

Spatial-Temporal Analysis and Visualization of Rural Development Works Implemented Under World's Largest Social Safety Programme in India—a Case Study

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Abstract

Regional- and national-level studies by researchers across the globe have used exploratory spatial data analysis (ESDA) to reveal interesting facts about the various environmental socioeconomic issues. However, its utility in rural development and planning has not been demonstrated at large. We used hotspot and emerging hotspot analysis tools of ESDA to analyse the spatial and temporal clustering of rural assets created under the world's largest social safety programme, i.e. MGNREGA, in Prakasam district of Andhra Pradesh, India. Results of hotspot and emerging hotspot analysis show that most of the assets tend to cluster at village level at selected locations and particular periods during the course of the project implementation. It also highlights the complementary nature of the two approaches in intuitively differentiating the geotagged rural assets. We also deployed a three-dimensional approach for visualizing the spatio-temporal associations among the event regions that enable a better understanding of the underlying spatial processes and the reasons behind their creation at a specific location by further corroborating with other spatial inputs and information. We conclude that ESDA tools are highly useful for simultaneous visualization of spatial and temporal clusters. The empirical results presented in the study could be helpful and valuable in enhanced planning and implementation of MGNREGA as well as other similar rural development programmes.

Keywords Spatial visualization · Exploratory data analysis · Hotspot · Rural development

Introduction

Sustainable Development Goals, adopted by all United Nations Member States in 2015, provides a shared agenda to stimulate coordinated action by the international community and national governments for promoting shared prosperity and overall well-being for the next 15 years and beyond. However, socioeconomic development and global sustainability are often posed as being in conflict. This is

mainly due to the trade-offs that exist between a growing world population, higher standards of living, and managing the effects of production and consumption on the global environment (Griggs et al. 2014). The economic uncertainties and insecurity, as well as the distributive conflicts that arise from globalization, could disrupt the economy from securing the benefits of globalization, and consequently could pose an impediment to economic growth. The role of government to stabilize the economy in terms of providing adequate social protection is therefore emphasized in order to ensure that benefits from globalization are realized (Rooslan and Mustafa 2020). The new approaches to social protection underpinning production as well as consumption patterns are looked upon as the promising solutions (Devereux 2001) in both urban and rural settings. There is great value to be gained through social protection programmes, by coordinating rural development initiatives that contribute to sustainable livelihoods for 70% of the global population. There exists significant disparity in spatial coverage as well as existing pathways for introducing safety net programmes as is evident across the globe (Gentilini 2015), depending on the socioeconomic fabric and political willingness.

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In India, the world's fifth-largest economy by nominal GDP and the third-largest by purchasing power parity (PPP), the development challenges are multifold. The large-scale disparity in income distribution, consumption, and living standards between rural and urban areas is the major cause of its massive rural-urban divide. There is a lack of opportunities for livelihood, modern facilities, and services necessary for a decent living in rural areas. Over the decades, the Government of India initiated a sequence of reforms to make the people self-reliant especially in rural areas. Presently, various schemes including Deendayal Antyodaya Yojana-National Rural Livelihoods Mission (DAY-NRLM), DeenDayal Upadhyay-GraminKaushalya Yojana (DDU-GKY), Pradhan Mantri Awaas Yojana-Gramin (PMAY-G), Pradhan Mantri Gram Sadak Yojana (PMGSY), Shyama Prasad Mukherjee National RuRBAN Mission and National Social Assistance Programme (NSAP), and Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) are being implemented to bring about the overall improvement in the quality of life of the people in rural areas through employment generation, strengthening of livelihood opportunities, promoting self-employment, skill development for rural youth, provision of social assistance and other basic amenities, etc. Among these schemes, MGNREGA represents a unique rural employment programme that guarantees 100 days of manual work a year to at least one member of every rural household across the country. It was put into law on 7 September 2005 and came into effect on 2nd February 2006. A federal government-sponsored scheme, using a decentralized approach (Giribabu et al. 2019) and hailed as a silver bullet (Jena and Ghosh 2013), MGNREGA has large economic and social costs. Over 380 billion rupees (US\$8 billion) was spent under it, to employ over 50 million households in 2009/2010 alone (MoRD 2018). During FY 2015–2018, the programme consistently generated 2.35 billion person days of unskilled employment every year and 2.65 billion person days in FY 2018–2019.

It is globally believed that features such as large project size, uniqueness, and complexity lead to corruption (Locatelli et al. 2017), and MGNREGA is no exception. Ever since the project has been launched, the government has been criticized for not maintaining a proper account of funds expenditure (Siddhartha and Vanaik 2008). Until a decade or two ago, a general lack of adequate data and methodological tools was a major hurdle in effective implementation of government schemes across the developing economies of the world. The fast adoption of information and communication technologies (ICTs) has resulted in reducing corruption by promoting good governance, strengthening reform-oriented initiatives, reducing the scope of corrupt behaviors, strengthening relationships between government employees and citizens, allowing for citizen tracking of activities, and monitoring and controlling behaviors of government

employees to a significant extent (Shim and Edom 2008). As a result, ICTs are ubiquitously becoming a cost-effective and convenient means to promote openness and transparency and to reduce corruption (Bertot et al. 2010). Advancements in the ICTs witnessed over the recent years have revolutionized the flow and timeliness of information across multiple nodes in the implementation of safety nets (Pingali et al. 2019) and the public service delivery schemes across the globe (Jaeger and Bertot 2010).

A rapid development in the data-driven technologies is also driving reconfiguration of systems in almost every sector including rural development. Explosion in the availability of sensor and mobile data resulted in massive volumes of data (Sacramento Gutierrez et al. 2019). Huge volumes of space and time stamped geotagged data are being generated at an unprecedented speed from different platforms, creating ample opportunities for studying human and environmental dynamics from different perspectives at different scales (Qiang and Van de Weghe 2019). Use of geographic information systems (GIS) and availability of fast and relatively inexpensive computer hardware have shaped the increase in the scale of traditional data sources due to global changes in Big Data Technologies (Kitchin 2014). The combination of e-government, social media, web-enabled technologies, mobile technologies, earth observation satellite data, geo-portals, transparency policy initiatives, and citizen desire for open and transparent government are leading to a new age of opportunity that has the potential to create open, transparent, efficient, effective, and user-centered ICT-enabled services (Bertot 2010). MGNREGA represents one of the best examples of technology-based disruption that has brought significant level of transparency and accountability in the entire service delivery chain of MGNREGA (Bhattacharjee 2017). Each work implemented under the programme is geotagged along with a field photo by means of mobile app. Its successful adoption is evident from over 4 crore geotagged assets under various categories that are available for visualization Geo-MGNREGA web portal for the entire Indian sub-continent (Fig. 1).

In spite of these positives, a careful watch is required to ensure that safety nets and service delivery programmes meet its objective in an inclusive manner rather than favoring certain areas or communities and excluding the others. Researchers across the globe are coming up with novel approaches to bring out methods for analysing and visualizing the data in the most judicious ways. Exploratory spatial data analysis (ESDA) in combination with GIS has emerged as a widely accepted tool for generating a better understanding of the spatial patterns and processes underlying the data (Messner et al. 1999). Regional- and national-level studies on the foundation of ESDA have been used to reveal interesting facts about the various socioeconomic and environmental issues analysed by researchers across the globe (Anselin et al.

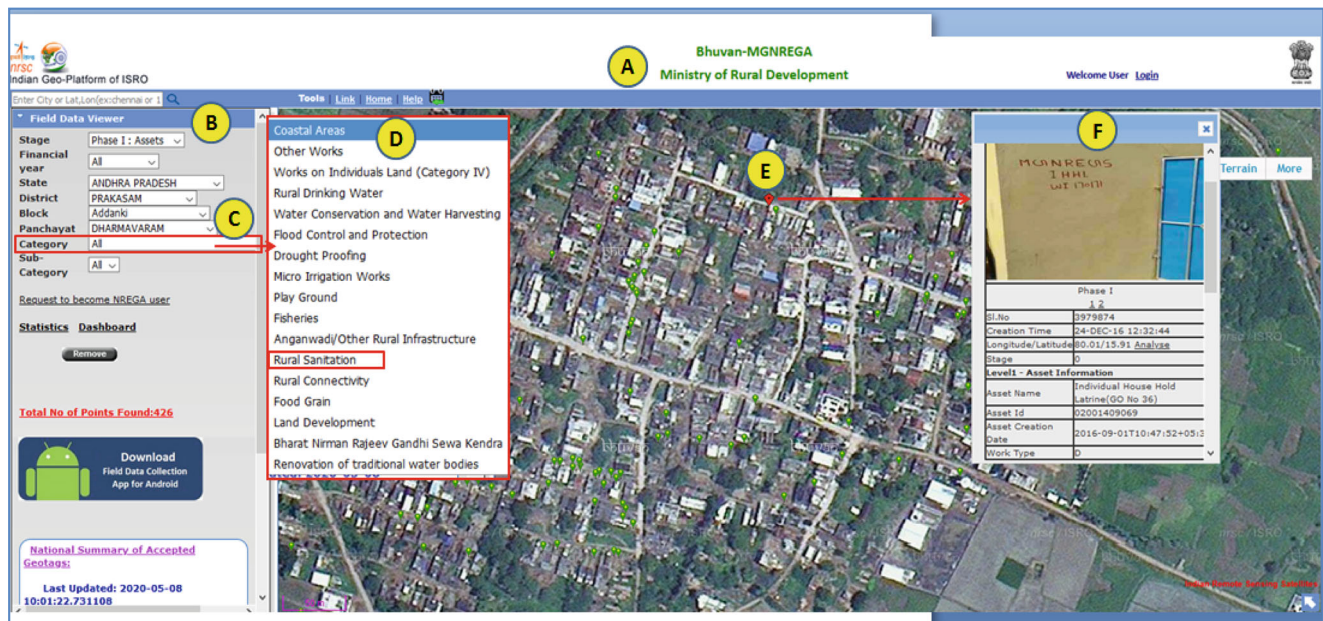


Fig. 1 (A) Geo-MGNREGA web visualization; (B) rural assets created under phase 1; (C) in Dharmavaram Gram Panchayat, Addanki Block, Prakasam district, Andhra Pradesh; (D) showing work category rural

sanitation; (E) geotag highlighted as red balloon; (F) along with the captured information and field photograph

2007). The utility of ESDA finds wide application in examining spatial patterns of socioeconomic attributes and environmental issues. It has been used widely across the domains such as crime (Messner et al. 1999), health and disease (Getis et al. 2003), poverty (Liu 2019), road traffic (Ouni and Belloumi 2018), and tourism (Rodríguez-Rangel and Sánchez-Rivero 2019). The scale of these studies also varies from local to regional (Murray and Grubestic 2019). However, its demonstrated utility in rural development and planning has not been presented at large. This study is thus carried out to showcase the potential of ESDA tools in monitoring the spatial and temporal patterns of the rural development works implemented under the world's largest social safety programme.

Methodology

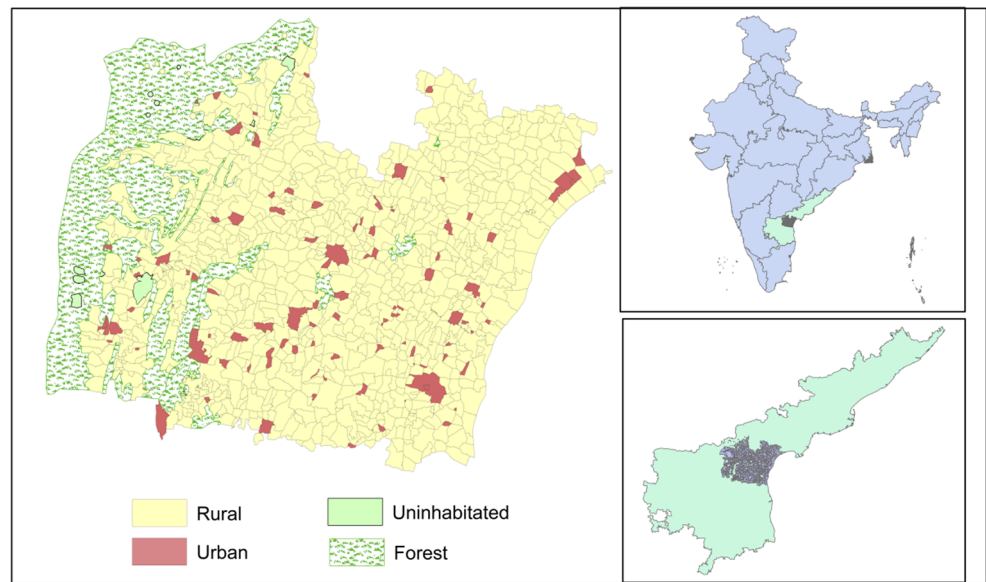
Study Area

Prakasam district is an administrative district in the coastal region of the Indian state of Andhra Pradesh (Fig. 2). It exhibits tropical wet and dry climate characterized by year-round high temperatures. The district has a record of temperature reaching more than 46 °C during the summers. December is the coldest month with a mean maximum temperature of about 27.1 °C and a mean minimum temperature of 19.2 °C. The average annual rainfall of the district is 798.6 mm, monthly rainfall ranges from nil in March to 182.9 mm in October. The district is located

between 78.43–80.25 east longitude and 14.57–16.17 north latitude. The district is bounded by Mahbubnagar and Guntur districts on the north, east Bay of Bengal, south by Nellore and Cudapah districts, and west Kurnool district. Administratively, it contains total 56 mandals; three revenue divisions, i.e. Kandukur, Ongole, and Andmarkapur; 945 revenue villages; 13 towns; one municipal corporation; 3 municipalities; and 4 nagara panchayats. The total district population is 3,392,764 according to the 2011, Census of India ; population density 192 people per km²; and average literacy rate 63.08%. The majority of the population, i.e. 78.21%, represents the rural in composition.

Physiographically, the terrain comprises of the varied nature of the plains and rocky hills. The areas near the coast are plain and fertile while the other parts are stony plains and hills. The district has a variety of soils like black cotton, red soil, red sandy loamy, and sandy loamy. The drainage of the study area is mainly under sub-parallel to sub-dendritic pattern. On the whole, the drainage pattern is sub-dendritic. However, other types of trellis, angulate, radial, dichotomous, etc. are present within it. Most of the stream courses are controlled by geologic structure (Asadi et al. 2011). Out of its total geographical area of 1,762,600 ha, the area in forests is 26% while the remaining is under the agricultural activities. A section of the Eastern Ghats Nallamalla forests with rich biodiversity also stretches over the district. Vegetation along the coastal line is mainly plantations of casurina and cashew nuts. The district falls under semi-arid zone in Peninsular India and has been identified as severely affected by drought with low and

Fig. 2 Location map of study area



erratic rainfall and predominantly dependent on bore wells for agriculture. Thus, the agro-ecological setting of the districts is characterized by the single crop system due to predominantly rain-fed cultivation.

Data Acquisition and Processing

We used a CSV file of time and date stamped geotagged data of 453,237 rural assets created in the study area under the MGNREGA programme during its implementation until March 2018. It contained information on *XY* location (latitude and longitude) besides several other attributes, i.e. stage, work financial year, category, subcategory, state, district, block, and panchayat/village etc. of each geotagged asset that are also available for visualization in the Bhuvan Geo-MGNREGA web portal. The data were checked for quality in terms of intangible properties such as completeness and consistency (Veregin 1999). It was found that the category name was missing in 32,419 asset records; thus, they were omitted from the analysis.

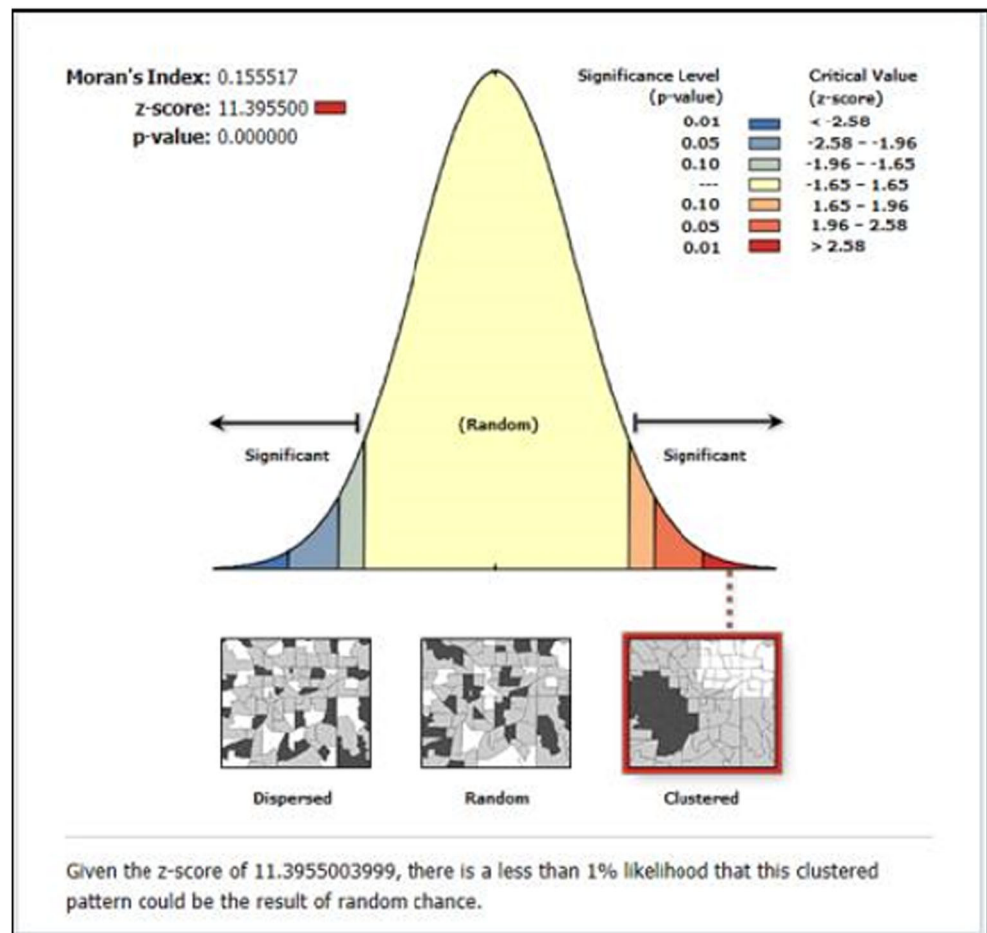
Further data handling and processing were done using ArcGIS software ver. 10.3.2 by converting the CSV file into a shape file of point features. The UTM projection zone 44 was used for further processing. The administrative boundary of the Prakasam district was obtained from the Space based Information Support for Decentralized Planning project (SIS-DP), one of the initiatives taken by the Govt. of India with ISRO/DOS for the generation and dissemination of spatial information for planning at the grassroots level (Rao et al. 2014). It has four main types of classes, i.e. rural, urban, un-surveyed forest villages, and forest ranges. The overlay of geotags with the administrative boundary was performed to further prepare in the geotagged asset data for the analysis. It was

found that 12,268 geotags were falling outside of the rural class and 1084 assets were found to be distributed in the forest ranges; hence, these were also omitted. Thus, the final analysis has been performed on 407,466 validated geotags distributed across the 945 revenue villages. These villages are designed as the lowest administrative unit in the settlement hierarchy designed to improve revenue collection mechanism and regulate the process for village planning and development. The spatial join tool was used to obtain the count of rural assets created in each village. Spatial autocorrelation was performed to understand the degree to which geotags are correlated based on Global Moran's *I* summary, which showed a high positive value of *z*-score—indicating high clustering of assets (Fig. 3). We also obtained a low value of *p* indicating that there is less than 1% chance that the clustering is occurring due to complete spatial randomness. Dataset information obtained from the spatial autocorrelation also resulted in the threshold distance of 7412 m using a zone of indifference model. It represents a Euclidean distance at which the clustering is occurring in the given set of the data.

Hotspot Analysis

We used hotspot analysis tool to identify the clustering of the rural assets. The null hypothesis says that there is no association between a specific feature of one region and its neighbors and that there exists a CSR either of the features themselves or the values associated with them (Getis et al. 2003). The local sum for a feature and its neighbors is compared proportionally with the sum of all features, when the local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance. This tool creates

Fig. 3 Spatial autocorrelation of the MGNREGA assets



a new output feature class with a *z-score*, *p value*, and confidence level bin (*Gi_Bin*) for each feature in the input feature class.

A high *z-score* and small *p* value of a feature indicate a spatial clustering of high values, i.e. hotspots. Wherever the values of *p* are very low, the null hypotheses can be rejected using another statistical measure, i.e. *Gi_Bin*. The *Gi_Bin* thus identifies statistically significant hot and cold spots, corrected for multiple testing and spatial dependence using the false discovery rate (FDR) correction method. Features in the ± 3 bins (features with a *GiBin* value of either +3 or -3) are statistically significant at the 99% confidence level; features in the ± 2 bins reflect a 95% confidence level; features in the ± 1 bins reflect a 90% confidence level; and the clustering for features with 0 for the *Gi_Bin* field is not statistically significant. There are six commonly available approaches under hotspot analysis, i.e. inverse distance, inverse distance squared, fixed distance, zone of indifference, contiguity edges, and contiguity edges and corners available in ArcGIS. For the current analysis, we found zone of indifference as most suitable as it resulted in high *z-score* with low variance *p* value as compared with the other models.

Emerging Hotspot Analysis

The distribution of MGNREGA works and the assets thus created in the study area varies over the years since the implementation of the scheme (Fig. 4). We used emerging hotspot analysis (EHA) to derive the temporal patterns of the works implemented under the MGNREGA. Unlike the hotspot analysis, which investigates the trend of assets/events over space, the EHA analyses the clustering patterns of point densities or summary fields of the assets/events across the area over a time step interval by generating space-time cube (STC). The STC structures the time stamped point features (geotagged assets) into the bins on the basis of location ID, time step ID, count value, and summary attributes that are aggregated at the time of generating the cube. Bins associated with the same physical location will share the same location ID and together will represent a time series. Bins associated with the same time step interval will share the same time step ID and together will comprise a time slice. The count value for each bin reflects the number of assets that occurred at the associated location within the associated time step interval. We used the work completion year under time field and 1 year in the time step interval, since the implementation, monitoring, and evaluation of

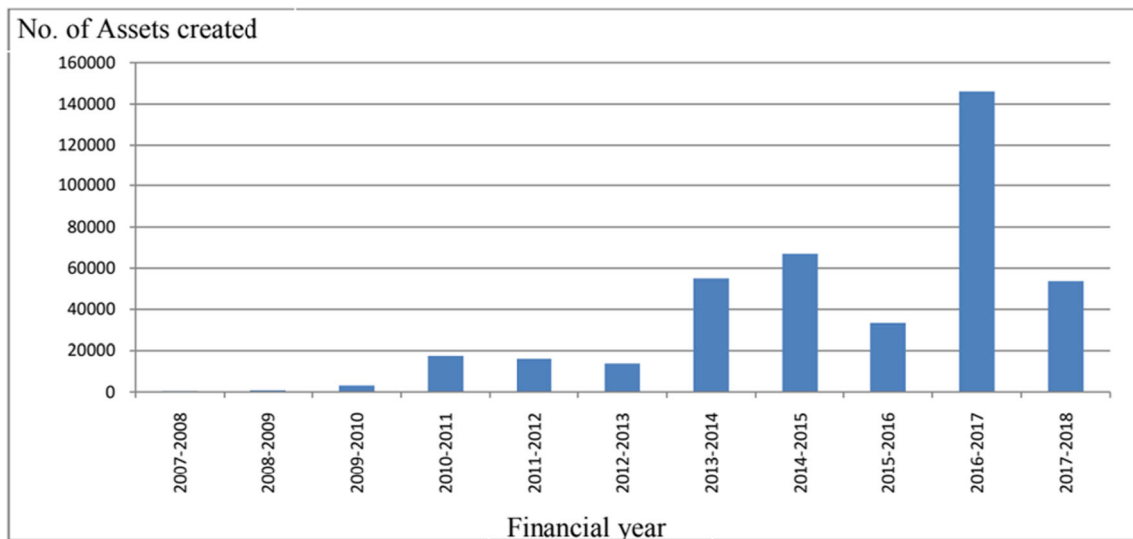


Fig. 4 Distribution of MGNREGA assets in Prakasam district based on completion financial year

MGNREGA are carried out on annual basis, mainly through the financial year, and this information is also stored in geotagged assets.

The EHA tool further conducts a hotspot analysis using the Getis-Ord G_i^* statistic for each individual bin in the STC. The neighborhood distance and neighborhood time step parameters define the number of surrounding bins, in both space and time, to be considered when calculating the statistic for a specific bin. Within each bin, the geotags are counted and the trend for bin values across time at each location is measured using the Mann-Kendall statistics. The Mann-Kendall trend analysis is a valuable tool for determining overall trends in data without making too many assumptions about the data itself. It is a non-parametric rating approach that is sensitive to slight overall trends rather than assessing the data based on fluctuations from a median value (Cotter 2009). It compares each bin value with the value from the previous year. If the value is greater than the previous year, the bin is given a 1 value. If the value is less than the previous year, the bin is given a -1 value. If there is no change, the bin is given a 0 value. The resulting values for each bin are added together to determine the overall trend. No trend results in a 0 value. Positive or negative scores indicate an overall trend in the data whether they are persistent, increasing, or decreasing over time (Steves 2018).

3D Visualization of Assets

Visual analytics is essential in applications where large information spaces have to be processed and analysed. 3D visualization offers improved insight into complex datasets, as the information which is otherwise hidden can be displayed and interpreted more effectively (Helbig et al. 2014). To facilitate an instant grasp of the overall project implementation, geotagged assets are visualized using a three-dimensional

geo-virtual environment in ArcGIS Pro, taking the time (work completion year) as the third dimension. Temporal visualization techniques consist of various techniques to visualize temporal data, by describing them as sequences of parametric operations applied to a conceptual STC taking joint count as the cube variable. The final visualisation provides a flexibility of displaying the results based on hot and cold spots (confidence values) as well as joint count value over the years in a stacked manner.

Results

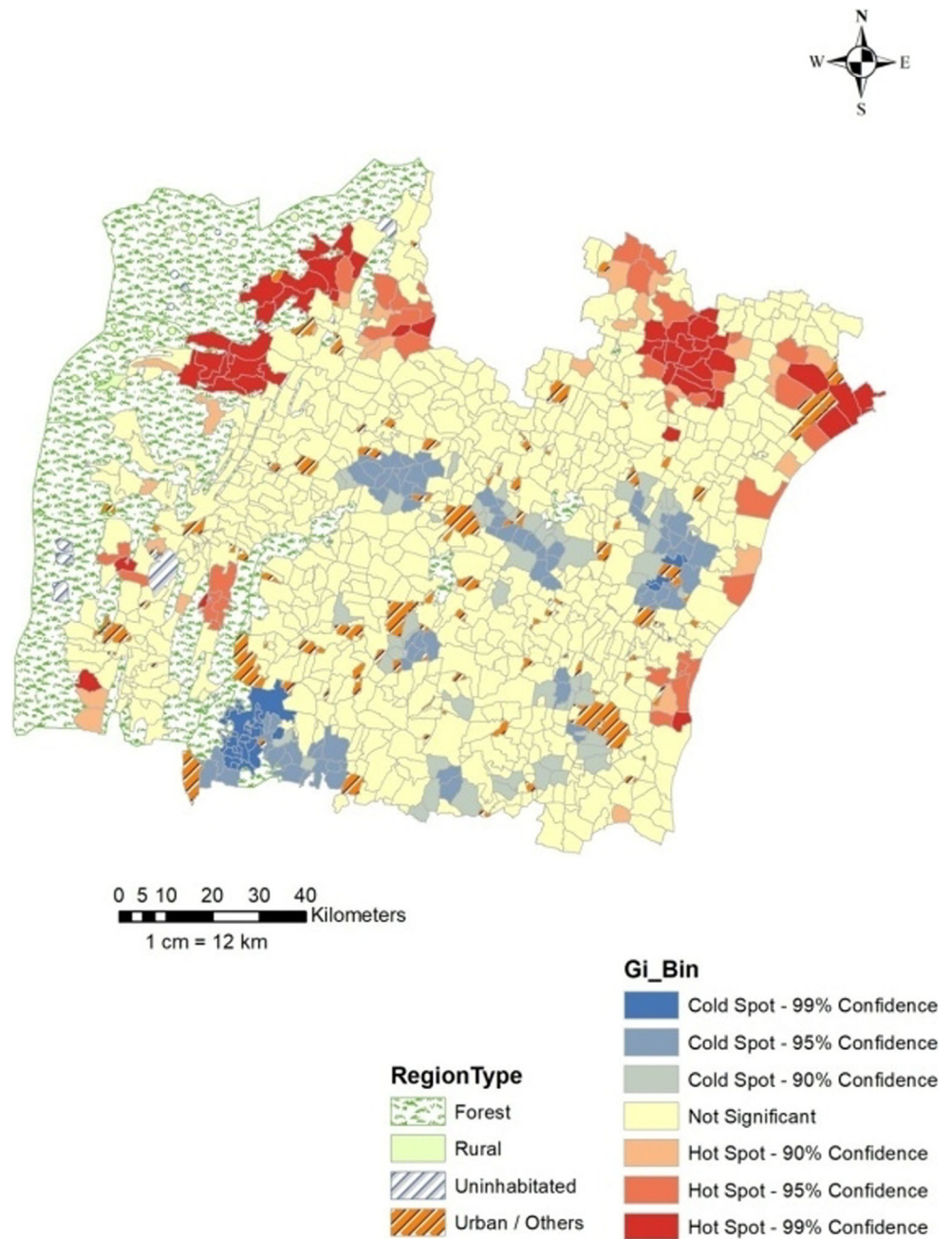
Hotspot Analysis

The results of the hotspot analysis, considering the number of assets created under MGNREGA in each village as a variable, show significant spatial clustering (Fig. 5). It has been found that a majority of the villages in the study area were in the non-significant category implying a lack of any spatial clustering of assets of high or low values. Few spatial clusters, comprising of hotspots with high confidence values, are mainly found in the northwest region adjacent to the forested areas and towards the northeastern part of the district along the coastline. There are also noticeable cold spots, mainly in the vicinity of the urban areas, which is indicative of the disinterest of the people towards MGNREGA activities in these areas due to better availability of other livelihood options available to them in the urban areas.

Emerging Hotspot Analysis

The results of emerging hotspot analysis show that the implementation of MGNREGA in the study area varies inherently

Fig. 5 Hotspot map showing spatial clustering of MGNREGA assets

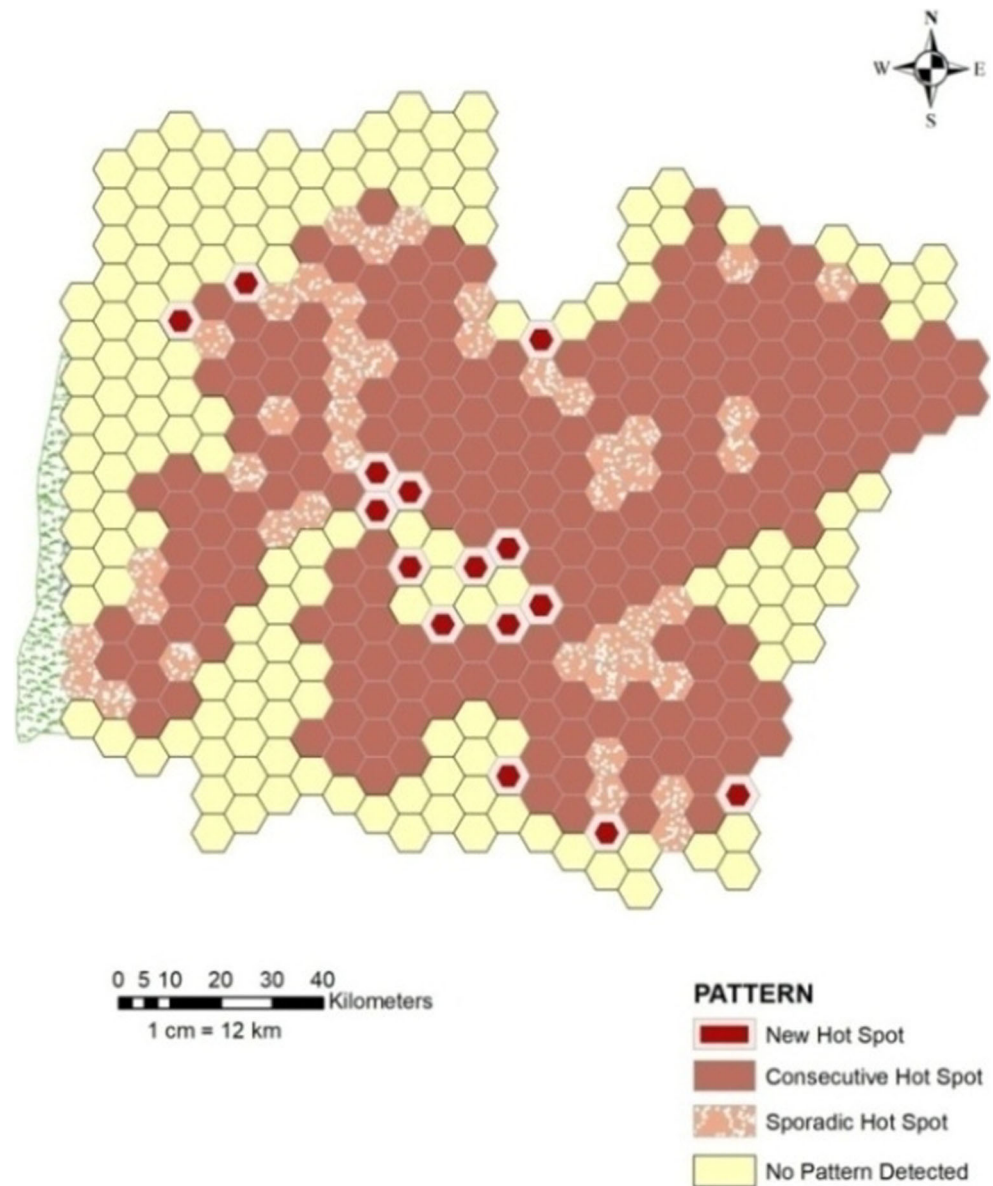


both in space and in time into four categories, viz. new hotspot, consecutive hotspot; sporadic hotspot, and no pattern detected (Fig. 6). By definition, a consecutive hotspot represents a location with a single uninterrupted run of statistically significant hotspot bins in the final time step intervals. These are the locations that have never been statistically significant hotspot prior to the final hotspot run and less than 90% of all bins are statistically significant hotspots. Similarly, a sporadic hotspot represents a location that is an on-again then off-again hotspot.

Less than 90% of the time step intervals have been statistically significant hotspots and none of the time step intervals

has been statistically significant cold spots. For any location to be qualified into a new hotspot, the statistical significance is observed only for the final time step and before in the previous bins. In addition to these, there are also the locations where there was no pattern detected in terms of temporal fluctuations though there have been significant assets created. By definition, it represents a location that does not fall under any of the hotspot or cold spot categories. It may contain a hotspot bin with far less significance and the remaining bins are insignificant. Out of the total 378 locations, each represented by a hexagonal grid in the output map, the number of consecutive hotspot grids was 192, followed by 41 grids of sporadic

Fig. 6 Emerging hotspot map showing temporal clustering of MGNREGA assets



hotspot and 18 grids of new hotspot. There was no pattern detected in the remaining 127 grids. The degree of variation may be attributed to several underlying factors that are beyond the scope of this work.

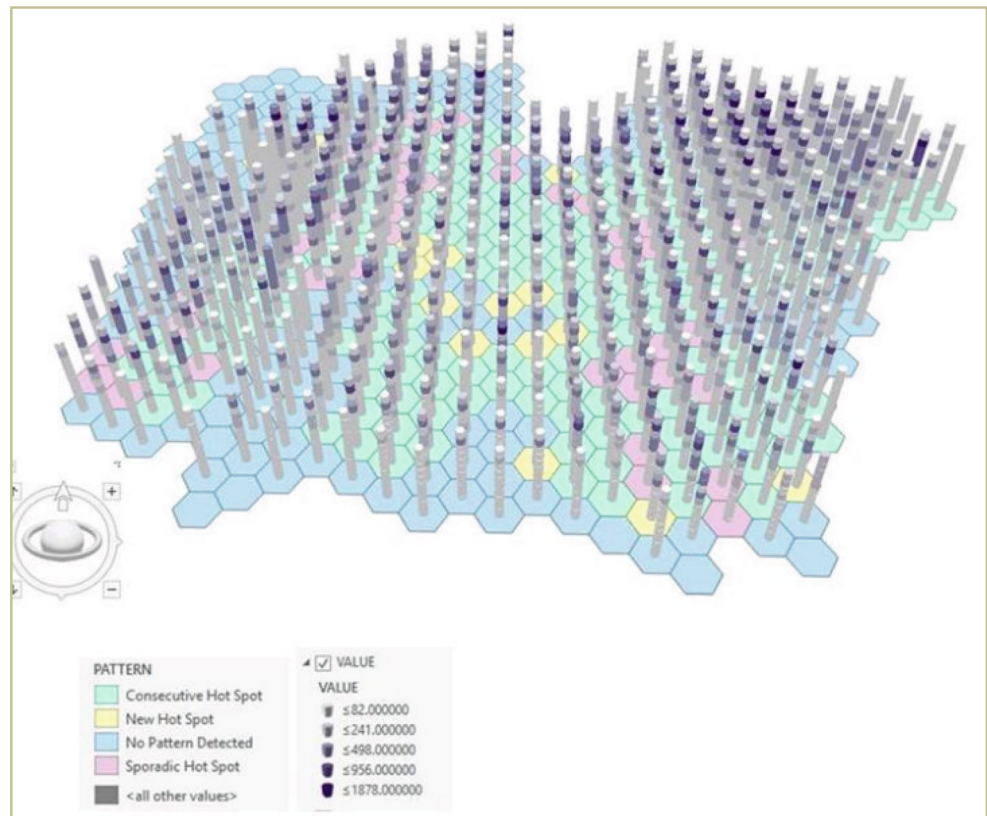
3D Visualization of Assets

A rapid reconstruction of 3D visualization of MGNREGA assets in the study area resulted in two variants. One is based on the asset values, i.e. the total number of geotags each year (Fig. 7) and the hotspot bins (Fig. 8) representing the statistical significance of each year in terms of z -score and p value in a vertical stack of 11 bins, each representing a financial year spread over from work completion year 2009–2010 to 2018–2019. We

investigated the nature of one grid cell under each category of emerging hotspot to assess the information that can be obtained from each one of them using both the variants.

Figure 9a depicts a *consecutive hotspot* at location ID350. It represents a vertical stack of 11 bins each representing a year, in graduated shades of blue. The darkest bin shows the highest number of assets created during the financial year 2016–2017. The sum value that represents a total number of asset created in this region was found to be 880, the maximum of 334 assets and minimum of 0 assets during any work completion year. Similarly, Fig. 9b represents the statistical significance of each year in terms of z -score and p value. Based on close visual observation, it can be seen that only two bins, i.e. 10th and 11th, are statistically significant as compared with

Fig. 7 3D visualization of MGNREGA assets based on hotspot bins (confidence levels)



the remaining bins in this grid cell, thereby indicating the significant clustering. Similarly Fig. 9c shows the information

on the geotags created each year that can be retrieved by clicking each bin interactively.

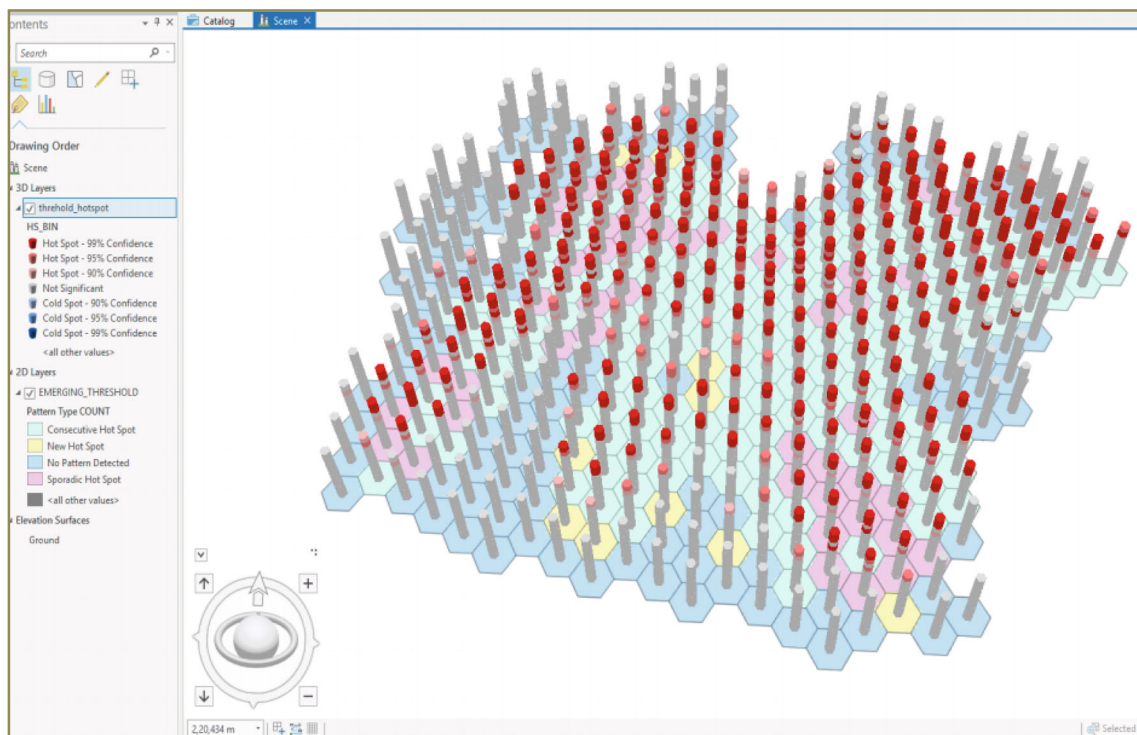


Fig. 8 3D visualization of MGNREGA assets based on value bins (joint count/asset count)

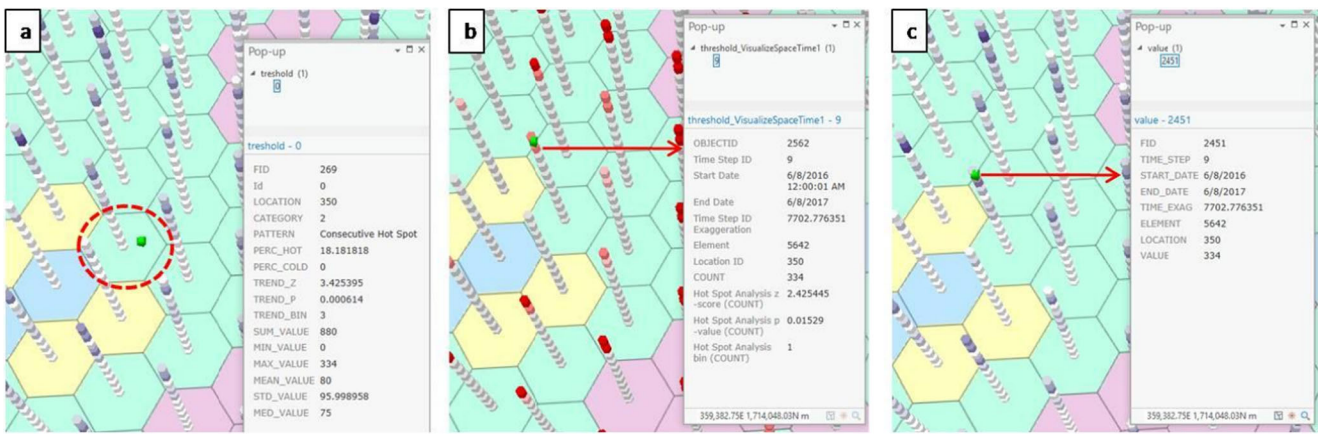


Fig. 9 Zoomed view 3D visualization of consecutive hotspot

Figure 10a shows a *sporadic hotspot* at location ID 232. The sum value that shows the total number of asset created at this location is 1594 with the maximum of 642 assets and minimum of 1 asset during a work completion year. Figure 10b shows that the 8th bin is significant but the 9th bin is not and again 11th and 12th bins are statistically significant. By definition, it represents a location that is an on-again then off-again hotspot. Less than 90% of the time step intervals have been statistically significant hotspots and none of the time step intervals has been statistically significant cold spots. Similarly, Fig. 10c shows the number of assets created in each year in terms of bins.

Figure 11a shows a *new hotspot* at location ID321. The sum value that shows the total number of asset created in that hexagon grid is 1383 with the maximum of 634 assets and minimum of 5 assets. Figure 11b shows that only 10th and 11th bins are statistically significant. This by definition thus represents a location that is a statistically significant hotspot for the final time step and has never been a statistically significant hotspot before. Similarly, Fig. 11c shows the number of assets created in each year in terms of bins.

Figure 12a shows a no pattern detected at location ID349. The sum value that shows the total number of asset created in

that hexagon grid is 346 with the maximum of 157 assets and minimum of 0 assets. Figure 12b shows that except the 10th bin, remaining bins are statistically insignificant. By definition, it thus represents a location that does not fall under any of the hotspot or cold spot categories. Similarly, Fig. 12c shows the number of assets created in each year in terms of bins.

Discussion

In a time of tight government budgets, research administrators are faced with the need to provide strong evidence that costs are justified by benefits (Alston et al. 1995). Credible and updated data and information form a backbone of good and consistence governance. The easiest way to understand and use data and information is through the display of the same in map and graphic forms, and in an integrated manner (Ottichilo 2019). Different types of representation of the MGNREGA works, as presented in this paper, provide differing perspectives of the geotagged data which each facilitates a different class of queries.

The hotspot analyses presented in the study provided a rigorous and objective approach to determine the locations of statistically significant clusters of assets as compared with the earlier

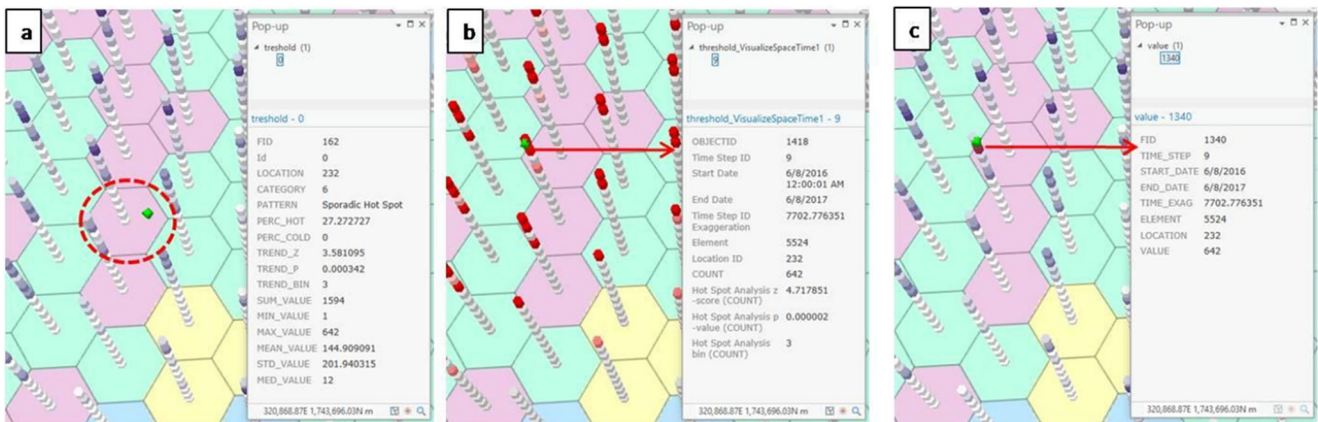


Fig. 10 Zoomed view 3D visualization of sporadic hotspot

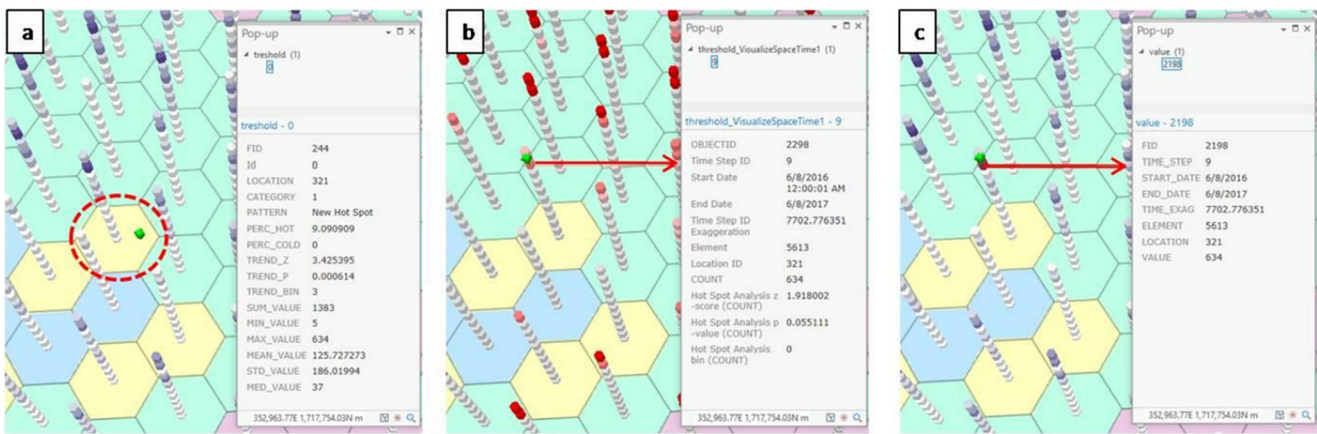


Fig. 11 Zoomed view 3D visualization of new hotspot

studies which deployed the KDE techniques for generating the hotspots/heat maps (Divya et al. 2018). Moreover, consideration of different cell sizes and search bands also affects the results of FDE (Kalinic and Krisp 2018); thus, hotspot analysis presents a better means for local-level analysis of geotag assets. Monitoring of the changes in socioeconomic and the land use land cover in the hotspots using locational overlay tools that are widely used to characterize locations on the basis or co-location of multiple changes or types of change (Peuquet and Duan 1995) might be very useful in evident-based decision-making. The findings may also help in providing crucial information on programme implementation with respect to funding decisions in the hotspot clusters and targeting the cold spot for future planning and creation of assets.

Associating the additional temporal information with individual entities provides a means of recording entity histories, and thereby allows histories of entities and types of entities to be easily traced and compared (Peuquet 2017). At the same time, it is widely believed that the temporal datasets are ubiquitous, but notoriously hard to visualize, especially rich datasets that involve more than one dimension in addition to time (Bach et al. 2014). With the availability of current location-based and entity-based representations available

within current GIS functionalities extended to temporal GIS (Siabato et al. 2018) it has become easier for the researchers to represent hidden/invisible patterns.

This study makes a novel attempt at exploring the temporal trends of the rural works using GIS capabilities. We found that emerging hotspot analysis is a useful tool for representing the temporal fluctuations and trend of asset creation over the years since project implementation in an insightful manner. The classification of clusters under the two approaches highlights their complementary nature in intuitively differentiating the geotagged rural assets.

It has always been realized that visual, interactive maps help in influencing the thinking of decision-makers and steer them in the direction of effective policy measures (Ratcliffe 2004). Whereas two-dimensional maps have their own inimitable value, it is also true that the 2D limits the number and ways in which variables can be visualized and combined. Overlay of the two-dimensional data represented on an *x-y* plane to compare multiple data sets can become cluttered and unintuitive (Krum 2013). The third dimension has the capability to hierarchically organize datasets into layers, or accurately and intuitively contextualize thematic information (Bannwarth 2018). In MGNREGA where large numbers of

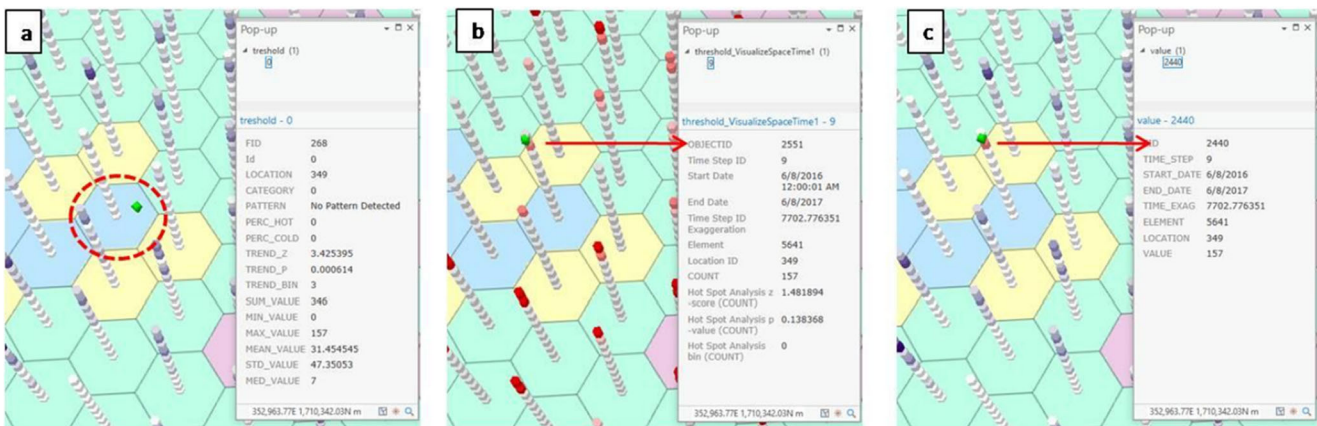


Fig. 12 Zoomed view 3D visualization of no pattern detected - a

assets are created in time and space, visual analytics offers a high value for planning and overall project monitoring and implementation. 3D visualization as presented in this study is a combined approach contributes to an intuitive comprehension of complex geospatial information for decision-makers as well as for authorities and implementing agencies.

In spite of highly insightful nature, the general usability of ESDA is impacted by a lack of depth cues, steep learning curve, and the requirement for efficient 3D navigation (Wagner Filho et al. 2019). All spatial clustering approaches, regardless of their theoretical underpinning, statistical foundation, or mathematical specification, have limitations in accuracy, sensitivity, and the computational effort required for identifying clusters (Grubestic et al. 2014). Thus, determining the most suitable technique for a specific analysis offers a big challenge for general applications.

To determine the appropriate size for both spatial and temporal neighborhoods, systematic data quality checks and analytic adjustments are needed to be performed to achieve desirable results (Tang et al. 2019). The spatial scale is another important consideration in such studies since aggregation of points across space is largely dependent upon the choice of the distance interval selected (Resende 2012). It is here the exploratory nature of the complete analysis finds its nomenclature. The potential utility of such analysis therefore lies in the ability of the researcher to discover the underlying patterns and characteristics of the spatial clusters and for practitioners to target these areas with effective impact assessment (Ratcliffe 2010; Henke et al. 2016).

Conclusion

Addressing iniquitous challenges in rural development planning requires working across and between time, space, jurisdictional, institutional, management, and social linkages for any visible outcomes. ESDA incorporates such tools as presented in this demonstration of the potential utility of data-driven and geointelligent monitoring mechanism for enhanced transparency and accountability in rural development initiatives. The findings and the knowledge gained in this study have been found to be highly insightful for analysing the assets created under MGNREGA over spatial and temporal domains. Insights gained can be further enhanced by combining a wealth of information from other sources. The empirical results presented in the study could be highly useful in enhanced planning and implementation of MGNREGA as well as other similar rural development programmes. It is recommended to include such analysis in resource allocation and programme planning in creating rural assets so that an inclusive rural development is addressed in a more holistic manner. We also recommend the use of such analytical tools to serve as a basis for developing a more reliable audit instrument for monitoring the implementation of various long-

term development schemes in rural setup where huge investments are involved.

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Compliance with Ethical Standards

The paper complies with the ethical standards.

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References

- Alston J, Norton G, Pardey P (1995) Science under scarcity: principles and practice for agricultural research evaluation and priority setting. Cornell University Press, Ithaca
- Anselin L, Sridharan S, Gholston S (2007) Using exploratory spatial data analysis to leverage social indicator databases: the discovery of interesting patterns. *Soc Indic Res* 82(2):287–309
- Asadi SS, Rao BV, Raju MV, Reddy MA (2011) Creation of integrated rural development information system using remote sensing and GIS-a model study on Prakasam district, AP. *International Journal on Computer Science and Engineering* 3(11):3587
- Bach B, Dragicevic P, Archambault D, Hurter C, Carpendal, S (2014) A review of temporal data visualizations based on space-time cube operations HAL Id: hal-01006140 <https://hal.inria.fr/hal-01006140>. Accessed 20 Jan 2019
- Bannwarth A (2018) Exploratory three dimensional cartographic visualization of geolocated datasets. Dissertation Victoria University of Wellington <https://researcharchive.vuw.ac.nz/xmliui/handle/10063/6904>. (Accessed Jul 3, 2020)
- Bertot JC, Jaeger PT, Grimes JM (2010) Using ICTs to create a culture of transparency: E-government and social media as openness and anticorruption tools for societies. *Government information quarterly* 27(3): 264–271
- Bhattacharjee G (2017) MNREGA as distribution of dole. *Economic & Political Weekly* 52(25-26): 29-33 <https://www.epw.in/journal/2017/25-26/commentary/mgnrega-distribution-dole.html> (Accessed on Aug 9)
- Cotter J (2009) A selection of nonparametric statistical methods for assessing trends in trawl survey indicators as part of an ecosystem approach to fisheries management (EAFM). *Aquat Living Resour* 22(2):173–185. <https://doi.org/10.1051/alr/2009019>
- Devereux S (2001) Livelihood insecurity and social protection: a re-emerging issue in rural development. *Dev Policy Rev* 19(4):507–519. <https://doi.org/10.1111/1467-7679.00148>

- Divya K, Reddy K M, Pujar GS, Rao P J (2018) Assessing the spatial patterns of geotagged MGNREGA assets. In Proceedings of International Conference on Remote Sensing for Disaster Management: Issues and Challenges in Disaster Management (p. 227) Springer
- Gentilini U (2015) Safety nets in urban areas: emerging issues, evidence and practices. In: The State of Social Safety Nets. World Bank, Washington, DC, pp 62–72
- Getis A, Morrison AC, Gray K, Scott TW (2003) Characteristics of the spatial pattern of the dengue vector, *Aedes aegypti*, in Iquitos, Peru. *Am J Trop Med Hygiene* 69(5):494–505
- Giribabu D, Mohapatra C, Reddy CS, Prasada Rao PVV (2019) Holistic correlation of world's largest social safety net and its outcomes with Sustainable Development Goals. *Int J Sustain Dev World Ecol* 26(2):113–128. <https://doi.org/10.1080/13504509.2018.1519492>
- Griggs D, Stafford SM, Rockström J, Öhman MC, Gaffney O, Glaser G, Kanie N, Noble I, Steffen W, Shyamsundar P (2014) An integrated framework for Sustainable Development Goals. *Ecol Soc* 19(4):49. <https://doi.org/10.5751/ES-07082-190449>
- Grubestic TH, Wei R, Murray AT (2014) Spatial clustering overview and comparison: accuracy, sensitivity, and computational expense. *Ann Assoc Am Geogr* 104(6):1134–1156 <https://asu.pure.elsevier.com/en/publications/spatial-clustering-overview-and-comparison-accuracy-sensitivity-a>
- Helbig C, Bauer HS, Rink K, Wulfmeyer V, Frank M, Kolditz O (2014) Concept and workflow for 3D visualization of atmospheric data in a virtual reality environment for analytical approaches. *Environ Earth Sci* 72(10):3767–3780. <https://doi.org/10.1007/12665-014-3136-6>
- Henke N, Bughin J, Chui M, Manyika J, Saleh T, Wiseman B and Sethupathy G (2016) The age of analytics: competing in a data-driven world. McKinsey Global Institute. <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world>
- Jaeger PT, Bertot JC (2010) Transparency and technological change: ensuring equal and sustained public access to government information. *Gov Inf Q* 27(4):371–376 <http://isiarticles.com/bundles/Article/pre/pdf/80622.pdf>
- Jena SK, Ghosh K (2013) MGNREGA—“silver bullet” for sustainable poverty eradication— a case study of Koraput District of Odisha, Proceedings on Rural Development in India: issues, Progress and Programme Effectiveness RGU, Archers and Elevators. , Bangalore
- Kalinic M, Krisp JM (2018) Kernel density estimation (KDE) vs. hot-spot analysis—detecting criminal hot spots in the City of San Francisco. In Proceeding of the 21st Conference on Geo-Information Science
- Kitchin R (2014) Big Data, new epistemologies and paradigm shifts. *Big Data Soc* 1(1):1–12 <http://mural.maynoothuniversity.ie/5364/>
- Krum R (2013) Cool infographics: effective communication with data visualization and design. John Wiley & Sons ISBN: 978-1-118-58230-5 October 2013 368 Pages
- Liu X (2019) Comparison and analysis of poverty measurement of farmland resources under different spatial and temporal conditions. *Ekoloji* 28(108):771–776 <http://www.ekolojidergisi.com/download/comparison-and-analysis-of-poverty-measurement-of-farmland-resources-under-different-spatial-and-6360.pdf>
- Locatelli G, Mariani G, Sainati T, Greco M (2017) Corruption in public projects and megaprojects: there is an elephant in the room! *Int J Proj Manag* 35(3):252–268. <https://doi.org/10.1016/j.ijproman.2016.09.010>
- Messner SF, Anselin L, Baller RD, Hawkins DF, Deane G, Tolnay SE (1999) The spatial patterning of county homicide rates: an application of exploratory spatial data analysis. *J Quant Criminol* 15(4): 423–450. <https://doi.org/10.1023/A:1007544208712>
- MoRD (2018) Ministry of Rural Development Implementation of Rural Development Schemes. <https://rural.nic.in/press-release/status-rural-development-schemes-2>
- Murray A T and Grubestic T H (2019) Evolving regional analytics in a rural world. *International Regional Science Review* p.0160017619827071. <https://doi.org/10.1177/0160017619827071>. Accessed 20 Jan 2019
- Ottichilo W K, (2019) Rational decision-making requires credible data. *Geospatial World Media*. <https://www.geospatialworld.net/article/rational-decision-making-requires-credible-data/>
- Ouni F, Belloumi M (2018) Spatio-temporal pattern of vulnerable road user's collisions hot spots and related risk factors for injury severity in Tunisia. *Transp Res F* 56(1):477–495. <https://doi.org/10.1016/j.trf.2018.05.003>
- Peuquet DJ (2017) Time in GIS and geographical databases. Richardson, D et al. (eds) *The international encyclopedia of geography: people, the earth, environment, and technology*. Wiley-Blackwell pp 91–103
- Peuquet DJ, Duan N (1995) An event-based spatiotemporal data model (ESTDM) for temporal analysis of geographical data. *Int J Geogr Inf Syst* 9(1):7–24. <https://doi.org/10.1080/02693799508902022>
- Pingali P, Aiyar A, Abraham M and Rahman A (2019) Reimagining safety net programs. In Prabhu Pingali, Anaka Aiyar, Mathew Abraham, Andaleeb Rahman (eds) *Transforming food systems for a rising India*, Palgrave Macmillan, Cham pp. 135–164. <https://doi.org/10.1007/978-3-030-14409-8>
- Qiang Y, Van de Weghe N (2019) Re-arranging space, time and scales in GIS: alternative models for multi-scale spatio-temporal modeling and analyses. *ISPRS Int J Geo Inf* 8(2):72. <https://doi.org/10.3390/ijgi8020072>
- Rao S S, Banu V, Tiwari A, Bahuguna S, Uniyal S., Chavan S B, Murthy M V R, Arya V S, Nagaraja R and Sharma J R, 2014. Application of geo-spatial techniques for precise demarcation of village/panchayat boundaries. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2(8):123. <https://doi.org/10.3390/ijgi8020072>
- Ratcliffe JH (2010) The spatial dependency of crime increase dispersion. *Security Journal* 23(1):18–36
- Ratcliffe JH (2004) Crime mapping and the training need s of law enforcement. *Eur J Crim Policy Res* 10(1):65–83
- Resende G M (2012) Essays on spatial scope of regional economic development in Brazil Dissertation The London School of Economics and Political Science <http://etheses.lse.ac.uk/453/>
- Rodríguez-Rangel C, Sánchez-Rivero M (2019) Analysis of the spatial distribution pattern of tourist activity: an application to the volume of travelers in Extremadura. In: Artal-Tur A, Kozak M (eds) *Tourism, hospitality & event management*. Springer, Cham, pp 225–245
- Rooslan AH, Mustafa MM (2020) Globalisation, unemployment, and poverty: the need for a new perspective on social protection in Malaysia. *Malaysian Manag J* 10(1&2):49–65 <http://repo.uum.edu.my/2921/>
- Sacramento Gutierrez FR, Torrente A, Torrent-Moreno M (2019) Responsive geographical information systems for spatio-temporal analysis of mobile networks in Barcelona. *ACE: Architect, City Environ* 14(40):163–192. <https://doi.org/10.5821/ace.14.40.5349> ISSN: 1886–4805
- Shim DC, Eom TH (2008) E-government and anti-corruption: Empirical analysis of international data. *Intl Journal of Public Administration*, 31(3):298–316
- Siabato W, Claramunt C, Ilarri S, Manso-Callej MÁ (2018) A survey of modelling trends in temporal GIS. *ACM Comput Surveys (CSUR)* 51(2):1–41 <https://hal.archives-ouvertes.fr/hal-01900660>
- Siddhartha and Vanaik A (2008) CAG report on NREGA: Fact and fiction. *Economic & Political Weekly*, 39. <http://www.indiaenvironmentportal.org.in/files/CAG%20Report.pdf>
- Steves C. (2018) Trends in the Alaskan bottom-trawl fishery from 1993 to 2015: a GIS-based spatiotemporal analysis. University of Southern California Digital Library. (Date of Accessed June 6, 2020). <https://spatial.usc.edu/wp-content/uploads/formidable/12/Carrie-Steves.pdf>

- Tang JH, Tseng TJ, Chan TC (2019) Detecting spatio-temporal hotspots of scarlet fever in Taiwan with spatio-temporal G_i^* statistic. *PloS one*, 14(4):e0215434
- Veregin H (1999) Data Quality Parameters, In *Geographical Information Systems: Principles and Technical Issues Vol.1*. Longley P, Goodchild M, Maguire D and Rhind D (eds) John Wiley, New York, pp.177–189
- Wagner Filho JA, Stuerzlinger W, Nedel L (2019) Evaluating an immersive space-time cube geovisualization for intuitive trajectory data exploration. *IEEE Trans Vis ComputGraph* 26:514–524. <https://doi.org/10.1109/TVCG.2019.2934415> . Accessed 20 Jan 2019

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