

USING CENTRALITY MEASURES ON ROADS TO HELP THE PEOPLE SUFFERING DUE TO KERALA FLOODS

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❖ Introduction

In India, during the months of July and August, floods can occur in cities and/or states due to heavy rainfall. This can occur all over the country, however, it is more prominently found in the more southern states and cities of the country. Mumbai is an example of a city that is flooded due to heavy rainfall almost every year.

However, over the past few days, several cities in the state of Kerala have experienced devastation caused by floods due to very heavy rainfall. These floods have submerged parts of cities and have led to severe loss of property and people. This type of rainfall in Kerala was very unusual, and it was proven by historical records of rains in the state, which reveal that these floods in Kerala are the worst they have ever been for nearly a century.

Within a fortnight's time, the lives of 445 people have been taken, and 15 people are still missing. Over a million people were evacuated and all 14 districts of the state were placed on red alert. According to the government of Kerala, nearly 1/6 of the entire population have been affected by these floods.

To conduct rescue operations and provide aid to the affected citizens, senior officers of the NDRF and the NDMA were instructed by the cabinet secretary to conduct meetings with the Kerala Chief Secretary. Following these, 40 helicopters, 31 aircrafts, 182 teams for rescue, 18 specialized medical teams, 58 teams of NDRF, and 7 companies of the Central Armed Police Forces were tasked with service to rescue and provide aid to the people affected by the floods, with the use of rescue equipment and over 500 boats.

Support has flown in from all over the country from businesses, private institutions, and citizens of other states. However, the affected citizens are still in need of aid, and thus, they need to be helped.

Identifying the closest relief areas and cities to affected areas, identifying the cities that are most vital for transfer of goods and funds are thus, and identifying the cities most in need of aid are thus very vital tasks, will lead to the betterment of the current poor condition of the state.

❖ Literature review summary table:

Authors and Year (Reference)	Title (Study)	Concept	Methodology	Dataset details/analysis	Relevant findings	Limitations/ future research/gaps identified
Kyoungjin Park, Alper Yilmaz	A social Network analysis approach to analyse road networks	Real world events or physical settings can be represented in different types of network structures. To realize this, a social network topology is used to represent road networks. Generally, road networks reside on a plane, which generate a specific network structure called a planar network. To analyse these special	A section was selected using google maps, and the junctions, crossroads, etc. were identified there. Then a graph of the road network was created, through which the node centrality: degree, closeness and betweenness were calculated. The entropy was then calculated from that.	4 sites were chosen and mapped: residential area of Columbus Ohio, downtown area of Columbus Ohio, residential area of Washington dc and downtown area of Washington dc. Number of nodes and links were found for each graph as well.	The experiment proved that the distribution dose does not have a distinction between downtown and residential area, when comparing the distribution of node centrality in downtown area and residential area. The road network is planar network, so the range of nodal degree is narrow. In a downtown area which had a grid like topology has a higher entropy than the	Finding and accurately labelling all the links present in the section.

		<p>networks, a new approach is introduced , using centrality and entropy of various distributions estimated from the network topology. The entropy will help to examine the characteristics of selected road networks in places.</p>			residential area have a radiant topology.	
Hu Weiping, Wu Chi	<p>Urban road network accessibility evaluation method based on gis</p> <p>Spatial analysis techniques</p>	<p>One of the most important problems in today's world is how to evaluate the accessibility of a road network. This paper tries to discuss it.</p>	<p>A section is separated, in which all the roads are labelled as nodes and links. The shortest time distance is calculated between each node. The lower the value, the higher its accessibility. The weighted average travel</p>	<p>A small city called Foshan city was used, and the roads were analysed in this case study.</p>	<p>From North-east to the South-west, the Foshan central region's accessibility value decreases gradually.</p> <p>In other findings, it mainly indicates the node's</p>	<p>Finding and accurately labelling all the links present in the section</p>

		<p>Then, the spatial analysis method on road network assessment has established based on the GIS spatial analysis technology, some urban road network accessibility evaluation models are built up. The models use ESRI Corporation's ArcGIS Engine components and Microsoft Corporation. Net Framework, and focus on the road network connectivity, the shortest travel time</p>	<p>time is also calculated between each node, so is the accessibility index. After which, ESRI Personal geodatabase is used to help with the data an build up the dataset, construct effectiveness network, and use Inetworkclass to carry on geometry network to build another geometric network. This will calculate the connectivity of each node, the shortest travel time and the distance between each node.</p>		<p>shortest general time.</p> <p>The central region of Foshan has relatively higher value of accessibility .</p> <p>on the one hand, the accessibility value displays the node shortest travel time characteristic. On the other hand, as the node has joined the weights on centrality and transportation rank, the northern region with a railroad, a national highway and provincial highway and so on,</p>	
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		<p>and the weighted average travel time. The paper presented three main road network accessibility evaluating indicators, introduced theory basis of the model construction in detail, and the model construction process.</p> <p>Finally, further urban road network accessibility evaluation models are discussed.</p>			<p>then it has a higher accessibility value.</p> <p>The western region has relatively lower value of accessibility</p>	
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<p>Fangxia Zhao, Huijun Sun, Jianjun Wu, Ziyao Gao, Ronghui Liu</p> <p>Published: March 16, 2016</p>	<p>Analysis of Road Network Pattern Considering Population Distribution and Central Business District</p>	<p>This paper proposes a road network growing model with the consideration of population distribution and central business district (CBD) attraction. In the model, the relative neighborhood graph (RNG) is introduced as the connection mechanism to capture the characteristics of road network topology. The simulation experiment is set up to illustrate the effects of population distribution</p>	<p>We develop the road network pattern framework considering population distribution and central business district based on the relative neighborhood graph. For simplicity, we present our road network pattern model only with the consideration of the population distribution and central business district. However, the some other social-economic mechanisms, such as land use and environment, can readily be incorporated into our proposed model. This work adds to the body of knowledge in the road network pattern by considering</p>	<p>All relevant data are within the paper.</p>	<p>The population distribution and CBD are two important factors that affect the topology of road network. The paper also discusses the topology of road network, circuitness and treeness, coverage and total length.</p>	<p>First, the travelers' route choice behavior and the limit financial budget during the process of building the road is not account for in this paper. One possible extension is to incorporate them into the proposed framework in future studies. Secondly, the some other social-economic mechanisms, such as land use and environment, can be introduced into the proposed framework.</p>
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		<p>n and CBD attraction on the characteristics of road network. Moreover, several topological attributes of road network is evaluated by using coverage, circuitness, treeness and total length in the experiment. Finally, the suggested model is verified in the simulation of China and Beijing Highway networks</p>	<p>the some social-economic phenomena.</p> <p>Our numerical experiments demonstrate that our simulation results are very similar with the real network topology structure. Moreover, our model can be extended to the case of multi-CBDs. Results can provide useful insights in the urban road network planning.</p>			
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<p>Geethu Lal,*, Divya L. G., Nithin K. J., Susan Mathew, Bennet Kuriakose</p> <p>Global Colloquium in Recent Advancement and Effectual Researches in Engineering, Science and Technology (RAEREST 2016)</p>	<p>Sustainable Traffic Improvement for Urban Road Intersections of Developing Countries: A Case Study of Ettumanoor, India</p>	<p>The spectacular increase of number of motor vehicles on the road is mainly attributed to the generation of traffic problems like accidents, congestion, delays etc., especially in the urban premises of developing countries. This paper examines the traffic problems and sustainable improvement of road intersection at Ettumanoor, India. The spatial and temporal constitutions of the</p>	<p>A case study of a prominent urban intersection – Ettumanoor was taken as a case study to propose the methodology to solve traffic congestion problems in developing countries. Field surveys were performed and relevant data regarding the commutation volume, land use activities, pedestrian movements and accident data were collected. The collected data was further analysed.</p>	<p>A direct field survey was performed to collect relevant data. Accident data were collected from the Ettumanoor Police Station for three years (2012, 2013 and 2014). Passenger Car Unit (PCU) was adopted for all the vehicular volume counts. Turning movements of vehicles at the intersection with respect to 12 identified directions were reckoned during morning and evening</p>	<p>Lack of road markings, signals, etc., as well as improper land use pattern trigger and sustain the traffic problem at the Ettumanoor intersection. During the peak hours, it was observed that the pedestrian volume is exceeding the permissible limits at the roads. Improvements in the planning of the intersection, parking, traffic movements as well as proper signalisation were suggested.</p>	<p>Not mentioned in this specific paper</p>
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		<p>vehicle as well as pedestrian traffic at the intersections were examined and the characteristics of the junction indicating the delay problems are identified. Data regarding the traffic volume, land use and pedestrian movement activities are collected through direct field surveys. Analysis of the collected data revealed that the improper planning of the junctions, lack of traffic signals</p>		<p>peak hours. Entry and exit of public transport buses to the bus stations were also counted during both the peak periods. Pedestrian movement characteristics in the lateral and cross movement directions with respect to the roads were also enumerated. A simple hand counter was employed for pedestrian and vehicle volume counts.</p>		
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		and unauthorised parking are the major factors contributing to the traffic congestions. Various remedial measures are also proposed, focusing on junction improvement, alternative operation plan and junction signalisation.				
Jean-Marc Tacnet, Eric Mermet, Somsakun Maneerat April, 24-27, 2012	Analysis of importance of road networks exposed to natural hazards	Roads in mountain areas are exposed to natural hazards such as snow avalanches, torrent floods and rockfalls. Risk depends both on hazard,	The methodology is based on two steps. The first step characterizes the initial state of socio-economic factors across the territories. The second one translates them into structural indicators	They use a generic tool called Geograph Lab which lies on a four parameters models : • Space is constituted of a set of Origin-Destination (OD)	The GeographLab software has been extended in order to import thematic layers from G.I.S. applications. This shows the feasibility and the interest of	The thematic approach of economic and social factors can still be improved in collaboration with economy, geography specialists. The case study of the Maurienne Valley

		<p>direct and indirect vulnerability. In case of roads, the indirect vulnerability relates to the consequences of road closures which is rarely assessed. The criticality of these closures depends on the importance of road sections. A new methodology is proposed in the context of natural risks management in mountains. Based on structural networks analysis, it aims to assess the accessibility level of mountain</p>	<p>(linked to importance) of each road section using both network structural properties and constraints issued from a multicriteria analysis of natural hazards.</p>	<p>relations on the network (figure 8). It is the set of definition for measure calculus;</p> <ul style="list-style-type: none"> • Measure is a mathematical property which synthesizes information collected on OD relations; • View is a graphical representation of the network which permits the variation of levels of details by vertices aggregation; • Legend allows better assessing results 	<p>such an approach in order to analyze the importance and criticality of roads sections exposed to natural hazards considered as constraints. This first application also showed that the initial geographic, economic, environmental data processing is an essential part but time-consuming of the global methodology.</p>	<p>relates to a very simple network structure. Therefore, the identification of critical sections is not spectacular due to the linear structure of network (in opposition to a high meshed structure).</p>
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		<p>territories and to identify critical roads sections depending both on their exposure to phenomena but also on the importance of roads on economic, social, environmental contexts. The structural network analysis allows to describe how far the network properties conditions the accessibility from one point to another. This approach is combined to multicriteria decision making to</p>		<p>displayed by operating variation on the number of boxes (classification) and colors (symbolization).</p>		
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		<p>assess importance according to economic, social or human factors but also fragility, resilience or risk sensitivity on road sections.</p>				
<p>Sreelekha. M.G.a *, Krishnamurthy.K.b , Anjaneyulu . M.V.L.R.c</p>	<p>Interaction between Road Network Connectivity and Spatial Pattern</p>	<p>Developed graph theory measures to quantify the spatial structure of road network and to verify their relationship with regional economic characteristics. Traditional interest in understanding network structure</p>	<p>The methodology involves application of GIS for evaluating the road network of the study area. Urban road network evaluation based on GIS involves collecting the data resources, digitizing the network, building road network database, extracting the network structure etc..Calicut corporation</p>	<p>Dataset is everything given on the paper.</p> <p>The main two objectives were:</p> <ul style="list-style-type: none"> • To understand the existing road network of the city in terms of connectivity and development • To characterize the spatial structure 	<p>Network Density is usually computed by dividing the mass length of road network by the surface on which this mass is located. Thus density only provides information about the mean occupation of the object by a mass; it doesnot take into account the spatial distribution</p>	<p>Analysis reveals that road network fractality is directly varying with respect to connectivity and coverage of the study area. Root Mean Square Error (RMSE) values showed that road network density is better suited to predict road network fractal dimension even though the data contain some</p>

		<p>has been limited to geographers who view the spatial nature of the road network as a vital input to regional development. In recent years, there has been considerable interest to understand the topology of transport networks that connects points in geographic space. investigated the potential application of proposed network measures namely, heterogeneity, connection patterns and</p>	<p>road network was taken from Google map and the zone wise corporation boundary from the Autocad drawing obtained from Calicut Corporation office. ArcGIS 9.3 was used for characterising the network based on various indicators and hence to identify the variation in their pattern. All the roads including Arterial, Sub-arterial, Collector Streets and Local Streets were digitised from the Google base map. The Autocad ward map was converted into ESRI shape file format. Both the maps were geo-rectified in ArcGIS to geographic</p>	<p>of the road network in terms of fractal dimension .</p> <p>The proposed network measures were later applied to trace the changes in network characteristics over time.</p>	<p>of the mass under consideration. From a mathematical point of view, this is a rather rough interpretation of the notion of density. If fractal dimension was a simple synonym of road density, the correlation between the two variables evaluated for the same road network would be close to 1.</p>	<p>amount of dispersion. This means that there is significant relationship between the level of road network development and the network spatial structure within the study area, suggesting that the road network development could explain the variation in the spatial pattern significantly. The indicators undertaken for measuring the spatial structure of road networks can be applied to identify its effect on the performance of the road transport system, as well as its subsequent effects on land use and urban form.</p>
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		continuity, in quantifying the structure of road networks.	co-ordinates for which the ground control points were used. In ArcGIS, the ward boundary and roads were converted into polygon and polyline features respectively.			
Andreas Hartmann a , Florence Yeang Yng Ling b	Value creation of road infrastructure networks: A structural equation approach	The analysis revealed that road cleanliness and road evenness have a significant effect on the experience of road maintenance. Important and significant indicators for the experience of traffic management are the clarity of road signs and the efficiency	The aim of this research is to shed more light on the role of road agency activities for the value creation process of road users. The research builds upon an earlier study of Ling and Ng (2011), which explored the relationship between activity outcomes and road user satisfaction in Singapore and found two activity outcomes	To estimate our conceptual model, we used structural equation modeling (SEM), which is a second generation multivariate analysis technique. SEM combines both econometric and psychometric perspectives in statistical modeling	The analysis of the PLS model is a two-step approach which first assesses the measurement model and then the conceptual model. Due to the lack of a global quality criterion, the criteria to evaluate reflective and formative constructs as well as the path model were based on the	The limitation of the research to the Singapore context and to the perspective of the Singapore road agency offers avenues for further research. First of all, future studies should further improve our understanding of the role of road infrastructure in the value-creation process of road users

		<p>of traffic redirection . A main conclusion of the research is that for traffic-intensive networks, both road maintenance and traffic management activities are important contributors to the value creation of road infrastructure with a slightly stronger contribution of traffic management activities.</p>	<p>(cleanliness of roads and efficiency of traffic redirection arising from road works) affecting satisfaction. Based on a structural equation approach, we extend the work of Ling and Ng (2011) by examining the relationship between the road user experience of road agency activities and the value that road users achieve through these activities. More specifically, our aim was to investigate the effect of road user experience with two main activity types: road maintenance and traffic management. Both activity types are central to the service</p>	<p>attempts and allows estimation of simultaneous relationships among unobservable predictor and predicted constructs, characterized by their respective block of measurement items. There are two approaches for estimating structural equation models: covariance-based SEM and variance-based partial least square (PLS) modeling. Covariance-based SEM is a confirmatory approach which</p>	<p>extant literature.</p>	<p>and the condition and traffic parameters that affect the service provision of a road. That may include a more detailed differentiation of road users, their characteristics and purposes of using road infrastructure networks. In addition, future studies could also fruitfully compare the effectiveness of road agencies in contributing to the value creation process of road users.</p>
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			<p>provision of road agencies and can be expected to have a great impact on the value proposition of road infrastructure.</p> <p>It is this notion of value offering which forms the theoretical lens of our research.</p>	<p>tries to minimize the discrepancy between the estimated and sample covariance matrices. Variance-based PLS is a prediction-oriented approach which tries to maximize the explained variance of the endogenous latent variable by applying a series of ordinal least square regressions.</p>		
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❖ Objective of the project:

The objective is to attempt to help the residents of cities affected by the floods in Kerala. This is done by visualising the road map of Kerala as a graph with the nodes being the prominent cities in Kerala, and the edges being the roads connecting the cities. Using centrality measures (such as degree, closeness, and betweenness) the closest unaffected cities are identified and the people who have experienced loss (such as the destruction of their houses, having severe injuries, and/or deaths) can be aided. These unaffected cities can act as relief areas for the people of affected cities and as distribution centres for goods and funds to these people.

❖ Innovation component in the project:

The project uses the measures of centrality in a social network to determine the reachability and connectivity of each city in the state. The innovative part of this project is the creation of a user friendly menu through which the user can input their city and find out if it is affected or unaffected. If affected, the user is provided with the closest unaffected city and the distance in kms through which relief can be sent. This program can be used in areas that are affected by natural calamities and disasters so that citizens can find the closest help centers.

❖ Work done and implementation

Methodology adopted:

Firstly, a dataset is made by using the road map of Kerala to create the graph. This will consist of the distance between cities. Thus, the edges that are used will be valued. Using the distances between each city, the most prominent city (which will be found using the prestige of cities), etc., a data set is created that will consist of all this relevant information.

The dataset will consist of the distances between cities with a direct path between them. For cities that have only indirect paths between them, the shortest path will be calculating by adding the distances of the roads in this path.

The dataset will also consist of information regarding whether or not a particular city is affected or not. The programmer will feed this information to the dataset. The names of affected and unaffected cities are derived from the internet

After this analysis of each city's centrality is performed based on the following measures:

1. Degree

$$C'_D(v_i) = d_i / (n - 1)$$

2. Betweenness

$$C_b(n_i) = \frac{\sum_{\substack{j \neq k \\ i \neq j, k}} \frac{g_{jk}(n_i)}{g_{jk}}}{(g-1)(g-2)}$$

3. Closeness

$$C_C(i) = \frac{1}{\sum_j d(i,j)}$$
$$C_C^*(i) = \frac{1}{n-1} C_C(i)$$

The most important cities are analysed for distribution by taking into consideration the betweenness of cities, the closest relief areas to the affected cities on the basis of degree values, and which cities are in need of most help by examining which cities have the smallest closeness values.

The closest cities are identified using the degree and geodesic values between cities. Once the cities with largest betweenness values are obtained, this helps in identifying the cities that are most important for transport of goods through indirect paths. For unaffected cities, closeness values is identified as well, as they can provide insight into which cities need more help (those with low values of closeness) in comparison to other cities (those with larger values of closeness).

The algorithm to calculate these values is:

1. Start
2. Import networkx library of Python.
3. Create a graph G with nodes labelled from 1 to 35.
4. Add the weighted edges from the dataset.
5. Compute the degree centrality, closeness centrality and betweenness centrality for each node using the inbuilt functions of networkx library of the unweighted graph.
6. Find the maximum for all three centrality measures.
7. Print the maximum values.
8. Compute the degree centrality for each node while considering weights using the formula:

```
q = q+s;
print("Sum of weights: ")
print(q)
for (r,s) in G.degree(weight='weight'):
    p = s/q;
    W_D.append(p);
    p=0;
```

9. Compute the maximum weighted degree centrality and print it.
10. Compute the closeness centrality for each node using inbuilt functions from networkx library while considering weights this time.
11. Compute the maximum weighted closeness centrality and print it.
12. Compute the betweenness centrality for each node using inbuilt functions from networkx library while considering weights this time.
13. Compute the maximum weighted betweenness centrality and print it.
14. On the basis of the maximum values of degree, closeness, and betweenness, find the most important city and print it.
15. If the most important city amongst all cities is affected by floods, create two separate subgraphs consisting of the affected and unaffected cities respectively.
16. Apply steps from 8 to 14 for the graph of unaffected cities.
17. Using the inbuilt function to calculate the shortest path between two nodes using the Dijkstra algorithm, calculate the shortest paths to each unaffected city for an affected city.
18. Calculate and print the minimum of the shortest paths for each affected city, along with the node number of the unaffected city to which this shortest path exists.
19. Print the list of all the cities and prompt the user to input a specific city's number.
20. Check if the city is affected or not, if not, print that it is an unaffected city
21. If affected, print that it has been affected, and then refer to the list created in 19 and print the distance to the nearest unaffected city along with the index number of that unaffected city.

Hardware and Software Requirements:

Hardware: A fast computer with a good processor and all the necessary functions that are expected from modern computers is all we need in terms of hardware.

Software: A coding language that is flexible and allows the creation of user-defined functions, ie, Anaconda Distribution of Python.

Basic Requirements other than these include road maps for Kerala, formulae for calculating centrality measures, etc.

Dataset used:

- a) Where are you taking your dataset from?

The road map for Kerala is taken from <https://www.prokerala.com> and the information regarding whether or not a city is affected will be obtained from the internet.

b) Is your project based on any other reference project? (Stanford University or MIT)

Stanford University (Texas Road Network, link given in references)

c) How does your project differ from the reference project?

Our project differs in several ways from the reference project:

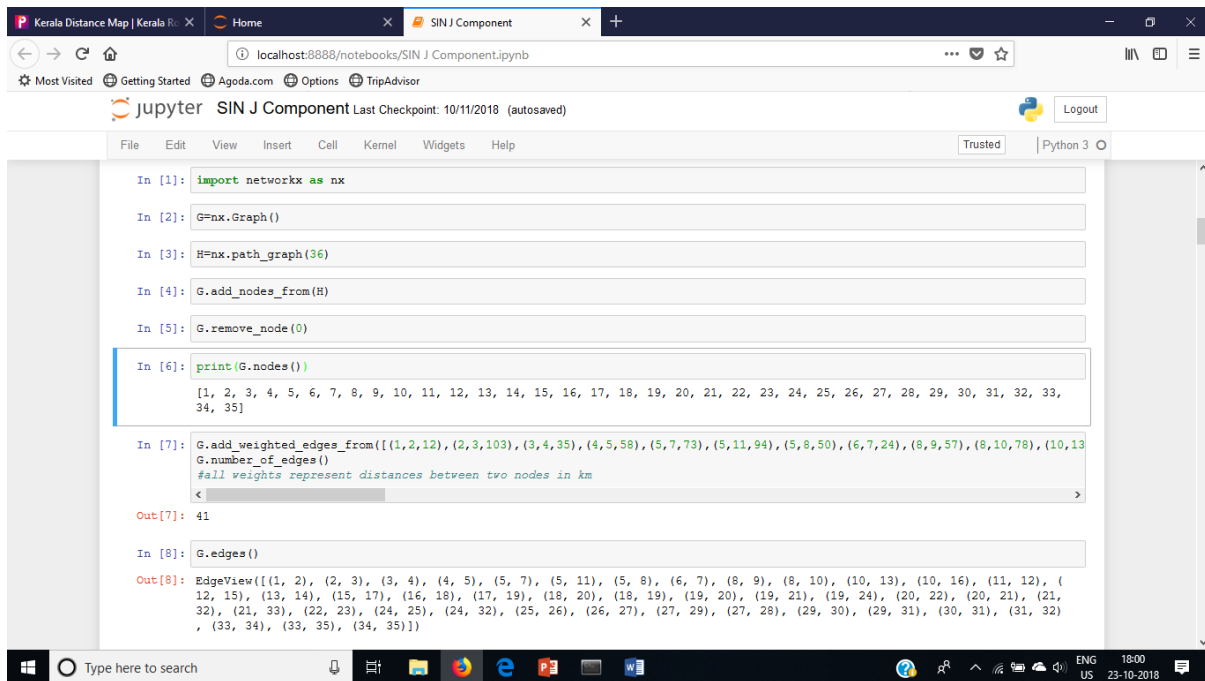
- We have taken the state of Kerala and not Texas.
- Along with defining the road network amongst major cities of Kerala, we are calculating the centrality measures (degree, closeness, and betweenness.) of each city while considering the distances of each path as weights. Based on these measures, we are identifying the cities of Kerala which can provide best support to the cities affected by floods.

Tools used:

The only tool we have used comprises of the Anaconda Distribution, which consists of the Anaconda Command Prompt, the Jupyter Notebook for Python, and several python libraries.

Screenshot and Demo:

Given below are screenshots of calculations of the weighted centrality measures, shortest paths, etc.



```
In [1]: import networkx as nx

In [2]: G=nx.Graph()

In [3]: H=nx.path_graph(36)

In [4]: G.add_nodes_from(H)

In [5]: G.remove_node(0)

In [6]: print(G.nodes())

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35]

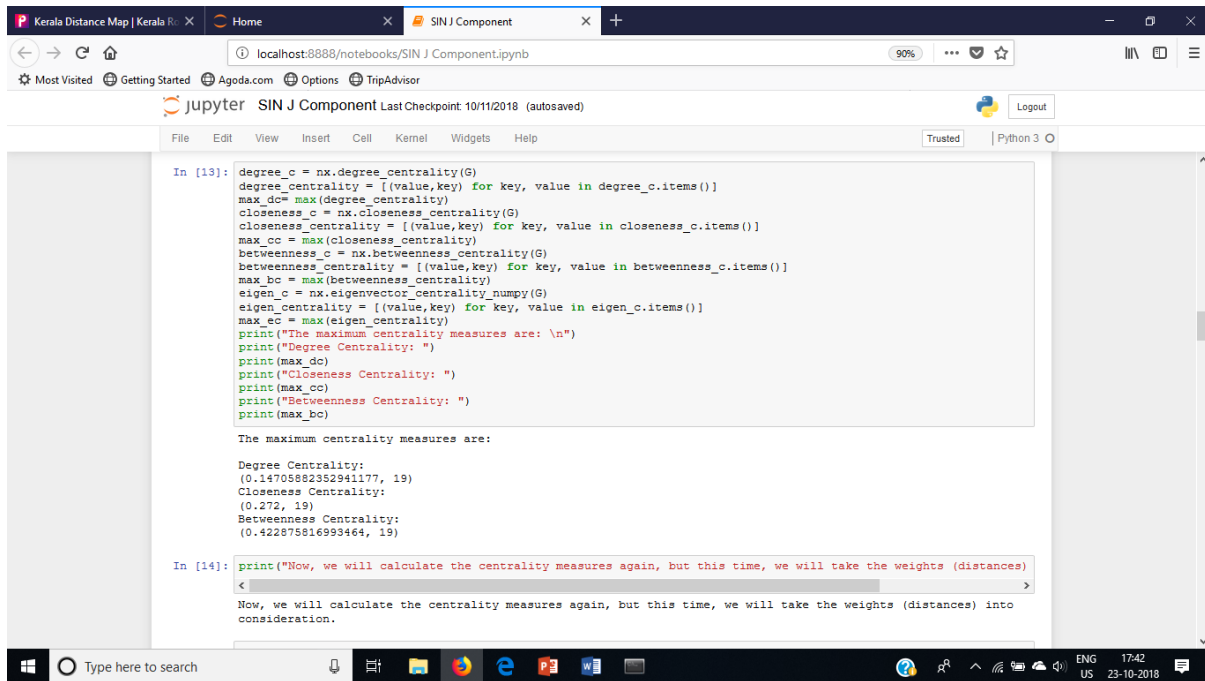
In [7]: G.add_weighted_edges_from([(1,2,12),(2,3,103),(3,4,35),(4,5,58),(5,7,73),(5,11,94),(5,8,50),(6,7,24),(8,9,57),(8,10,78),(10,13,12,15),(13,14),(15,17),(16,18),(17,19),(18,20),(18,19),(19,20),(19,21),(19,24),(20,22),(20,21),(21,32),(21,33),(22,23),(24,25),(24,32),(25,26),(26,27),(27,29),(27,28),(29,30),(29,31),(30,31),(31,32),(33,34),(33,35),(34,35)])
G.number_of_edges()
#all weights represent distances between two nodes in km
<

Out[7]: 41

In [8]: G.edges()

Out[8]: EdgeView([(1, 2), (2, 3), (3, 4), (4, 5), (5, 7), (5, 11), (5, 8), (6, 7), (8, 9), (8, 10), (10, 13), (10, 16), (11, 12), (12, 15), (13, 14), (15, 17), (16, 18), (17, 19), (18, 20), (18, 19), (19, 20), (19, 21), (19, 24), (20, 22), (20, 21), (21, 32), (21, 33), (22, 23), (24, 25), (24, 32), (25, 26), (26, 27), (27, 29), (27, 28), (29, 30), (29, 31), (30, 31), (31, 32), (33, 34), (33, 35), (34, 35)])
```

Fig 2: Creating the graph of nodes, with the paths between all pairs (if any), and respective weights of each path.



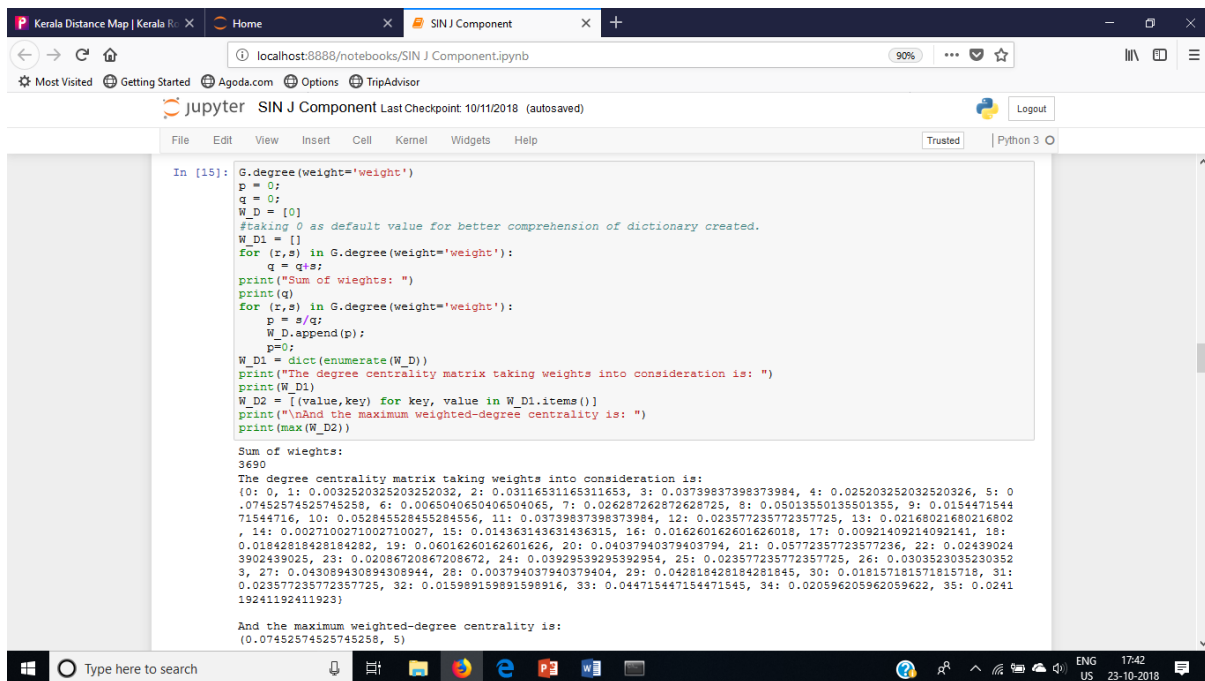
```
In [13]: degree_c = nx.degree_centrality(G)
degree_centrality = [(value, key) for key, value in degree_c.items()]
max_dc = max(degree_centrality)
closeness_c = nx.closeness_centrality(G)
closeness_centrality = [(value, key) for key, value in closeness_c.items()]
max_cc = max(closeness_centrality)
betweenness_c = nx.betweenness_centrality(G)
betweenness_centrality = [(value, key) for key, value in betweenness_c.items()]
max_bc = max(betweenness_centrality)
eigen_c = nx.eigenvector_centrality_numpy(G)
eigen_centrality = [(value, key) for key, value in eigen_c.items()]
max_ec = max(eigen_centrality)
print("The maximum centrality measures are: \n")
print("Degree Centrality: ")
print(max_dc)
print("Closeness Centrality: ")
print(max_cc)
print("Betweenness Centrality: ")
print(max_bc)

The maximum centrality measures are:

Degree Centrality:
(0.14705882352941177, 19)
Closeness Centrality:
(0.272, 19)
Betweenness Centrality:
(0.422875816993464, 19)

In [14]: print("Now, we will calculate the centrality measures again, but this time, we will take the weights (distances)
Now, we will calculate the centrality measures again, but this time, we will take the weights (distances) into consideration.
```

Fig 3: Finding the maximum of centrality measures without considering weight.



```
In [15]: G.degree(weight='weight')
p = 0;
q = 0;
W_D = [0]
#Taking 0 as default value for better comprehension of dictionary created.
W_D1 = []
for (z,s) in G.degree(weight='weight'):
    q = q+s;
print("Sum of wiegths: ")
print(q)
for (z,s) in G.degree(weight='weight'):
    p = s/q;
    W_D.append(p);
p=0;
W_D1 = dict(enumerate(W_D))
print("The degree centrality matrix taking weights into consideration is: ")
print(W_D1)
W_D2 = [(value, key) for key, value in W_D1.items()]
print("\nAnd the maximum weighted-degree centrality is: ")
print(max(W_D2))

Sum of wiegths:
3690
The degree centrality matrix taking weights into consideration is:
{(0: 0, 1: 0.0032520325203252032, 2: 0.03116531165311653, 3: 0.03739837398373984, 4: 0.025203252032520326, 5: 0.07452574525745258, 6: 0.0065040650406504065, 7: 0.026287262872628725, 8: 0.05013550135501355, 9: 0.015447154471544716, 10: 0.052845284528452845, 11: 0.03739837398373984, 12: 0.023577235772357725, 13: 0.02168021680216802, 14: 0.0027100271002710027, 15: 0.014363143631436315, 16: 0.016260162601626018, 17: 0.00921409214092141, 18: 0.01842818428184282, 19: 0.06016260162601626, 20: 0.04037940379403794, 21: 0.05772357723577236, 22: 0.024390243902439025, 23: 0.02086720867208672, 24: 0.03929539295392954, 25: 0.023577235772357725, 26: 0.03035230352303523, 27: 0.043089430894308944, 28: 0.003794037940379404, 29: 0.042818428184281845, 30: 0.018157181571815718, 31: 0.023577235772357725, 32: 0.015989159891598916, 33: 0.044715447154471545, 34: 0.020596205962059622, 35: 0.024119241192411923})

And the maximum weighted-degree centrality is:
(0.07452574525745258, 5)
```

Fig 4: Finding the weighted degree centralities of each node, and the maximum weighted degree centrality.

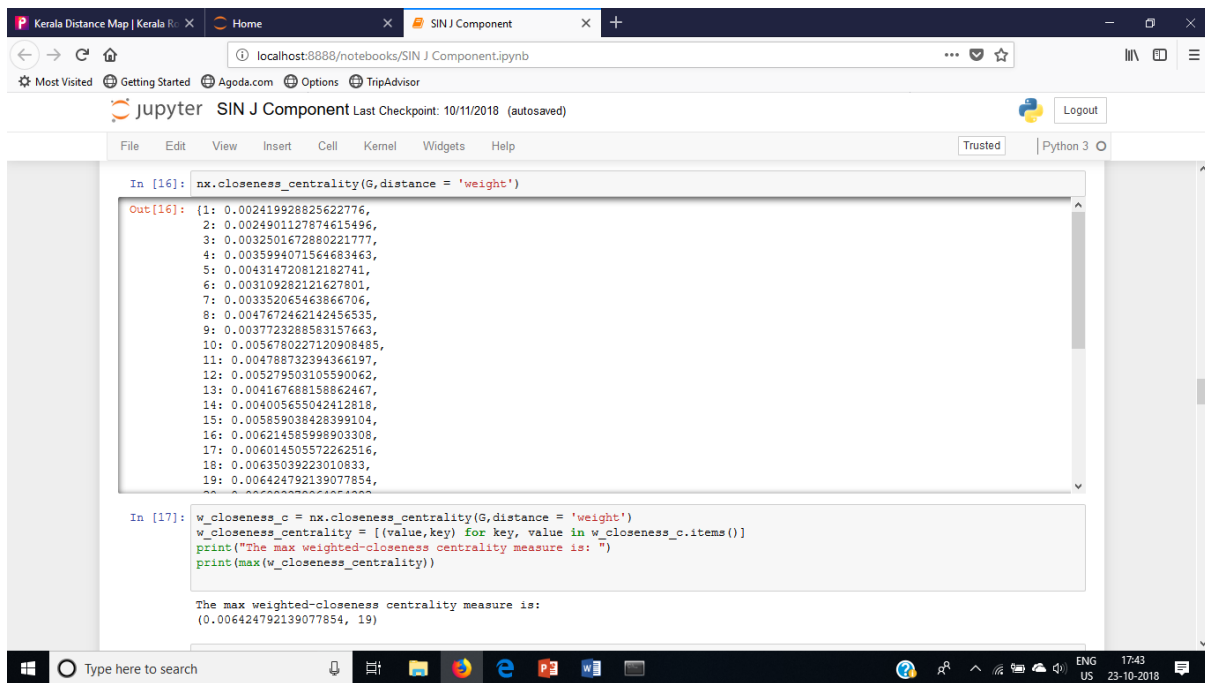


Fig 5: Finding the weighted closeness centralities of each node, and the maximum weighted closeness centrality.

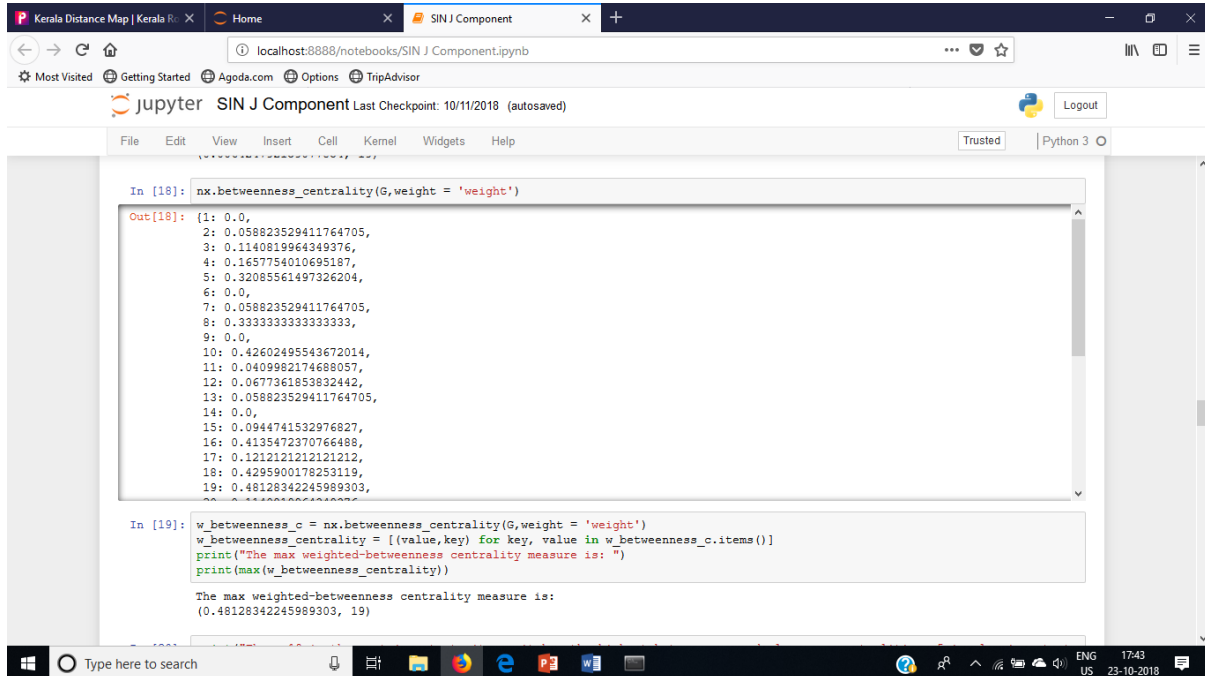


Fig 6: Finding the weighted betweenness centralities of each node, and the maximum weighted betweenness centrality.


```
has the highest degree centrality. (In all calculations, distances between cities are taken into consideration). However, 19
is affected by the floods. Thus, we must look at a city that isn't affected by floods. We will accomplish that in several w
ays and find the following:
1. The shortest path for every affected city to a city that isn't affected.
2. The maximum values of degree, betweenness, and closeness centralities for the nodes in the Unaffected cities.

In [20]:
Affected = G.subgraph([10,13,17,18,19,20,21,23,24,26,30,31])
print("The graph of affected cities is: \nNodes: ")
print(Affected.nodes())
print("Edges: ")
print(Affected.edges())

The graph of affected cities is:
Nodes:
[10, 13, 17, 18, 19, 20, 21, 23, 24, 26, 30, 31]
Edges:
[(10, 13), (17, 19), (18, 20), (18, 19), (19, 20), (19, 21), (19, 24), (20, 21), (30, 31)]

In [21]:
Unaffected = G.subgraph([1,2,3,4,5,6,7,8,9,11,12,14,15,16,22,25,27,28,29,32,33,34,35])
print("And the graph of unaffected cities is: \nNodes: ")
print(Unaffected.nodes())
print("Edges: ")
print(Unaffected.edges())

And the graph of unaffected cities is:
Nodes:
[1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 16, 22, 25, 27, 28, 29, 32, 33, 34, 35]
Edges:
[(1, 2), (2, 3), (3, 4), (4, 5), (5, 7), (5, 11), (5, 8), (6, 7), (8, 9), (11, 12), (12, 15), (27, 29), (27, 28), (33, 34),
(33, 35), (34, 35)]
```

Fig 7: Creating the graphs of affected and unaffected cities.

```
In [23]:
p1 = 0;
q1 = 0;
W_D = [0]
#taking 0 as default value for better comprehension of dictionary created.
W_D1 = {}
for (r,s) in Unaffected.degree(weight='weight'):
    q1 = q1+s;
print("Sum of wiegths: ")
print(q1)
for (r,s) in Unaffected.degree(weight='weight'):
    p1 = s/q1;
    W_D.append(p1);
    p=0;
W_D1 = dict(enumerate(W_D))
print("The degree centrality matrix taking weights into consideration is: ")
print(W_D1)
W_D2 = [(value,key) for key, value in W_D1.items()]
print("\nAnd the maximum weighted-degree centrality is: ")
print(max(W_D2))

Sum of wiegths:
1618
The degree centrality matrix taking weights into consideration is:
{0: 0.0, 1: 0.007416563658838072, 2: 0.07107540173053152, 3: 0.08529048207663782, 4: 0.057478368355995055, 5: 0.1699629171817
058, 6: 0.014833127317676144, 7: 0.05995055624227441, 8: 0.06613102595797281, 9: 0.03522867737948084, 10: 0.085290482076637
82, 11: 0.05377008652657602, 12: 0.0, 13: 0.02657601977750309, 14: 0.0, 15: 0.0, 16: 0.0, 17: 0.05377008652657602, 18: 0.0
865265760197775, 19: 0.04511742892459827, 20: 0.0, 21: 0.057478368355995055, 22: 0.04697156983930779, 23: 0.055006180469715
7}

And the maximum weighted-degree centrality is:
(0.1699629171817058, 5)
```

Fig 8: Finding the degree centralities of each of the unaffected cities and the maximum degree centrality amongst them.

The screenshot shows a Jupyter Notebook titled 'SIN J Component' with the following code and output:

```

058, 6: 0.014833127317676144, 7: 0.05995055624227441, 8: 0.06613102595797281, 9: 0.03522867737948084, 10: 0.085290482076637
82, 11: 0.05377008652657602, 12: 0.0, 13: 0.02657601977750309, 14: 0.0, 15: 0.0, 16: 0.0, 17: 0.05377008652657602, 18: 0.00
865265760197775, 19: 0.04511742892459827, 20: 0.0, 21: 0.057478368355995055, 22: 0.04697156983930779, 23: 0.055006180469715
7)

And the maximum weighted-degree centrality is:
(0.1699629171817058, 5)

In [24]: u_w_closeness_c = nx.closeness centrality(Unaffected,distance = 'weight')
u_w_closeness_centrality = [(value,key) for key, value in u_w_closeness_c.items()]
print("The max weighted-closeness centrality measure is: ")
print(max(u_w_closeness_centrality))

The max weighted-closeness centrality measure is:
(0.0042471042471042475, 5)

In [25]: u_w_betweenness_c = nx.betweenness centrality(Unaffected,weight = 'weight')
u_w_betweenness_centrality = [(value,key) for key, value in u_w_betweenness_c.items()]
print("The max weighted-betweenness centrality measure is: ")
print(max(u_w_betweenness_centrality))

The max weighted-betweenness centrality measure is:
(0.19047619047619047, 5)

In [26]: print("Thus, as we can see, node number 5 is the most important in terms of centrality measures for the unaffected cities. The
Thus, as we can see, node number 5 is the most important in terms of centrality measures for the unaffected cities. The city
with label is 5 is Calicut. Thus, Calicut is the best choice and can act as the hub of transport and storage of resources

```

Fig 9: Finding the closeness and betweenness centralities of each of the unaffected cities and the maximum closeness and betweenness centralities amongst them and thus printing the city with maximum of each centrality i.e. Calicut (node number 5).

The screenshot shows a Jupyter Notebook titled 'SIN J Component' with the following code and output:

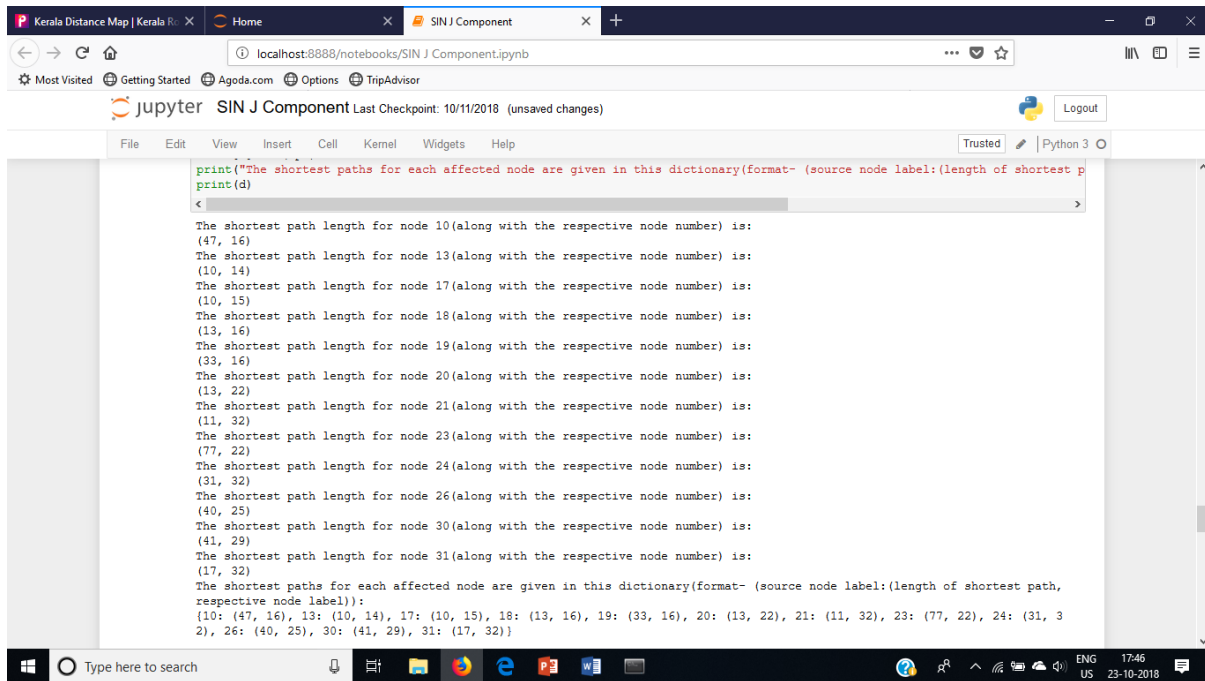
```

In [28]: d={}
for x in Affected.nodes():
    sp_x = nx.single_source_dijkstra_path_length(G,x,weight = 'weight')
    sp_x = [(value,key) for key, value in sp_x.items() if value != 0 and key not in Affected.nodes()]
    print("The shortest path length for node {}(along with the respective node number) is: ".format(x))
    print(min(sp_x))
    d[x]=min(sp_x)
print("The shortest paths for each affected node are given in this dictionary(format- (source node label:(length of shortest p
print(d)

The shortest path length for node 10(along with the respective node number) is:
(47, 16)
The shortest path length for node 13(along with the respective node number) is:
(10, 14)
The shortest path length for node 17(along with the respective node number) is:
(10, 15)
The shortest path length for node 18(along with the respective node number) is:
(13, 16)
The shortest path length for node 19(along with the respective node number) is:
(33, 16)
The shortest path length for node 20(along with the respective node number) is:
(13, 22)
The shortest path length for node 21(along with the respective node number) is:
(11, 32)
The shortest path length for node 23(along with the respective node number) is:
(77, 22)
The shortest path length for node 24(along with the respective node number) is:
(31, 32)
The shortest path length for node 26(along with the respective node number) is:
(40, 25)
The shortest path length for node 30(along with the respective node number) is:
(41, 29)

```

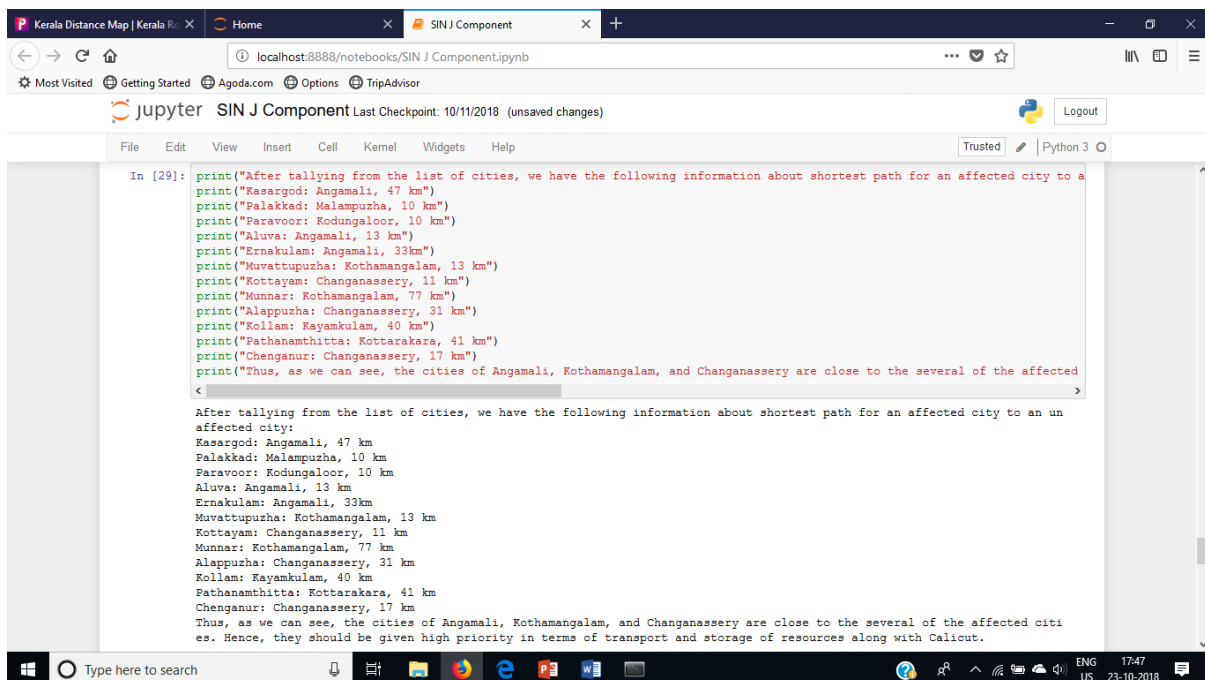
Fig 10 (a): Finding the shortest path for each affected city to an unaffected city.



The screenshot shows a Jupyter Notebook interface with a single code cell. The code prints the shortest paths for affected nodes. The output is as follows:

```
print("The shortest paths for each affected node are given in this dictionary(format- (source node label:(length of shortest p
print(d)
<
The shortest path length for node 10(along with the respective node number) is:
(47, 16)
The shortest path length for node 13(along with the respective node number) is:
(10, 14)
The shortest path length for node 17(along with the respective node number) is:
(10, 15)
The shortest path length for node 18(along with the respective node number) is:
(13, 16)
The shortest path length for node 19(along with the respective node number) is:
(33, 16)
The shortest path length for node 20(along with the respective node number) is:
(13, 22)
The shortest path length for node 21(along with the respective node number) is:
(11, 32)
The shortest path length for node 23(along with the respective node number) is:
(77, 22)
The shortest path length for node 24(along with the respective node number) is:
(31, 32)
The shortest path length for node 26(along with the respective node number) is:
(40, 25)
The shortest path length for node 30(along with the respective node number) is:
(41, 29)
The shortest path length for node 31(along with the respective node number) is:
(17, 32)
The shortest paths for each affected node are given in this dictionary(format- (source node label:(length of shortest path,
respective node label)):
{10: (47, 16), 13: (10, 14), 17: (10, 15), 18: (13, 16), 19: (33, 16), 20: (13, 22), 21: (11, 32), 23: (77, 22), 24: (31, 3
2), 26: (40, 25), 30: (41, 29), 31: (17, 32)}
```

Fig 10 (b): Finding the shortest path for each affected city to an unaffected city (continued).



The screenshot shows a Jupyter Notebook interface with a single code cell. The code prints the shortest paths for affected nodes. The output is as follows:

```
In [29]: print("After tallying from the list of cities, we have the following information about shortest path for an affected city to a
print("Kasargod: Angamali, 47 km")
print("Palakkad: Malampuzha, 10 km")
print("Paravoor: Kodungalloor, 10 km")
print("Aluva: Angamali, 13 km")
print("Ernakulam: Angamali, 33km")
print("Muvattupuzha: Kothamangalam, 13 km")
print("Kottayam: Changanassery, 11 km")
print("Munnar: Kothamangalam, 77 km")
print("Alappuzha: Changanassery, 31 km")
print("Kollam: Kayamkulam, 40 km")
print("Pathanamthitta: Kottarakara, 41 km")
print("Changanur: Changanassery, 17 km")
print("Thus, as we can see, the cities of Angamali, Kothamangalam, and Changanassery are close to the several of the affected
<
After tallying from the list of cities, we have the following information about shortest path for an affected city to an un
affected city:
Kasargod: Angamali, 47 km
Palakkad: Malampuzha, 10 km
Paravoor: Kodungalloor, 10 km
Aluva: Angamali, 13 km
Ernakulam: Angamali, 33km
Muvattupuzha: Kothamangalam, 13 km
Kottayam: Changanassery, 11 km
Munnar: Kothamangalam, 77 km
Alappuzha: Changanassery, 31 km
Kollam: Kayamkulam, 40 km
Pathanamthitta: Kottarakara, 41 km
Changanur: Changanassery, 17 km
Thus, as we can see, the cities of Angamali, Kothamangalam, and Changanassery are close to the several of the affected citi
es. Hence, they should be given high priority in terms of transport and storage of resources along with Calicut.
```

Fig 11: Printing each affected city and their respective closest unaffected cities.

The screenshot shows a Jupyter Notebook titled "SIN J Component" running on a local host. The notebook contains a Python script that prompts the user to enter an index number from a list of 16 cities. The script checks if the city is affected by floods and, if not, prints the shortest distance to an unaffected city. The list of cities is: 1. Kasargod, 2. Bakel, 3. Kannur, 4. Mahe, 5. Calicut, 6. Sultan, 7. Kalpetta, 8. Kottackal, 9. Shornur, 10. Thrissur, 11. Ponnani, 12. Guruvayoor, 13. Palakkad, 14. Malampuzha, 15. Kodungalloor, 16. Angamali.

```
In [*]: print("1. Kasargod\n2. Bakel\n3. Kannur\n4. Mahe\n5. Calicut\n6. Sultan\n7. Kalpetta\n8. Kottackal\n9. Shornur\n10. Thrissur\n11. Ponnani\n12. Guruvayoor\n13. Palakkad\n14. Malampuzha\n15. Kodungalloor\n16. Angamali")
nc=int(input("Enter the index number(list given below) of the city you wish to find info about.: "))
if (nc <= 35 and nc >=1):
    if nc in Affected:
        print("The city is affected by the floods.")
        sp_nc = nx.single_source_dijkstra_path_length(G,nc,weight = 'weight')
        spnc = [(value,key) for key, value in sp_nc.items() if value != 0 and key not in Affected.nodes()]
        print("The shortest distance (in km) for this city to an unaffected city (along with the index number of that city) is")
        print(min(spnc))
    else:
        print("The city hasn't been affected by the floods.")
```

Enter the index number(list given below) of the city you wish to find info about.:
|

1. Kasargod
2. Bakel
3. Kannur
4. Mahe
5. Calicut
6. Sultan
7. Kalpetta
8. Kottackal
9. Shornur
10. Thrissur
11. Ponnani
12. Guruvayoor
13. Palakkad
14. Malampuzha
15. Kodungalloor
16. Angamali

Fig 12 (a): Taking info from user to print info regarding that city.

The screenshot shows the same Jupyter Notebook as in Fig 12 (a), but now displaying the output of the script. The user has entered the index number 10, and the script has printed that the city is affected by floods and the shortest distance to an unaffected city is 47 km to city 16.

```
9. Shornur
10. Thrissur
11. Ponnani
12. Guruvayoor
13. Palakkad
14. Malampuzha
15. Kodungalloor
16. Angamali
17. Paravoor
18. Aluva
19. Ernakulam
20. Muvattupuzha
21. Kottayam
22. Kothamangalam
23. Munnar
24. Alappuzha
25. Kayamkulam
26. Kollam
27. Thiruvananthapuram
28. Kovalam
29. Kottarakara
30. Pathanamthitta
31. Chengannur
32. Changanassery
33. Peermede
34. Kumali
35. Kattapana
```

Enter the index number(list given below) of the city you wish to find info about.: 10
The city is affected by the floods.
The shortest distance (in km) for this city to an unaffected city (along with the index number of that city) is:
(47, 16)

Fig 12 (b): Printing info of the city (whether it is affected and shortest path to an unaffected city) based on the user's input.

❖ Results and discussion

Our project is based on achieving several results which are:

- Centrality Measures (with weights) for all cities
- Centrality Measures (with weights) for all unaffected cities only
- Shortest path for each affected city to an unaffected city

Based on all these results, we are identifying the most important unaffected cities which can act as hubs for transport of goods and services. We are also identifying the affected cities which should be helped first.

Based on our calculations, we have found that the most important city overall is Ernakulam, as it has the highest weighted closeness and betweenness centrality measures of 0.0064 and 0.4813 respectively. Calicut is an important city as well, with the highest weighted degree centrality value of 0.0745.

However, Ernakulam is a city that is affected by the floods. Thus, we need to find the most central city amongst unaffected cities as well. Based on our calculations, we have found that Calicut has the highest measures of degree, closeness, and betweenness centralities amongst unaffected cities with values of 0.1699, 0.0042, and 0.1905 respectively.

Furthermore, we have found the shortest paths for each affected city to an unaffected city, which has been shown on our screenshots. The cities of Angamali, Kothamangalam, and Changanassery are very important as well as they are the closest unaffected cities to 3, 3, and 2 affected cities respectively.

Munnar is the most remote affected city as the closest unaffected city to it is 77 km away (Kothamangalam). Ernakulam is a city that must be prioritized as it is the most central city in terms of closeness and betweenness values in Kerala.

Any user can use our project to identify if a city in Kerala is affected by the floods or not. If the city is affected, the user will be provided info on which unaffected city is the closest to it, and the distance to that city.

❖ References:

- <https://snap.stanford.edu/data/roadNet-TX.html>
- <https://www.prokerala.com>
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- https://en.m.wikipedia.org/wiki/2018_Kerala_floods?wprov=sfla1
- Research Papers:
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- Analysis of Road Network Pattern Considering Population Distribution and Central Business District by Fangxia Zhao, Huijun Sun, Jianjun Wu, Ziyu Gao, Ronghui Liu
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