Estimation of the effect of precipitation on traffic in the urban networks of Bangalore

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***Abstract*—Precipitation has an effect on traffic. Though there may not be a universal correlation(i.e a magical formula) between the two, some correlation exists. Given the time of day, likelihood of water collection , precipitation and the amount of traffic present before the period in question, we use a neural network to predict the effect of precipitation in one time period, on traffic in the next. We also present an easy to use GUI for the same.**

***Index Terms*—traffic, waterlogging, thiessian polygon, convex hull**

I. Introduction

Bangalore woke up to a flooded city on the 15th of August, 2017. The overnight torrential rains was the heaviest downpour in 127 years, with 129 millimetres rainfall under three hours. The intensity of the weather event was unprecedented, with the actual figure turning out to be 3-4 times the intensity forecast by the Karnataka State Natural Disaster Monitoring Centre (KSNDMC). While the entire city was purged with blackouts in various regions, the commercial hubs were reported to be the worst affected. This was mainly due to the substantial increase in traffic as a consequence of the waterlogging from the downpours. Similarly, on the 30th of July, 2016, hours of rains inundated the two cities of Bangalore and Gurgaon in India, leading to severely waterlogged streets which in turn left thousands of people stranded in unnerving traffic jams lasting for several hours [1]. Other than these two events, a multitude of cities in the developing countries such as Dhaka (Bangladesh) and Beijing (China) have been suffering a similar fate in the past decade [2].

Waterlogging of streets has been a major cause of disruption in developing cities for a long period of time, its repercussions being intensified in the rainy seasons. The rapid urbanisation of these cities coupled with the lack of urban planning has made various streets susceptible to waterlogging in heavy rains.

Prediction of waterlogged areas can serve as a boon to the public. If given an early warning, travellers can factor into account waterlogged sections and adjust their routes accordingly to avoid and escape potential traffic. Various agencies could also take preventive measures to alarm and rescue the general public beforehand. Currently, the only reliable source of information about waterlogged areas in Karnataka is Varuna Mitra, an initiative by KSNDMC to estimate the vulnerability due to flooding. However, not only is this restricted to a time limit of 24 hours, but this might also not provide information regarding all possible routes all the time. This lack of information leads to traffic jams causing loss of precious man hours. Moreover, if the information is incorrect, people end up taking longer routes so as to avoid waterlogged roads, wasting both fuel and time. Hence, coping with waterlogging and its side-effects by providing an accurate prediction of the affected locations becomes an issue of utmost importance. In order to overcome these issues, the authors have proposed a method for detection of waterlogging-prone areas along with the prediction of severity of traffic in these areas in the next segment of the day. The areas susceptible to rainfall induced traffic are detected with the help of elevation of an area and the past time segment's travel time data, which are used to calculate the severity of traffic with respect to parameters such as the amount of rainfall and time segment of the day via a neural network. This is then used to predict the possibility of traffic congestion and its intensity in that area in the future.

The paper is organised as follows: Section II gives an overview of the related work and section III provides details on the dataset used. This is followed by the methodology proposed by the authors in section IV. The experimental results are presented in section V and an interfacing tool is developed with the results, whose details are provided in section VI. Finally, section VII concludes the paper with a summary and suggestions for future work.

II. Related Work

A reasonable amount of work has been done before on the effect of precipitation on traffic. [3] shows in a study on a small arterial road in Karachi, that rainfall causes traffic delay, especially when traffic is already high. [4] claims that there is little to no universal correlation between precipitation and traffic and that additional factors such as runoff and capacity play a role. In [5] the macroscopic theory of MFD is used to show the significant negative effects of rainfall on traffic.

Though these works use various metrics to show the impact of rainfall on traffic, there have not been significant attempts to create a model which is capable of predicting the effect of current rainfall on future traffic. Moreover these works analyze a particular road/ intersection.

In [6] a model is actually created to carry out prediction. However the labels predicted are the vulnerablities of areas to urban waterlogging.

In this work, we attempt to use a simple neural network model to estimate the traffic in the next time segment based on the precipitation and traffic in the current time segment. We aim to apply this model for all roads and not just one.

III. Dataset

A. Uber Movement

Uber Movement is an online tool that provides dynamic insights about traffic and mobility in cities where Uber operates. The data from Uber Movement has been utilized to determine the average time taken for different cab rides across pairs of regions determined by wards all over Bangalore. This in turn provides the necessary information of the status of traffic during different times of a particular day.

Uber Movement Data divides a day into 5 segments:

- Early Morning(12 AM - 7AM)
- AM Peak(7 am-10am)
- Midday (10 AM - 4 PM)
- PM Peak(4 PM - 7 PM)
- Evening(7 PM - 12 AM)

A map of Bangalore with its various ward demarcations by Uber is depicted in 5

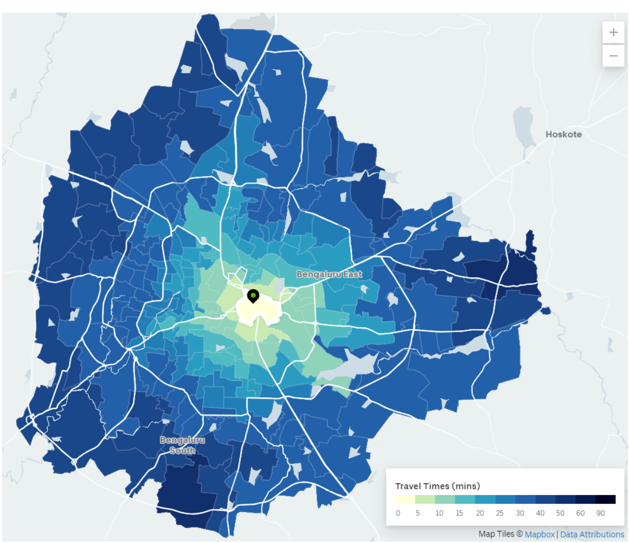

Fig. 1. Bangalore Uber Movement Map

B. Yuktix

Yuktix is a DIPP (Department of Industrial promotion and Policy) recognised startup working to create indigenous remote monitoring and sensor analytic solutions. This private enterprise has various rain gauges stationed across different regions of Bangalore, and provides acute rainfall measurements across approximately five minute intervals. Apart from the millimeter of rain, it also provides a metric of various other variables of hydrological importance such as temperature, relative humidity and atmospheric pressure.

The Yuktix data, as provided, contained null values for certain time segments of the day. These null values were imputed using MICE [7]. The particular chain imputation method was chosen to ensure that the corresponding null values were replaced with appropriate rainfall values in accordance with the respective traffic situation.

A sample of the preprocessed data as obtained from Yuktix is illustrated in I

TABLE I
Sample Yuktix Data

DateTime	Temperature	Humidity	Rain	Pressure
17-Apr-2019 16:11:58	27.2	64	0	100
17-Apr-2019 16:17:19	26.8	62	0	100
17-Apr-2019 16:22:40	25.6	76	4	100
17-Apr-2019 16:28:01	24.5	80	2	100
17-Apr-2019 16:33:22	24.2	82	0	100
17-Apr-2019 16:38:43	24.2	83	1	100
17-Apr-2019 16:50:24	24.1	74	0	100
17-Apr-2019 16:55:45	24.6	78	0	100
17-Apr-2019 16:01:07	24.4	77	0	100
17-Apr-2019 16:06:27	24.3	75	0	100

The entire dataset, spanning across three months, has been depicted as a time series plot in 2

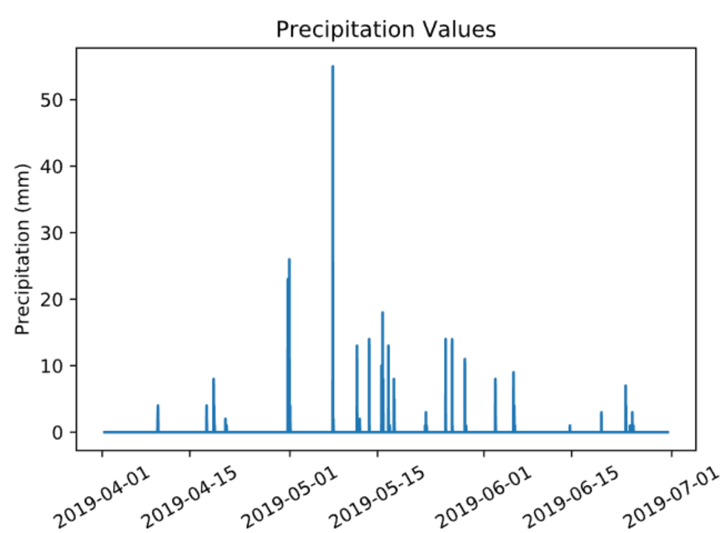

Fig. 2. Precipitation Time Series Graph

C. Google Elevation

Google Elevation is an API (application program interface) that provides elevation data for all locations on the surface of the earth, including depth locations on the ocean floor (which return negative values). The necessary data for the Bangalore region has been obtained by scraping via an HTTP (Hyper Text Transfer Protocol) interface, with requests constructed as a URL string, using latitude/longitude coordinates to identify the locations or path vertices.

For every road connecting two wards, we are utilizing 1000 points for calculating the elevation score. A subset of 250 points, connecting HSR Layout and Koramangala, has been depicted in 3

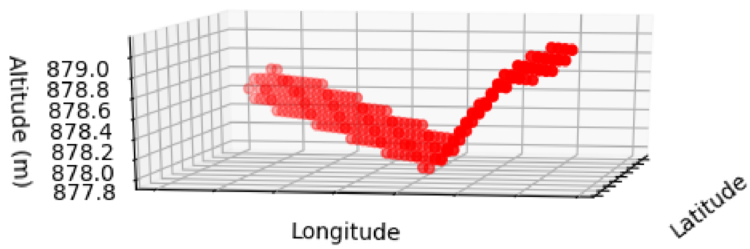

Fig. 3. 3-Dimensional Elevation Plot

IV. Methodology - S

As described in section III A, Uber Movement Data divides the day into several time periods(segments). We attempt to predict the impact of rainfall in one time period on the very next time period. The increase in traffic from the mean in that period) predicted by our model can be categorized into three parts.

1) Low (< 110% of mean)
2) Considerable (110-125% of mean)
3) Severe (> 125% of mean)

Most of our methodology has been inspired by [6], which utilizes Uber Movement traffic data, rainfall data and GPS elevation data to predict the vulnerability of areas in Manila to flooding, using a simple neural network.

A. Rainfall Estimation

Our rainfall readings have been obtained from Yuktix's telemetry gauges. Each of these provides a point estimate of rainfall. Studies have that the spatial variability of rainfall is of the order of 100m [8]. As a result, the readings of a single rainfall gauge are only applicable to areas within a radial distance of 100m from the gauge.

However, given a network of gauges, several methods may be used to arrive at a more reliable estimate of rainfall over particular area. One such method is Thiessen polygon method.

An area around each gauge is obtained by drawing a bisecting perpendicular to the lines joining gauges, as shown in the. The portion of each resulting polygon lying within the catchment boundary is measured and the rainfall upon each is assumed to equal the gauge reading. The total precipitation is the weighted average of these values

Using this method, we have arrived at a formula to use to calculate the precipitation over an area of road.

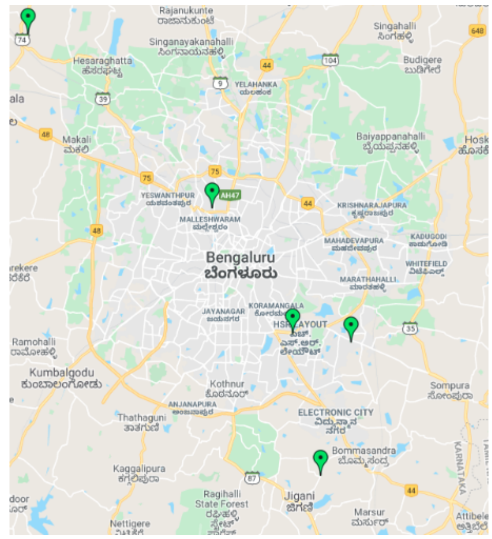

Fig. 4. Yuktix Stations in Bangalore

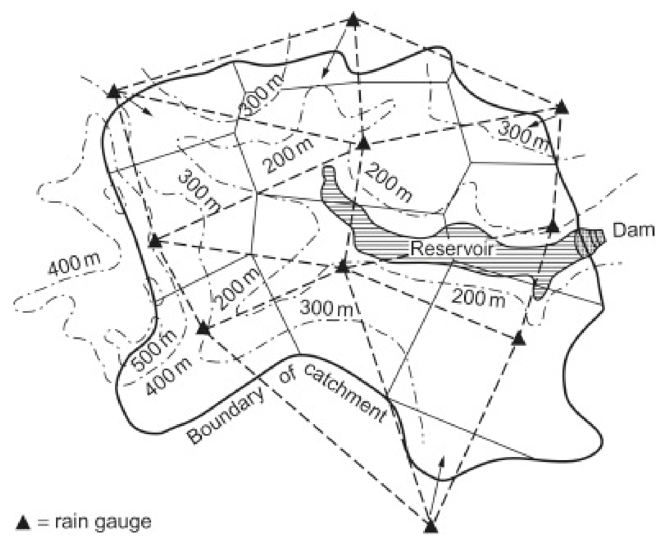

Fig. 5. Thiessen Polygon Method

B. Elevation Score

Waterlogging is one large reason for an increase in traffic in the event of rainfall. Waterlogging is more likely to occur where there are basins for the water to accumulate. Taking inspiration from [6], here we incorporate the elevation data of the road which we are considering by calculating an elevation score.

While [6] used a 2D model to calculate elevation score, in this work we use a 3 dimensional model in an attempt to make a more accurate estimation of the likelihood of water collection.

We use the volume of the convex hull formed by the points on the road, scaled down by the area of the rectangle which defines the road.

We pass this value directly to the neural network as an input parameter.

C. Sequential Model

A Sequential Keras model has been chosen for our primary architecture, with four layers as illustrated in 6.

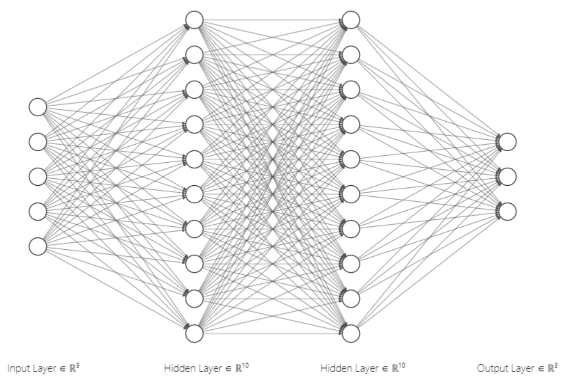

Fig. 6. Network Architecture

The input to the neural network is a vector which consists of the following values:

- Elevation Score of Location
- Previous Time Segment Precipitation
- Previous Time Segment Traffic
- Time Segment Index
- Day of Week Index

The Day of Week Index is an integer from 1-7 (Monday - Sunday), which indicates the day of the week. As the traffic on any given day does have some dependency on the day of the week, this is an important input to give.

We utilize the Sigmoid and Relu activation functions, and a Softmax activation in the output layer. An Adam optimizer is used to train the network.

The output of the network is a one hot encoded vector which indicates the prediction of the network for the increase in traffic in the next time segment (Low, Considerable or Severe)

D. Training and Prediction of Traffic Intensity

Training was carried out on a machine with an Intel core i5 processor and an NVIDIA GTX-1050Ti graphics card. The network was trained for 100 epochs.

V. Experimental Results and Analysis

The neural network achieves an accuracy of 85.71% with an 8:2 training-testing split of the input dataset. The loss function observes a gradual decrease in its values, as shown in 7.

As expected, a majority of the points were classified as Low Intensity regions. The distribution of the prediction is depicted in II.

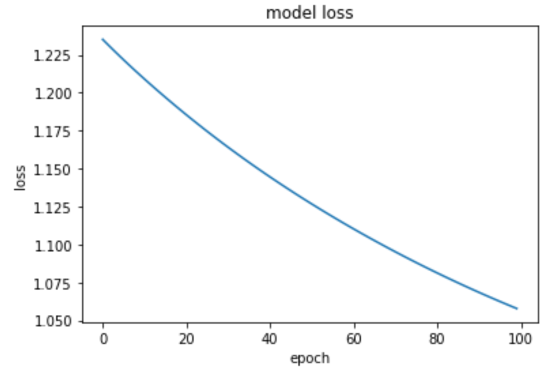

Fig. 7. Loss

TABLE II
SEVERITY PREDICTION

	Prediction Percentages
Low Traffic	61.54%
Considerable Traffic	28.21%
High Traffic	10.25%

VI. Interfacing Tool

An interfacing tool has been developed to enable users to predict the traffic after a bout of rain. A user can input the date, time and road where they want to see the effect of rainfall on traffic. The GUI displays the road queried,shaded in a colour corresponding to the predicted intensity of traffic.

- Green: Low Traffic
- Considerable Traffic
- Severe Traffic

A sample run of the UI has been depicted in 8.

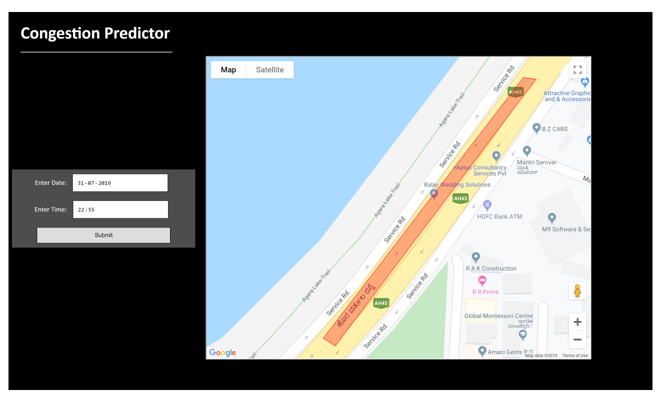

Fig. 8. UI

VII. Conclusions and Future Works - S

From this work we show that even with limited data it is possible to make a reasonably accurate prediction regarding the effect of precipitation on the traffic in the next four hour window, for a particular location.

This information can be used beforehand to help estimate traffic in an area and to hence make appropriate changes in plans for travel. We present an easy to use GUI for this task.

In the future the accuracy of our model can be increased by training with more data. Apart from simply increasing the number of data points used in training, using different sources may help as well. Runoff data, DEM data and drainage data may help a great deal.

It is also reasonable to believe that a deeper or more complex neural network architecture will perform better. However, such a network will require additional data.

The GUI can also be improved to be more user friendly, and additional functionality can be added as well.

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