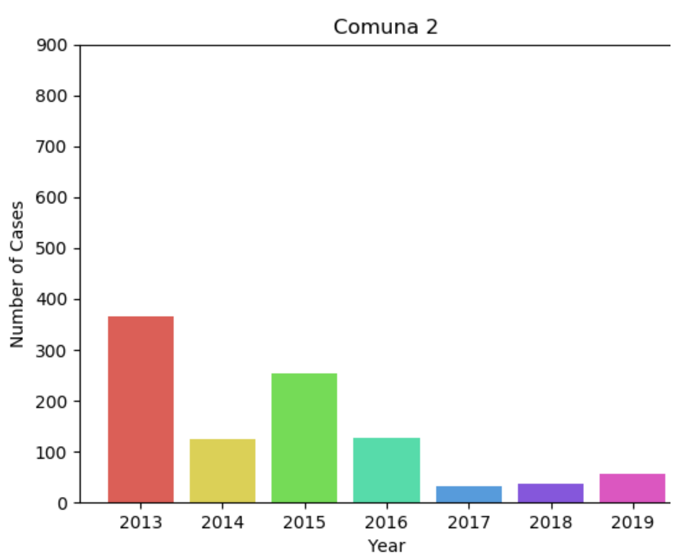

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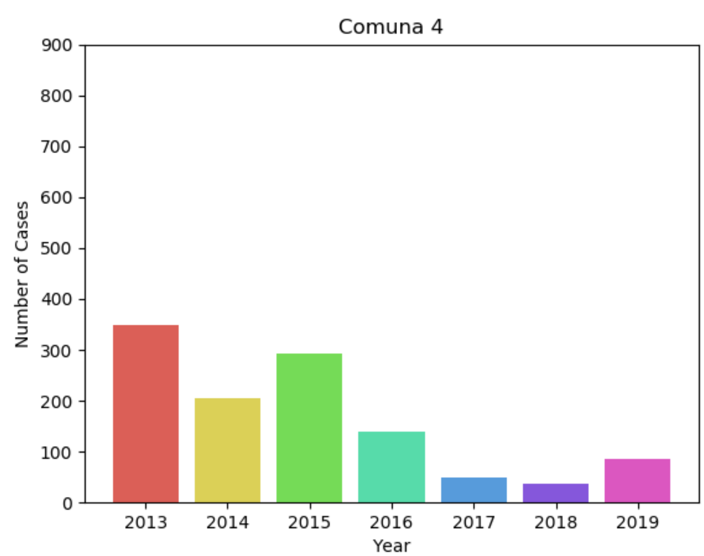

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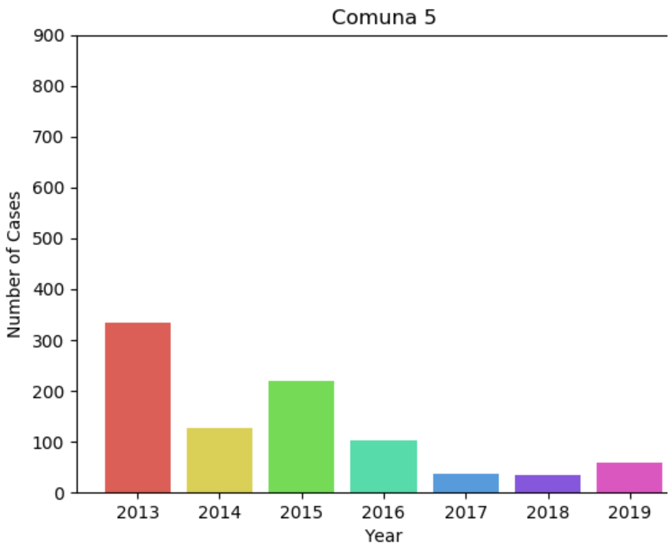

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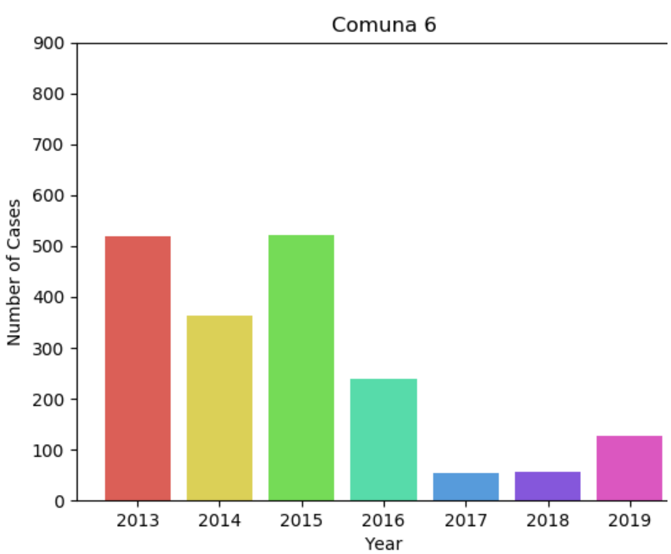

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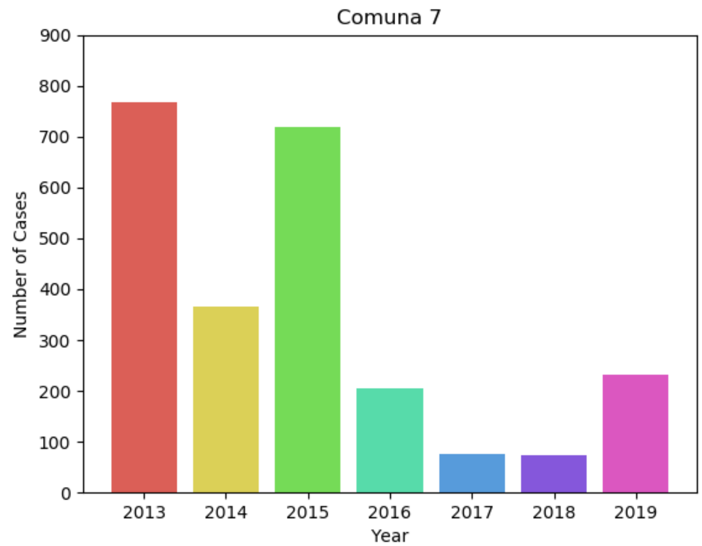

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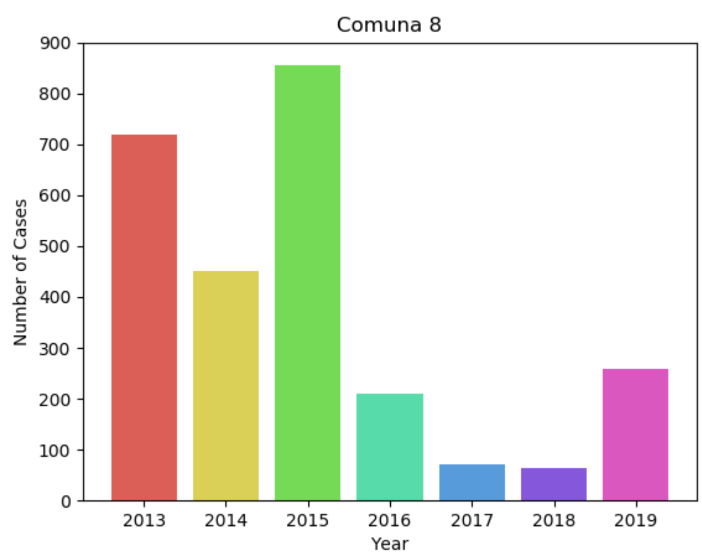

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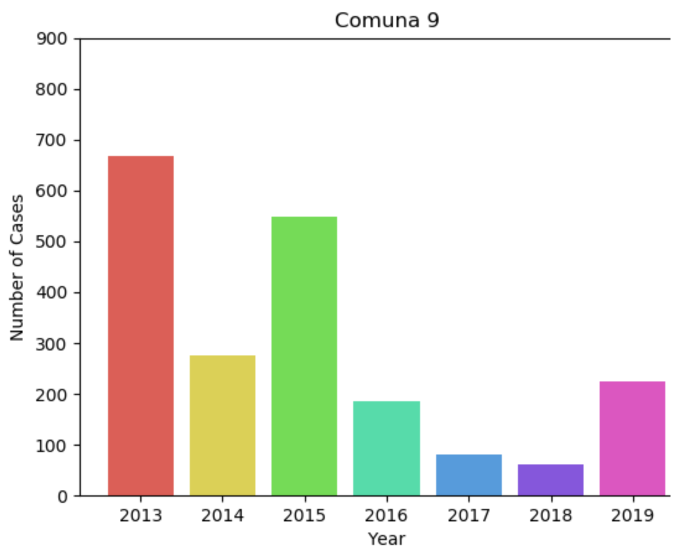

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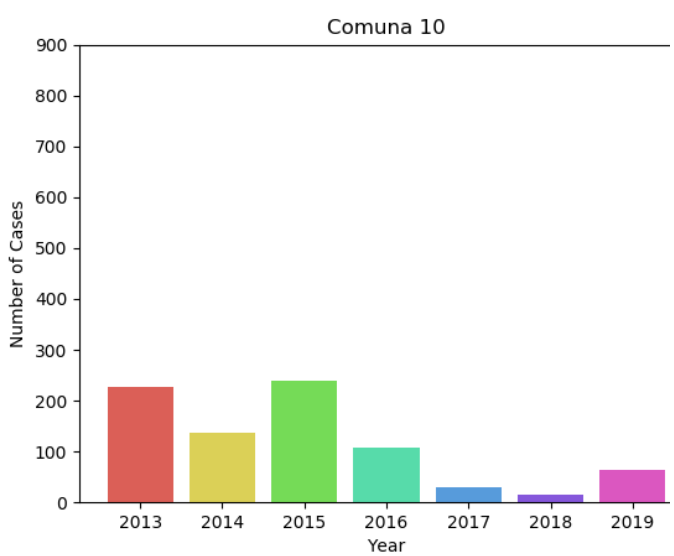

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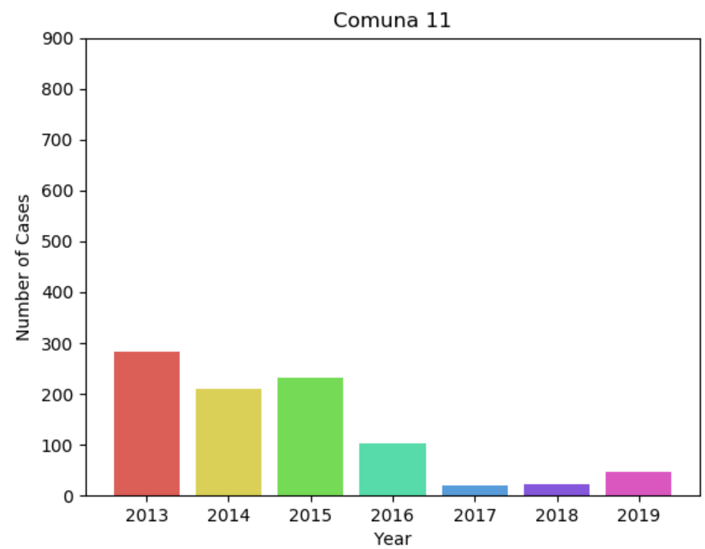

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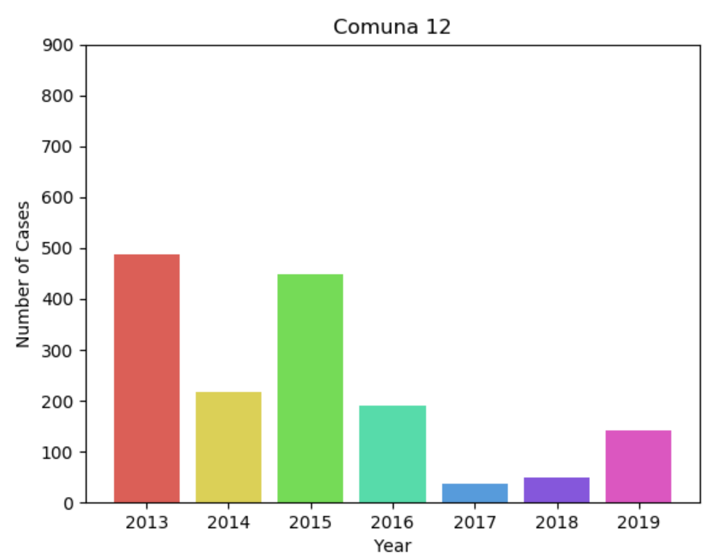

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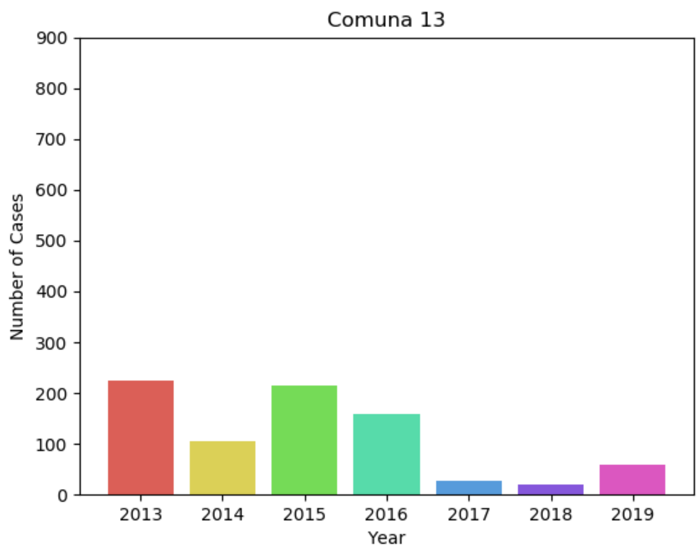

Figure 15. Caption