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Areal Interpolation Approach for Covid -19 Cases in India: A Case of Geospatial Modelling

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Abstract

Covid-19 ever since its attack on human has left no trace of breaking the chain in this World. India started its first Covid- 19 case in March first week and the positive cases has raised to a count of 380532. In this study, Areal Interpolation approach is performed to analysis the distribution of the confirmed cases. For this analysis, the dataset has been obtained from the Ministry of Health and Family Welfare Government of India. The aim of the paper is to analyze the spatial distribution and prediction using the cases as on March 15, April 12, May 12, and June 19, 2020. The results of the models obtained for the confirmed cases on March 15 (Model: 19.786 Spherical(30.018)); April 12 (Model: 118170 Spherical(30.018)), May 12 (Model : 1.475e7 Spherical(30.018)) and June 19, 2020 (Model: 2.4625e8 Spherical(30.018)). The highlight of this study is the state district wise spatial distribution in four states and their respective daywise increase of confirm cases graphs.

Keywords: Covid-19, Areal Interpolation, Spatial, Distribution, District-wise, Daywise Increase

Introduction

Areal interpolation is the method for making estimates from a source set of polygons to an overlapping but dissimilar set of target polygons (Prener, 2020). Spatial data are usually combined into spatial units. Spatial unit convergence is known as areal interpolationthat addresses to the problem where differences in spatial units are found (Murakami &Tsutsumi, 2011). There exist various types of spatial units for aggregation;these differences in aggregation units makethe system difficult in handling data. Therefore, moving spatial data from one zonal structure to another is beneficialin solving such problem. Such a process is called areal interpolation.

Zhang & Qiu (2011) in a case study of population data introduced a point-based intelligent approach to the interpolation problem by using zero-dimensional points as ancillary data that are associated locationally with the variable of interest. The study of interpolating the population data at a suburbanized area proposed areal interpolation (Ar. Ip.) solutions based on the evaluationof its results with accuracy and efficiency.Comber& Zeng(2019) in their study discusses about the four Ar. Ip approaches using the *Newhaven* census tracts(source zones) and the 500-m polygon grid (target zones). The four interpolations are dasymetric, streetweighted, statistical and point-based that is demonstrated. The spatial and statistical distributions of the house estimates using data from the propertywebsite is also demonstrated with the large number of target zones with a house estimate of 0. Murakami &Tsutsumi (2011) in a case study on the Ar. Ipon the population demonstrated in improving thepredictive accuracy. The study suggests that the consideration of spatial autocorrelation is imperative foraccurate areal interpolation.

Discussion and Results

Spatial analysis is the approach of examining locations, attributes and relationships of features in spatial data to gain better understanding. For instance while looking at a map at the features and relationships with the Covid-19, rainfall or wildfire, one can draw certain conclusion based on the spatial data available. Spatial interpolation is the assumptions carried out using the spatially distributed objects are spatially correlated; i.e items that are close together tend to have similar characteristics. Spatial interpolation is of two categories namely point and areal interpolation. Figure 1 shows the types of spatial interpolation methods.

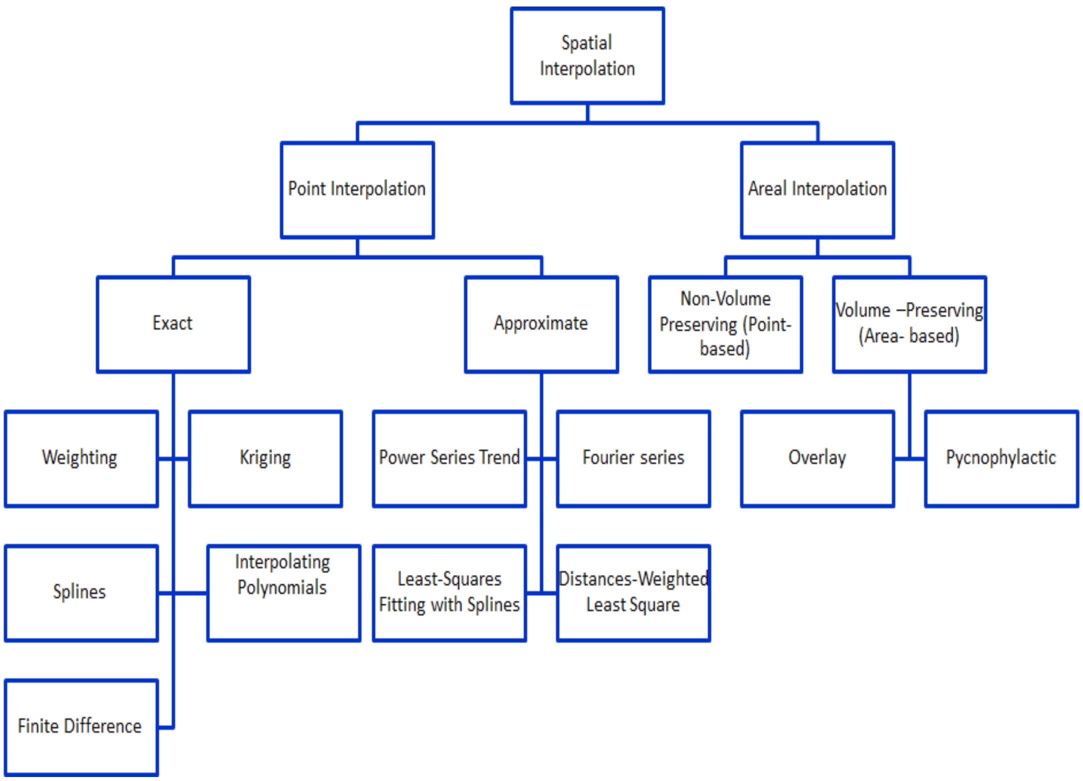


Fig 1. Various types of Spatial Interpolation

This study is carried out using areal interpolation on confirmed cases of Covid-19 dataset to analysis the distribution of spatial data geographically. Ar. Ipis a kriging-based interpolation method designed to work with data collected in polygons. Data comes in three forms. First, Gaussian data averaged over polygons. Secondly, binomial counts indicating the number of successes and trials per polygon. Thirdly, poisson data counting the number of events in a polygon over a specified time. In this study, the dataset was obtained from https://www.mohfw.gov.in/was analysis is carried out on ArcGIS. The figure 2 shows the interpolated prediction map for the first, fourth, eighth and twelfth week of the Covid-19 confirm cases in India.

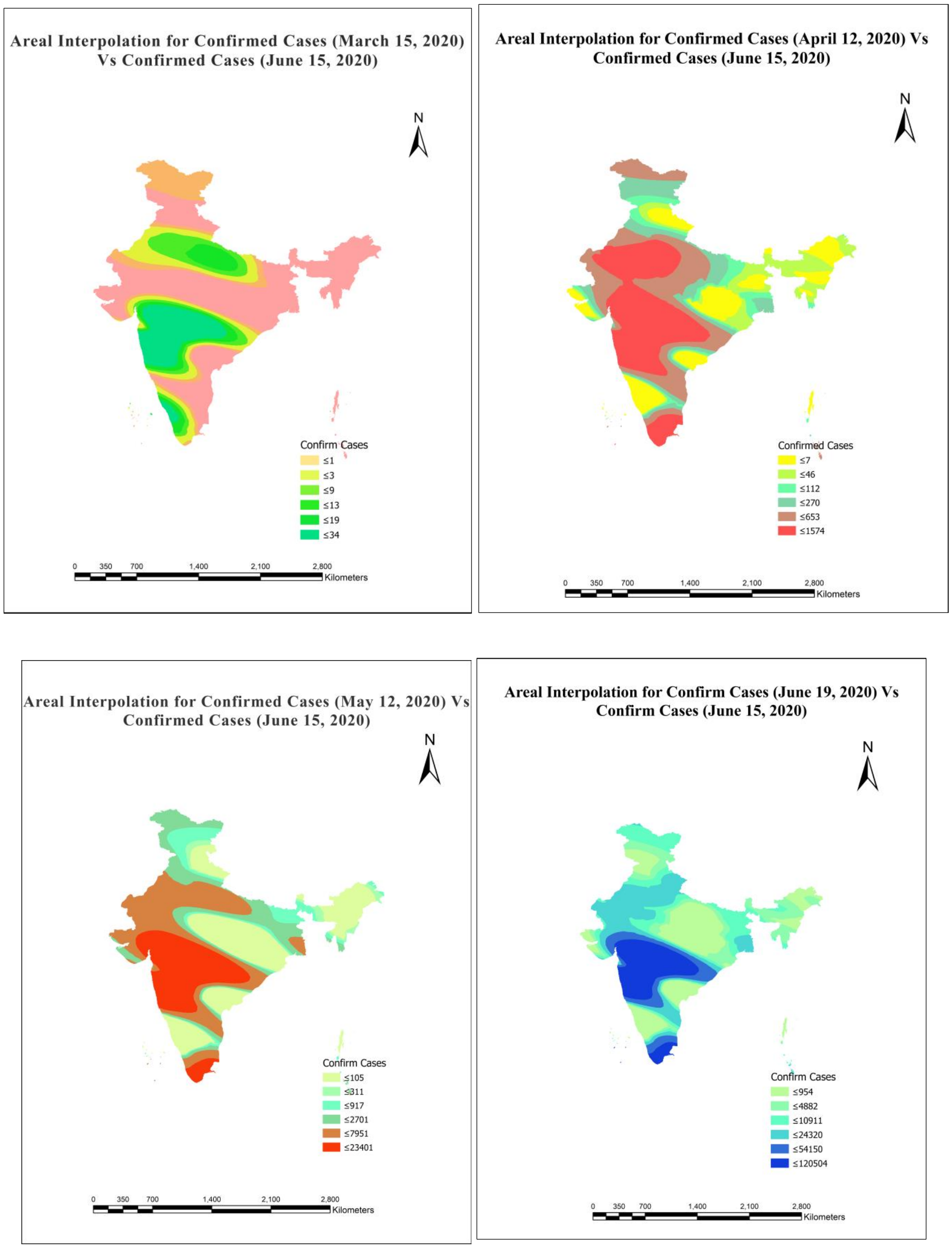


Fig2. Areal Interpolation of confirm cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

The summary of empirical covariancesof Spherical model and K-Bessel model of the different week cases are shown in the table 1 for the lag size (2.50149) and number of lags (12).

Table 1.Summary of Spherical and K-Bessel modelfor the Covid-19 cases

Week	Date	SphericalModel		K-Bessel		Mean	Average standard error
		Location		Model	Location		
First	March 15	19.786	30.018	58.428	8.2585	0.9660	4.1667
Fourth	April 12	118170	30.018	228690	8.3104	76.1065	259.7061

Eighth	May 12	1.475e7	30.018	2.9168e7	8.7924	738.0731	2830.35
Twelfth	June 19	2.4625e8	30.018	6.3155e8	8.1047	4930.488	13864.6677

Anisotropy is the correlation between two points which depends on their orientation and their distance. When anisotropy is true, it allows fitting the model in different semivariograms or covariances for different directions. The figures 3 and 4 are obtained when anisotropy is true.

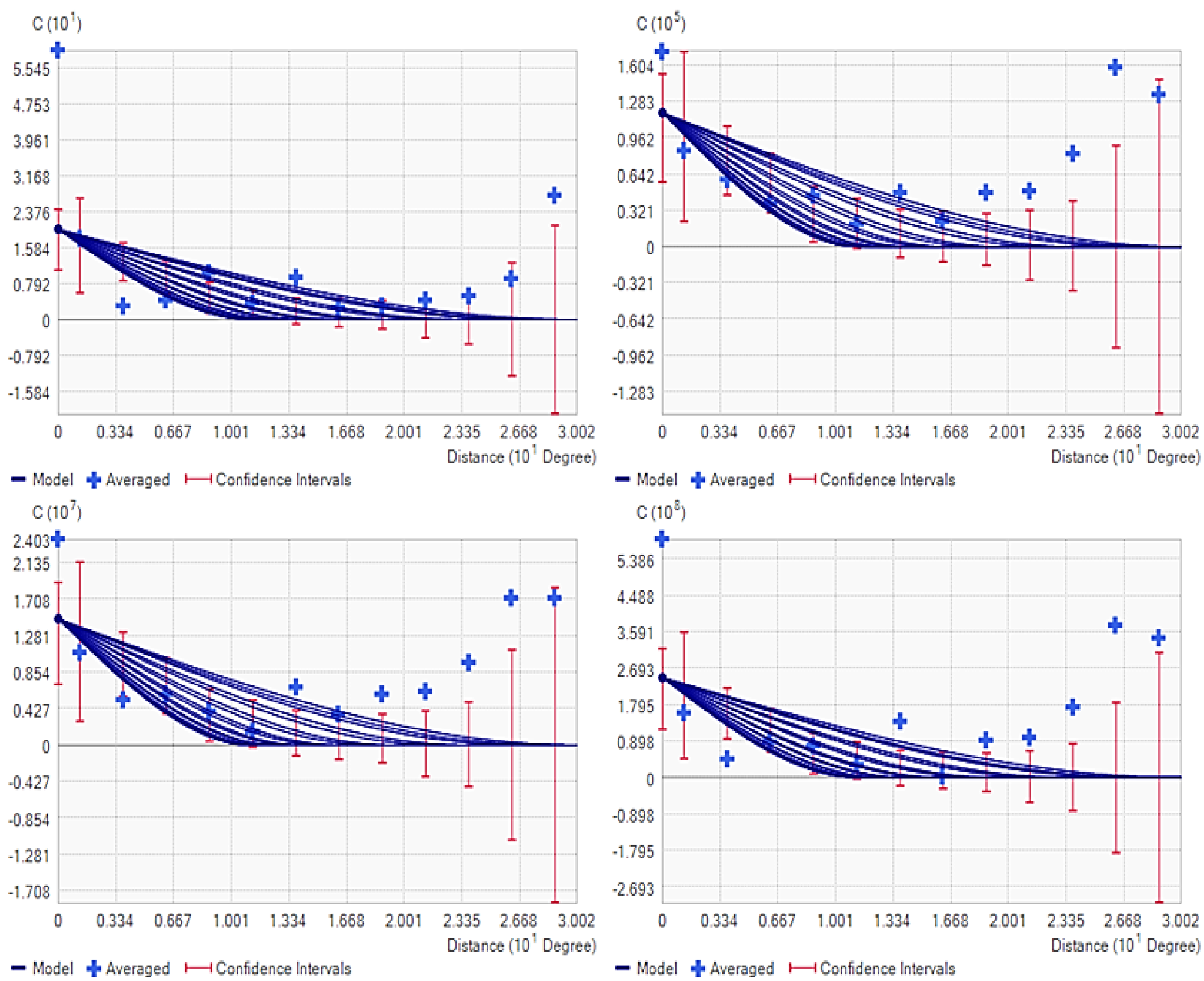


Fig 3. Spherical Model of Confirmed Cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

The models of Spherical and K-Bessel are better fit at the respective location given in the table 1.At this location one can find the model is best with covariance curve that appears better and most of empirical covariances fall within the confidential interval.

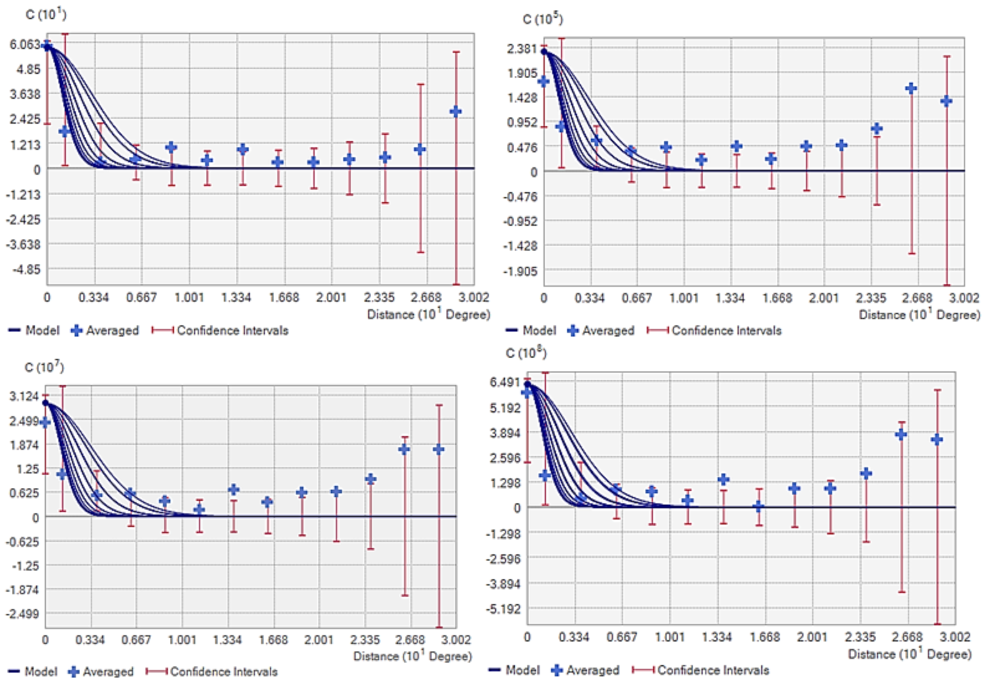


Fig 4. K-Bessel Model of Confirmed Cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

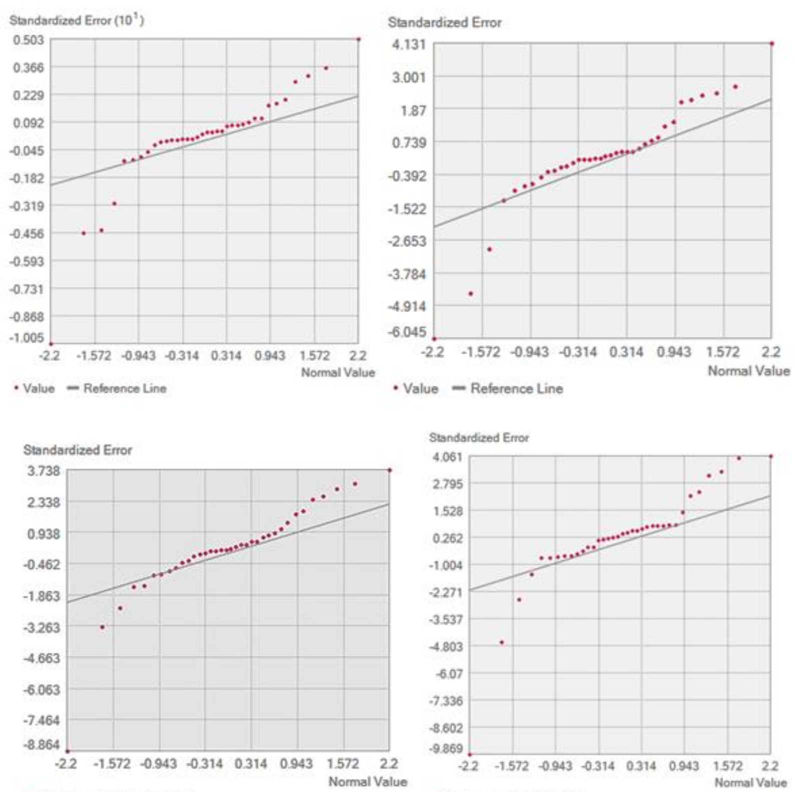


Fig 5. Normal QQ Plot for confirm cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

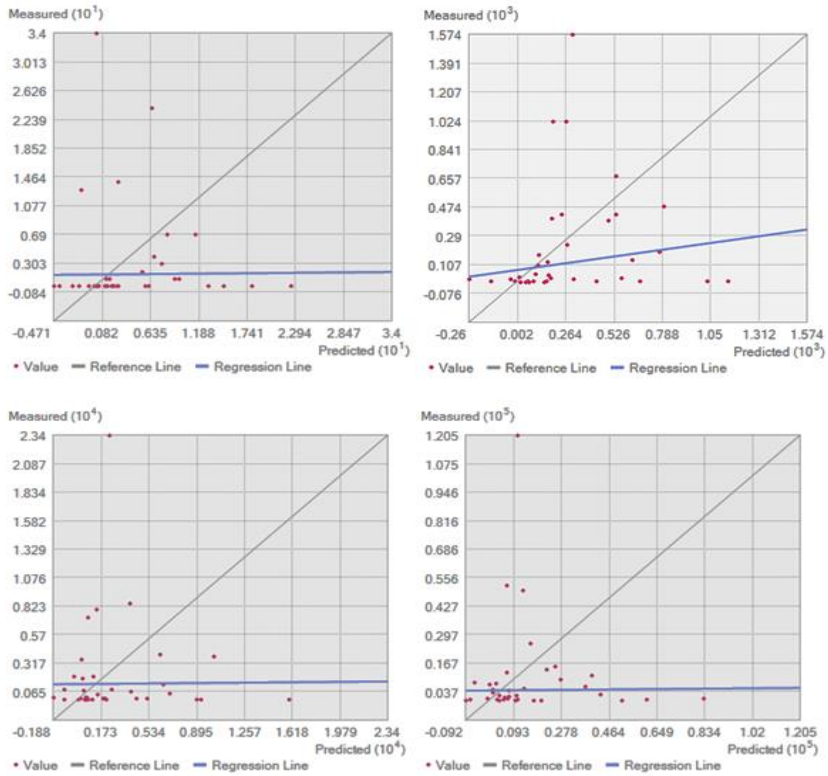


Fig 6. Predicted Plots for confirm cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

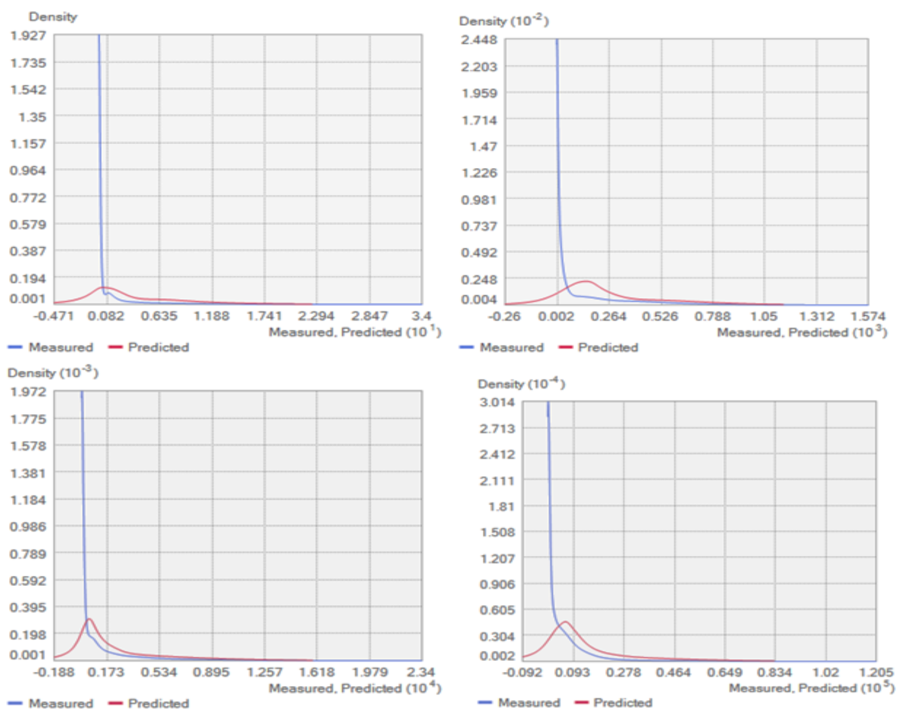


Fig 7. Measured –Predicted Plot for confirm casesa. March 15, b. April 12, c. May 12, d. June 19, 2020.

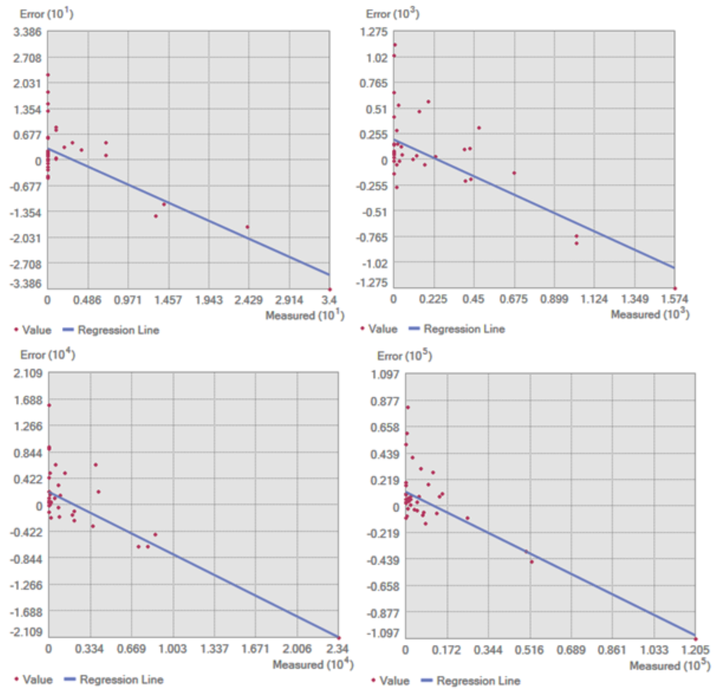


Fig 8. Errors plot for confirm cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

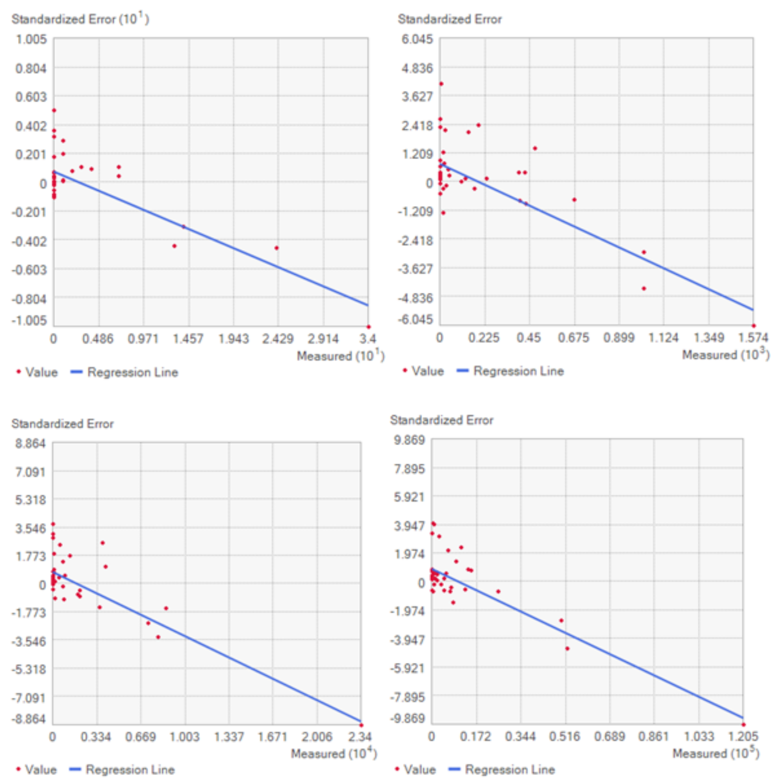


Fig 9. Standardized Errors plot for confirm cases a. March 15, b. April 12, c. May 12, d. June 19, 2020.

From figure 5, Normal QQ plot shows that the model is perfect with Root-Mean-Square Standardized (RMSS) nearer to 1. RMSS for the confirmed cases of March 15 (2.51), April 12 (1.82), May 12 (2.11) and June 19 (2.37) is obtained. Also Mean Standardized for March 15 (0.09), April 12 (0.15), May 12 (0.12) and June 19 (0.17) and the values lies in between 0.1 to 1. Figure 6 shows the prediction plot for the cases and the following equation is obtained for respective models of the corresponding week.

1. y = 0.0101 * x + 1.54 --------- eq (1)

2. y = 0.1638 * x + 73.49--------- eq (2)

3. y = 0.0099 * x + 1324.91---------- eq (3)

4. y = 0.0095 * x + 4339.36 ---------- eq (4)

Figure 7 represents the measured-predicted plot for each week respectively and similarly, figure 8 shows the error plot for each predicted plot of the model. Figure 9 shows the standardized error plots for the confirm cases and average standardized error values are mentioned in the table 1.

Temporal Analysis of Covid-19

The day wise increase in the confirmed cases is obtained using same dataset with STATA software shown in figure 10. India's total confirmed case are 9,36,181 as on July 15, 2020. In few states like Sikkim (209), Meghalaya (318), Mizoram (238) Nagaland (896), and Chandigarh (600) show minimum number of confirmed cases. States such as Kerala (8930) showed inclination in cases in the month of March but later the cases were found to be declined gradually.

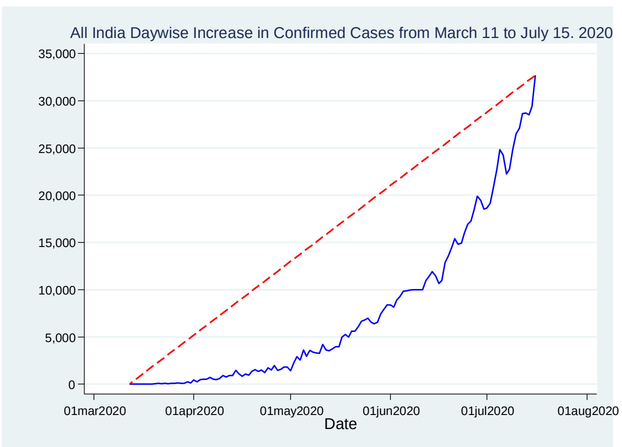


Fig 10.Daywise increase in confirmed cases in India

The data for the graph (figure 11) is obtained from www.mohfw.gov.in from April 12, 2020 to July 15, 2020 where Maharashtra is still on the peak with 267665 confirmed cases, total samples tested (641,441), test per million (5,251), positive rate was found to be 16.3%. Andhra Pradesh has 33019 confirmed cases, with total samples tested (11,53,849), tests per million (21,364), average growth rate (6.0%). In Telangana, the average growth rate is 8% with 37745 positive cases, and tests per million (3,782) whereas in Kerala had average growth rate has 5% with 8930 cases, and tests per million were (9,124). Kerala curve is flat when compared to TS and AP. TS curve finds rapid increase due to unlockdown(2.0).

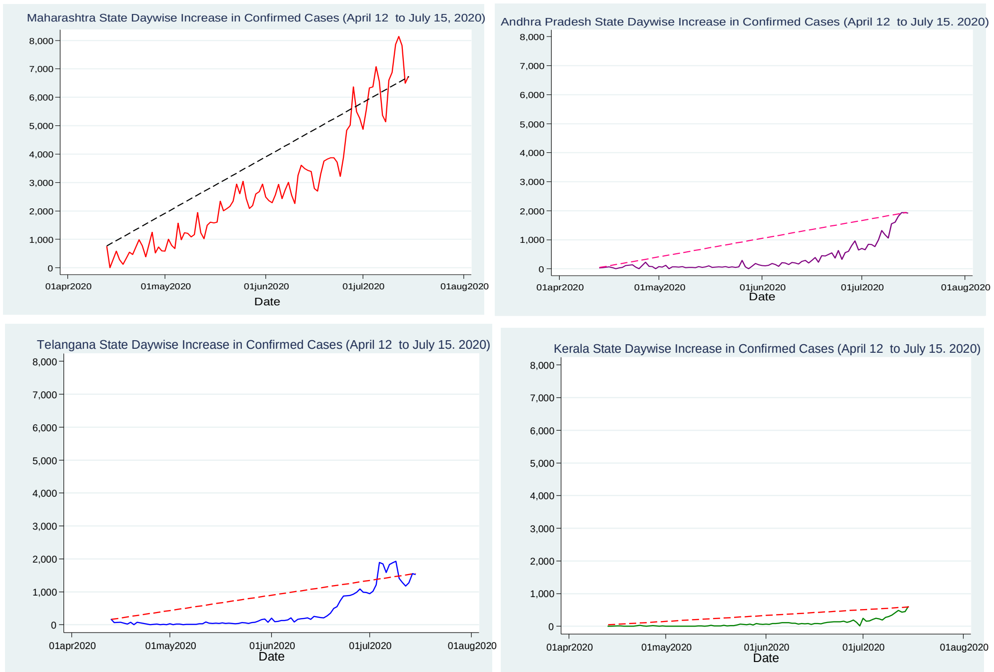
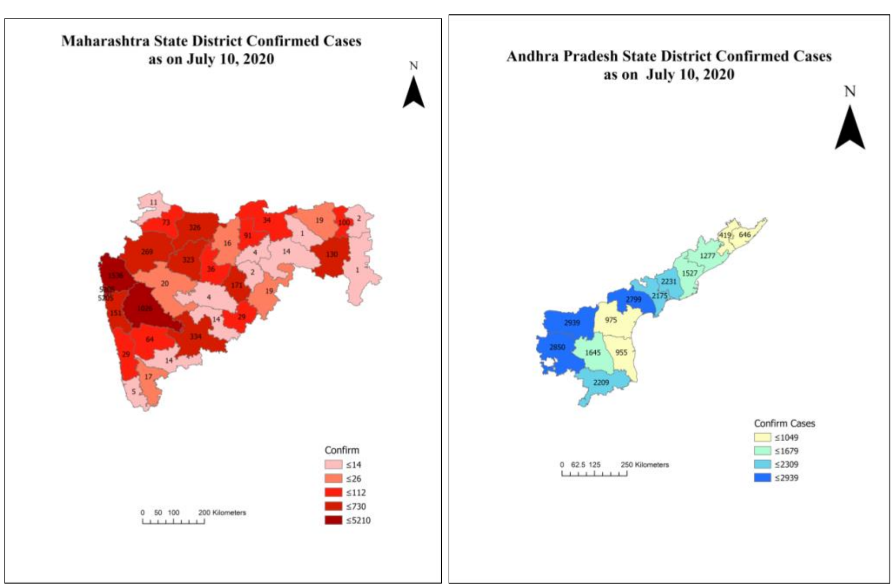


Fig 11. Daywise increase in confirmed cases in four states- Maharashtra, AP, TS and Kerala

Distribution of Covid-19 in Districts

In this study,four different states were considered for analyzingthecumulative cases as on July 10, 2020 (figure 12) with the peak, average and medium cases. The district data was obtained from https://www.covid19india.org/. Maharashtra has thirty four districts which were affected by Covid-19 virus with the highest number in the Mumbai (5205) followed by Thane (1536). Similarly, the highest cases were found in Kurnool district (2939) followed by Anantapur (2850) in Andhra Pradesh, Hyderabad (24,710) followed by Ranga Reddy district (2112). Finally in Kerala, Malappuram district (897) and Palakkad (776) were highest compared to other districts in Kerala.



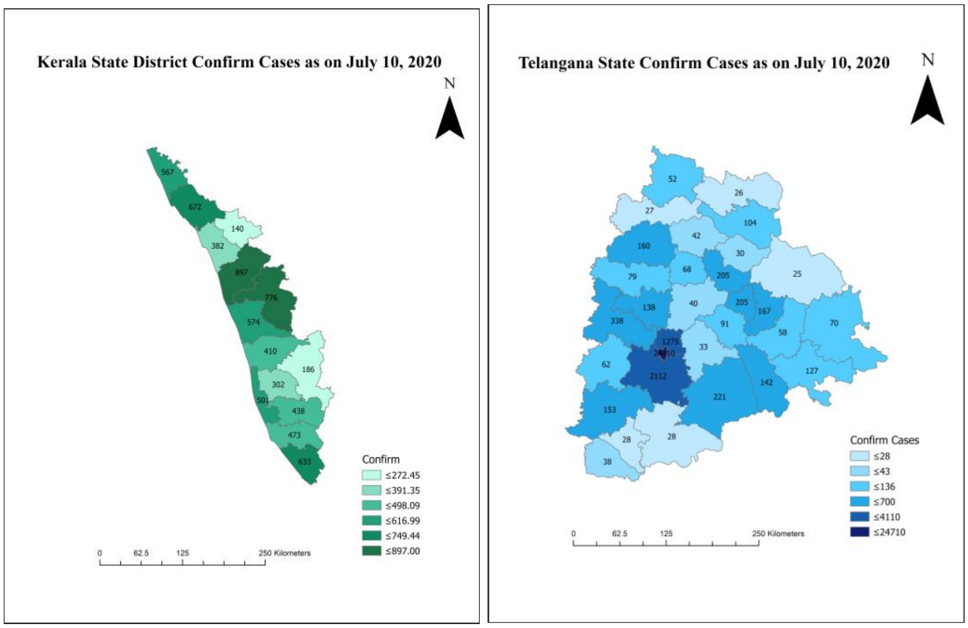


Fig 12. District wise distribution of confirmed cases in four states- Maharashtra, AP, TS and Kerala

Conclusion

Areal Interpolation is used widely and found to be efficient with Root-Mean-Square Standardized and with Mean Standardized. The best model seems to be April 12 dataset as the RMSS is very close to 1 compared to others. K-Bessel model helps to fit the model covariance curve appropriate and better. The models of the datasets with Spherical (19.786) and K-Bessel (58.428)for March 15; Spherical (118170) and K-Bessel (228690)for April 12; Spherical (1.475e7) and K-Bessel (2.9168e7)for May 12 and Spherical (2.4625e8) and K-Bessel (6.3155e8) for June 19 were obtained.The results are found to be accurate based on RMSS and K-Bessel location value. Hence, areal interpolation helps in distributing the spatial data across the geographical map. The state district wise spatial data distribution was carried out on ARCGIS.

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