Appraisal of infrastructural amenities to analyze spatial backwardness of Murshidabad district using WSM and GIS-based kernel estimation

Farhana Parvin · S. Najmul Islam Hashmi · Sk Ajim Ali

Abstract Backwardness is the result of different factors that exist in a society. The present study focused on infrastructural facilities and basic amenities to estimate the spatial distribution of backward areas in the Murshidabad district of West Bengal, India. An adequate supply of infrastructure has long been essential for economic development for both academicians and policymakers. Improved infrastructure has an aggregate impact on income and economic development. From this point of view, the present study aimed to appraise the infrastructural facilities and basic amenities to analyze the spatial extension of backwardness. For the same, 17 decision criteria under four parameters including physical infrastructure, medical and health service, educational amenities and recreational facilities were selected and geospatial technique i.e. kernel density estimation was used for spatial mapping of those decision criteria to show the spatial density of available services. Concurrently, weight sum model as a multi-criteria decision approach was applied for map overlaying and displaying backward areas by considering reverse scale factor from 1 to 5. 5 indicate the high spatial density of infrastructural facilities and low backward areas and 1 indicates the low density of infrastructural facilities and high areas of backwardness. Using the above rating scale, the spatial extension of backwardness was estimated. Unlike using the traditional method to estimate backwardness, the present study applied a geospatial technique which is quite new in this type of study. The present study also measured the accuracy of the result using prediction accuracy. The result revealed that the overall prediction accuracy signifies 82% (Pa = 0.82) which validates the weight sum model and kernel density applied in spatial analysis of backwardness. The present study evidences the efficiency of geospatial technique which may also helpful for applying in different fields of research.

Keywords Infrastructural facilities · Kernel density estimation · Weight sum model · Spatial backwardness · Murshidabad district

Introduction

Infrastructure is the structure of interconnected elements that support the framework of an entire structure of development. It indicates an interrelated system which offers service and facilities access to sustain living conditions from physical and societal point of view (Dash and Sahoo 2010; Kumari and Sharma 2016). Infrastructure is a fundamental system which use to stimulate the economic dynamics of a region and it is considered as the base on which different

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activities are maintained for promoting economic development and backwardness (Ramírez and Vargas 2018). The accessibility of proper infrastructure facilities is vital for the overall economic development of a region. Improve infrastructure helps in determining production, trade, managing with population growth, poverty reduction and improving environmental conditions (Siddaram 2014). Thus, an area with better infrastructure is the indication of economic development and concomitantly, bad and poor infrastructure is the sign of backwardness. The present study focused the infrastructural facilities and basic amenities to define backwardness of a backward district of West Bengal, India.

Murshidabad district is one of the Muslim dominated districts of West Bengal with more than 63% residential Muslim population (District statistical handbook 2014). Murshidabad was the capital of Bengal during the Mughal period and important district town during British India. The district was once the home of Nawabs and royal families are now the house of migrants, rickshaw pullers, agricultural laborers and Masons (Falahi 2009). Now, it is known as one of the eleven districts in West Bengal that presently receiving funds from the Backward Regions Grant Fund Programme (BRGF) (Ministry of Panchayati Raj 2009). The Ministry of Panchayati Raj declared Murshidabad as one of the country's 250 most backward districts out of a total of 640 in India (Ministry of Panchayati Raj 2009). The planning commission, Ministry of Rural Development identified Murshidabad district as a backward district with district rank order of 300 throughout India (Ministry of Rural Development 2014). So, Murshidabad is a backward district and that is the main reason to select it as a study area for analyzing the spatial extension of backwardness.

There are a variety of indicators which measures the backwardness of a region; including natural resources like forest, minerals, rivers and stream; human resources like working population group, level of employment or unemployment, skill available; economic bases like per capita income and GDP; infrastructure like access to roads and rail, telecommunication, hospital, health centre, bank, post office, school, college and recreational sites. The present study used infrastructure and basic amenities to define spatial backwardness because of two reason, firstly, infrastructure is a chief factor that describes long-run

economic impact and support others related activities (Kumari and Sharma 2017; Ramírez and Vargas 2018) and second, there are not available this type of study in literature that used infrastructural indices to show backwardness of a region. Thus, geospatial technology was utilized for the same as the geospatial database has the best competence to define the spatial integration that will helpful for carrying out this type of study.

The core task of a geographic information system and geospatial technology is to drive information by integrating spatial data (Hofer 2015). This research aimed to use spatial data and geospatial technique to assess the extent of spatial backwardness because the value of information is much higher with the use of geospatial data in comparison with numeric data (Satapathy et al. 2008). This study emphasized on discussing the application of geospatial technology in social sciences and extensively analysis of backward areas for planning, development, decision making, and policy implementation. Several scientific studies revealed the application of geospatial tools in social science (Entwisle et al. 1997; Skinner et al. 2000; Reardon et al. 2008; Logan et al. 2010). The effectiveness of geospatial technique in offering accurate result has been shown from different studies like assessing environmental impact and management (Gontier et al. 2006; Satapathy et al. 2008); estimating prevalence of diseases (Ackerman and de Klerk 2002; DeGroote et al. 2012; Moise and Kalipeni 2012); social media feeds (Stefanidis et al. 2013); analysing natural hazards (Ercanoglu and Gokceoglu 2002; Pradhan et al. 2011); detecting and monitoring land use and land cover (Rawat et al. 2013); delineation of contamination (Thapa et al. 2017); spatial ecology (Skidmore et al. 2011) etc. These types of application and their accurate findings have influenced to apply such a technique in the present study.

Geographical information system (GIS) functions as a common tool for merging multi-criteria to offers spatial result. Therefore, the present study aimed to apply the GIS technique by assessing spatial data and tool for estimating spatial backwardness of Murshidabad district. To achieve such aim GIS-based Geospatial technique i.e. kernel density and weight sum model as a multi-criteria decision approach was applied to show backward areas based on infrastructural facilities and basic amenities available in the study area.

Literature review

Infrastructure is a set of general properties that generates an environment where social interaction and economic processes take place (Piedras 2003). Infrastructure has three characteristics i.e. it is a collective input, it includes both physical resources and human capital and it is integrative (Diamond 1990). These components are combined through communications networks and transport. According to classical economists like Adam Smith, David Ricardo considered that land, labor and capital are the main factors of production which have a major contribution to a nation's development (Rasul and Sharma 2014). The followers of classical economists also considered the natural resources like land, soil, and water, etc. are the main basis of development (Gallup et al. 1999; Ding and Field 2005; Stijns 2005). The different level of natural resources in different regions leads to differential rates of economic development and backwardness (Stijns 2005). In comparison to a classical economist for measuring economic development or backwardness, neo-classical economists consider human-made resources as the base of development or backwardness because the knowledge, technology, asset, capital formation, and savings can drive the economy (Romer 1986; Auty 2007). In their view, infrastructure and improvement of technologies are essential for sustainable economic growth.

There are numerous studies that focused on infrastructural facilities to define a region as developed or backward. Many investigative and empirical literature have been concerned with the effects of infrastructure on the development of income, productivity, and welfare (Aschauer 1989). Improved infrastructure can access link between market and peripheral regions to generate higher productivity for new and privately-owned firms (Brown et al. 2008). Nearness to transportation networks affects a large positive causal impact on per capita GDP growth (Banerjee et al. 2012). Rural road program has a great impact on short-run village-level consumption and poverty. Study result revealed that access to the road increases the village's consumption and decreases the poverty level (Khandker et al. 2006). Different studies have been carried out in order to assess the infrastructural facilities for social and economic development or backwardness.

Saleh (1989) carried out a systematic study of economic development in Nagaland. She made a critical analysis of Nagaland from 1960 to 1980 during the third, fourth and fifth five-year plans by highlighting economic development. The study revealed the significant impact of transport and communications, power supply, facilities of education and public health on the overall status of the state.

Nagar and Basu (2002) suggested a method to compute a composite measure of infrastructure development by combining the available services of physical infrastructure. They assessed the value of infrastructural development index (IDI) for 17 major Indian states for the period 1990-91 to 1996-97. They also acquired the weights of different physical infrastructural facilities. The transport and communication services turn out to be the most dominant among the chosen infrastructure services, followed the availability of energy and power services. Their analysis showed a positive relationship between infrastructural development index and per capita net state domestic product.

Agénor and Moreno-Dodson (2006) found a link between infrastructure availability and health as well as education of society that shows infrastructure facilities is essential for health and education quality and availability of which have great effects on well-being.

Baishya and Deka (2010) examined the prevailing situation of infrastructure services in Nagaland by considering communication and transport, financial institution, power, education, and health. They found that inadequate infrastructure facilities are the main reason for the poverty of the people belonging to various sectors of the State.

Ogun (2010) tried to measure the impact of infrastructural development in Nigeria for the period 1970–2005 on poverty reduction by using secondary data and structural vector autoregressive (SVAR). The results proposed that infrastructural development leads to poverty reduction. He also found that social infrastructure describes a higher proportion of the forecast error on poverty indicators relative to physical infrastructure.

Rasul and Sharma (2014) investigated the basic causes of poor economic growth of Bihar and Uttar Pradesh (UP) in India. Their finding revealed that low financial resources received to invest in health, education, and other social and physical infrastructure

have resulted in low human development and backwardness of these state.

Kumar and Sharma (2017) used Augmented Dickey-Fuller test and Phillips Perron unit root tests to examine the relationship between physical and social infrastructure with economic development in India. They found that both physical and social infrastructure has a positive relation with economic growth in India.

However, most of this literature agree that better infrastructure has a positive effect on employment, productivity, and development, but poor infrastructure has a negative impact on these components and responsible for the backwardness of a region (Feltenstein and Ha 1995). The present study tried to find the research gap that this important parameter has a great role for estimating development or backwardness index, but not any reasonable study available that used geospatial technique to show spatial variation and distribution of different infrastructural indicators to analyze backwardness of a region.

Study area

Murshidabad is a famous district of West Bengal for its historical perspective and rich culture from the Muslim emperor. It is the northernmost district of Presidency division which geographically located along the western side of Ganga River (Fig. 1). The district shared one of the largest international boundaries with Bangladesh in the eastern part, and surrounded by Birbhum district and Jharkhand state in the western part, Malda in the north and Bardhamman and Nadia district in the southern part. The total geographical area of the district is 5324 km^2 and become the 7th largest district of West Bengal in terms of land area (District census handbook 2011).

According to the latest census, Murshidabad district has a population of 7,102,430 which is roughly equal to the nation of Bulgaria or the US state of Washington (https://www.Census2011.co.in). The district has a population density of 1334 Km^2. The trend of population growth rate over the last decade was 21.07%. The sex ratio of Murshidabad has 957 per 1000 males and the average literacy rate has 67.53% with a male–female literacy rate gap of 6.86. The male and female literacy rates in the district are 69.95 and 63.09 respectively. The majority of people of the district are Muslim, around 70%.

From a residential point of view, it has been seen that above 75% of resident are rural. There are total 17 blocks out of 27, where the urban population is completely zero and others remaining 10 blocks, where above 70% population are rural. As far as the housing facilities are concerned, many areas are found in deprived condition from basic infrastructure and amenities. The district is primarily an agriculture base. The major work-force of the district is engaged agriculture sector which is the main source of the district's total income. The district is not gifted with valuable natural resources. In term of secondary and tertiary sector i.e. manufacturing and other, the district's performance is lower than the desired level. The district has been considered as economically backward. From this point of view, the present study aimed to appraise the infrastructural facilities and basic amenities to analyze the spatial extension of backwardness.

Materials and method

Aim and research design

The present study aimed to examine and recognize the level of backwardness in Murshidabad district of West Bengal, India using the geospatial technique. Thus, the effort was made to analyze the multi-dimensional aspect of backwardness in Murshidabad and mapping the spatial backwardness within the district. As development or backwardness is a relative concept and is multi-dimensional in nature; researcher and planner chose different aspect to measure the backwardness in a region; like education, health and political rights (Stiglitz et al. 2009); SC and ST population (Planning Commission 2014); the rate of food scarcity, poverty rate, literacy, infant mortality rate, sex ratio and immunisation rate (Borooah and Dubey 2007); infrastructural facilities (Baruah 2010); social, economic and infrastructural disparities (Mittal et al. 2008); agriculture, industries, tourism and recreation (Kar 2007). Hence, in order to reach the desired aim, multiple indicators or criteria is required to analyze the backwardness index. Multi-criteria decision analysis (MCDA) is a widely used technique which helps in taking complex decision by structuring, measuring and judging the decision criteria (Ali and Ahmad 2019b). In MCDA it is required to select
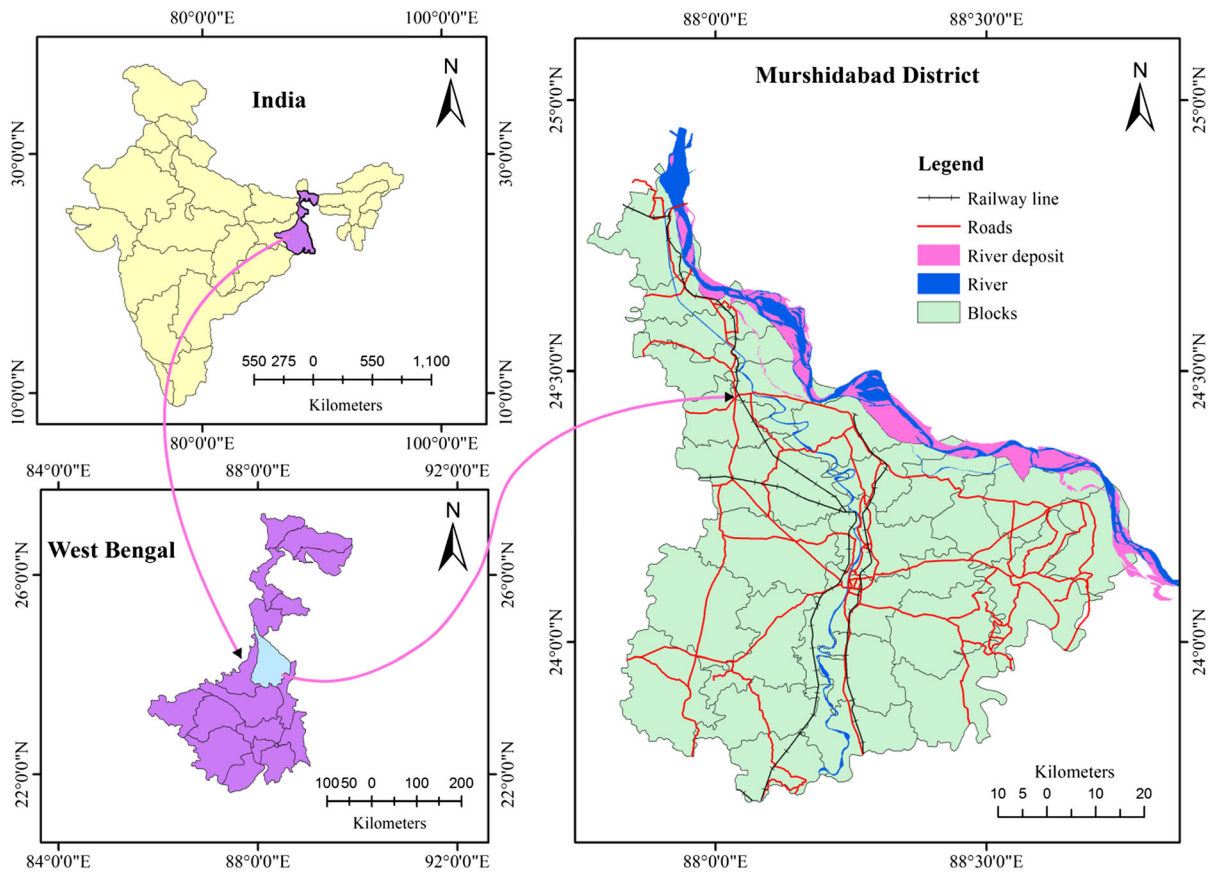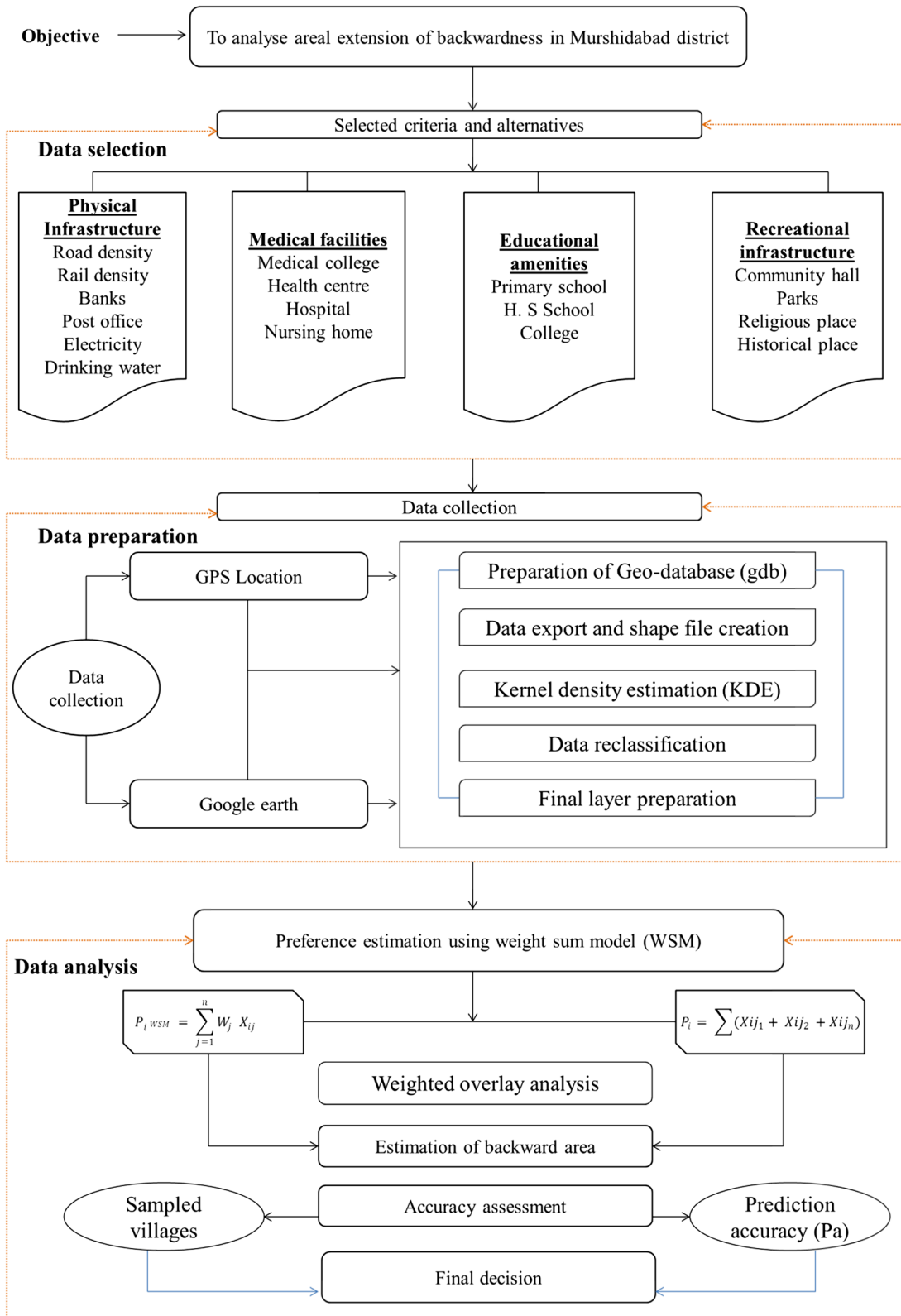
Fig. 1 Location of the study area

related multi-criteria and choose more weighted or preferred criteria using a different technique. Weight sum model (WSM) is a simple and very used MCDA technique, which was used in the present study for calculating the preference value of selected criteria to analyze the areal extension of backwardness of the district.

The research design and methodology assumed in the present study is presented in the following figure (Fig. 2). On defining the aim of the present study, relevant parameters (taken as decision criteria) that connected to backwardness were chosen first. Total 17 indicators associated with backwardness measure were considered which were categorized into four groups i.e. physical infrastructure and services, medical infrastructure and facilities, educational infrastructure and amenities and recreational facilities. Kernel density estimation was used for spatial mapping of selected criteria and weight sum model was applied for calculating the preference value for

complex weight-based overlay analysis (WOA). As a part of spatial analysis, the spatial database of each parameter was created in GIS Environment. GIS integration was performed to identify the spatial extent of the backward area. Finally, to check the accuracy of the geospatially based result, prediction accuracy (*Pa*) was used.

Data source

Looking towards selected decision criteria and method applied, the study required to use geospatial data. Generally, geospatial data are those which have locational information; more elaborately, these are geographic data in the form of location and coordinates. The geospatial data were stored from GPS, Google Earth, satellite imagery and Geo-tagging. The selection, gathering, accumulation, and store of such dataset were due to geospatial analysis.

Objective → To analyse areal extension of backwardness in Murshidabad district

Selected criteria and alternatives

Data selection

Physical Infrastructure
Road density
Rail density
Banks
Post office
Electricity
Drinking water

Medical facilities
Medical college
Health centre
Hospital
Nursing home

Educational amenities
Primary school
H. S School
College

Recreational infrastructure
Community hall
Parks
Religious place
Historical place

Data collection

Data preparation

Data collection

GPS Location

Google earth

Preparation of Geo-database (gdb)

Data export and shape file creation

Kernel density estimation (KDE)

Data reclassification

Final layer preparation

Preference estimation using weight sum model (WSM)

Data analysis

$$P_{i\,WSM} = \sum_{j=1}^{n} W_j\ X_{ij}$$

$$P_i = \sum (Xij_1 + Xij_2 + Xij_n)$$

Weighted overlay analysis

Estimation of backward area

Sampled villages

Accuracy assessment

Prediction accuracy (Pa)

Final decision

◄ **Fig. 2** Decision tree and methodology that applied to analyze the spatial extension of backwardness

Thus, datasets used in the present study were spatial in nature, because the study itself emphasized on spatial analysis and demarcation of the backward area in the defined study area. Datasets in the form of vector format (line and pint features) were collected from different sources. Satellite data i.e. Sentinel-2 L1C dated 2019-03-21 with 16 bit unsigned were collected from Sentinel Hub EO browser (https://www.sentinel-hub.com/explore/eobrowser) to know the current land features. Excluding GPS location and ground-level information, Google earth professional version 4.0 was used for creating geo-database. Google earth is an open-source and geospatial software application that offers a real-time location with geographic information and suitable tools like the search for finding any geospatial data, layers for acquiring direct information, my place for data capturing, storing, exporting and creating geo-database. Thus, for density estimation, all datasets were created using GPS navigator and Google earth. Along with these spatial data, aspatial data like electricity connection and source of light, source of drinking water were collected from district primary census handbook. A detailed of different spatial data source, types, specific uses and other information is presented in the following table (Table 1). These all selected datasets were then processed further for analysis by converting and reclassifying in equal Projection and Cell size.

Kernel density estimation

Spatial analyst tool of GIS environment offers three types of density estimator i.e. line density, point density and kernel density. Line and point density estimates distinctly two different features that are assumed to fall under the search area and then divided by the size of the search area to obtain the value of the cell's size. Simple density is defined as:

$$D_s = \frac{p_i}{a_i}$$

where D_s is the simple density including point and line density, p_i is the specific features that fall in unit area, a_i is the size of unit area.

Simple density (line and point) only calculates the quantity given by the population field and estimates the density of that field around each output cell. But simple density has not the ability to estimate the density of each point out from the point location. This shortage reduces and overcomes with the application of kernel density. Kernel estimates the density of defined field for each point out from the point location. The resulting raster from kernel density is based on a quadratic formula defined by Silverman with the highest value at the center of surface features (point, line, polygon, and polyline) and pointing to zero with distance at the search radius (Silverman 1986). Each output cell in kernel density is calculated by considering the total number of the accumulated intersection of the individual features. Kernel function K is defined by the following equation (Silverman 1986).

$$\int_{-\infty}^{\infty} K(x)dx = 1$$

Not always, but K will be a probability density function or weight function 'w' used to define the naive estimator (used to join the first and last observations point and divided by the height of horizontal distance). With the definition of the naive estimator, the kernel estimator K is defined as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - Xi}{h}\right)$$

where K is the kernel function with density $f(x)$, x is the data sample, n is the number of sample and h is the smoothing parameter or say bandwidth. Bandwidth is very important that controls the degree of smoothing applied to the data (Chiu 1992). The bandwidth algorithm, displayed as default search radius in spatial analyst tool, is expressed as:

$$SR = 0.9 * min\left(SD, \sqrt{\frac{1}{In(2)} * Dm}\right) * n^{-0.2}$$

where SR is search radius, SD is the standard distance, Dm is the median distance, n is the number of sample features (if used 'None' in population field), otherwise n is the sum value of population field (if value supplied to population field), min indicates the smaller value will be used from result.

Kernel density is a non-parametric technique used to estimate density based on an infinite data sample.

Table 1 Sources of data and their application

Data types	Dataset	Source	Date	Processing	Application
Line features (vector)	Road network and Rail transport	GPS location and Google earth Pro	12-31-2018	Creating Geo-database and shape file → preparing raster database and reclassification	To show the road and rail density
Point features (vector)	Banks, post office, Primary health centre, hospital, nursing home, medical college, primary school, HS school, college, Community hall, parks and grounds, religious place, historical place	GPS location and Google earth Pro	12-31-2018	Creating Geo-database and shape file → preparing raster database and reclassification	To prepare areal density of selected vector
Satellite data (raster)	Sentinel-2 L1C	Sentinel Hub EO browser	21-03-2019	RGB band composition and land use classification using SVM	To verify the current land use features that taken in this study as decision criteria
Others (vector)	Availability of electricity, drinking water source	District census handbook, primary census abstract (PCA), Govt. of India	2011	Data based features to raster conversion and reclassification	To prepare the spatial map of household having electricity and using hand pump and tube well

This technique used to visualize and analyze spatial data for mapping and understanding spatial pattern and event (Smith et al. 2015). Surface estimation and prediction using kernel density have a wide field of application like in simple boundary correction (Jones 1993), fast Clustering (Hinneburg and Gabriel 2007), emergency planning and rescue service (Krisp et al. 2005), risk analysis and loss assessment (Ahola et al. 2007), traffic accidents (Xie and Yan 2008; Anderson 2009), crime estimation (Rey et al. 2011; Gerber 2014; Mburu and Zipf 2014) etc. Giving emphasize the accuracy in result and estimation, the effort was made in the present study to use kernel density estimator for spatial mapping of selected parameters and analyzing the areal extension of backwardness.

Selection of parameters

The reasonable finding of any study depends on the selection of appropriate parameters and indicators. The main objective of this study was to evaluate spatially infrastructural facilities to estimate the spatial distribution of backwardness. Backwardness is not insurmountable (Shah 1991). But the factors

responsible for estimating backwardness changes with changing the geographical location and one single factor is not always responsible for the same in all regions. Looking towards the geographical features of the study area, more relevant decision criteria in the form of indicators were selected based on previous studies and their significance in leading an area as backwardness. The chosen indicators were categorized into four parameters i.e. physical infrastructure and service, medical and health service, educational amenities and recreational facilities. The selected decision criteria under these four parameters and the reason behind their selection are discussed below.

Physical infrastructures are basic physical structure of a region that required for functioning and surviving of an economy. Physical infrastructures include mean transport communication like air, road, and rail, per capita electricity consumption, availability and source of drinking water, etc. (Nayak 2008; Kumari and Sharma 2017). Road and rail connectivity is the key component of development. Better communication and connectivity can create opportunities for economic growth and poverty reduction (Samanta 2015). Road density had a highly significant and positive

influence on consumption growth at the farm-house-hold level (Jalan and Ravallion 2002). Improve transport and communications services facilitate modernization and technological up-gradation (Demetriades and Mamuneas 2000). Better access to electricity may raise educational attainment (Agénor 2011). Studies revealed that there is direct relationship exist between physical infrastructure and economic development which helps in improving the living standard and quality of community (Dash and Sahoo 2010).

From this point of view, six indicators on physical infrastructure including roads, rail, households having electricity, using only hand pump and tube well for a drinking water source, availability of banks and post offices were selected for estimating backwardness. The input layers of these selected indicators were marked using GPS location, SOI toposheets, satellite imagery and Google earth open software. The shapefile of line and point location was first created for density analysis and then the feature files were converted into raster format and reclassified with a scale value of 1 to 5. 1 to 5 indicates less to high infrastructural density and high to low backward areas respectively (Fig. 3).

Adequate medical and health care infrastructure mans the availability of medical facilities including laboratory, training institution and college and other support facilities that provide immediate service to the community. Public health infrastructure is the key elements of human development of a society which helps in improving the quality of human resource and parallelly improves the state of human life. The main indicators of health and medical infrastructure include variables such as medical college and institutions, hospitals, health center etc. (Ramírez and Vargas 2018). Better medical and health infrastructure positively correlates with regional prosperity and economic growth, on the other hand, lack of availability of health care and poor service is the indication of backward areas and low human development index (Alin and Marieta 2011; Ramírez and Vargas 2018). Looking this point, the decision was made to select four indicators i.e. location of medical college, primary health center/dispensary, hospital, and nursing homes for estimating spatial backwardness based medical facilities and service available in the study area. Similarly, like physical infrastructure, input layers of these four indicators were created using GPS location and Google earth open software. The

point shapefile was first created for kernel density estimation and then the feature files were converted into raster file and reclassified accordingly to above-mentioned scale. High to the low density of medical and health facilities depicts low to high backward areas respectively (Fig. 4).

Education is as an important factor to consider a region as develop or backward. Education is an important indicator for measuring the human development index (Narayana 2006). From every sense, education is the chief factor of development and no country can achieve sustainable development goal excepting investment in human resource. In addition, educations have a crucial role in acquiring social integration, economic development, poverty reduction, labor productivity and enhancing technology, health, income distribution and family structure (Ozturk 2001). The analytic review showed that education and the propose strategies that enable the process of innovation and knowledge creation have a long-term impact on social development and economic growth (Barro 1991; Rebelo 1991; Benhabib and Spiegel 1994). Studies also evidenced that availability and quality of education is the main factor to emphasize social and economic development (Hanushek and Kimko 2000; Barro 2001; Masino and Ninõ-Zarazua 2016). The availability and number of higher educational institutions have also a significant role in determining development index (Ross 1973). On giving emphasize on these findings, three important indicators on educational amenities available in the study area were selected. These indicators are the availability of primary and middle school, higher secondary schools and colleges. Same as GPS and Google earth open software was utilized for spatially locating these features and density analysis. Densely location of educational amenities was considered as low backward areas while rating scale in weight sum model for spatial location of backward areas (Fig. 5).

Four decision criteria were also chosen from recreational perspective including locality to community hall, parks and play grounds, gathering places or religious places and historical sites. Although these criteria are not too much significant for determining a region as backward or develop, these were considered as the study area is a famous historical place of West Bengal and still, now different small tourism activities are seen by centering of a historical religious place, parks, community hall, historical palace and site.
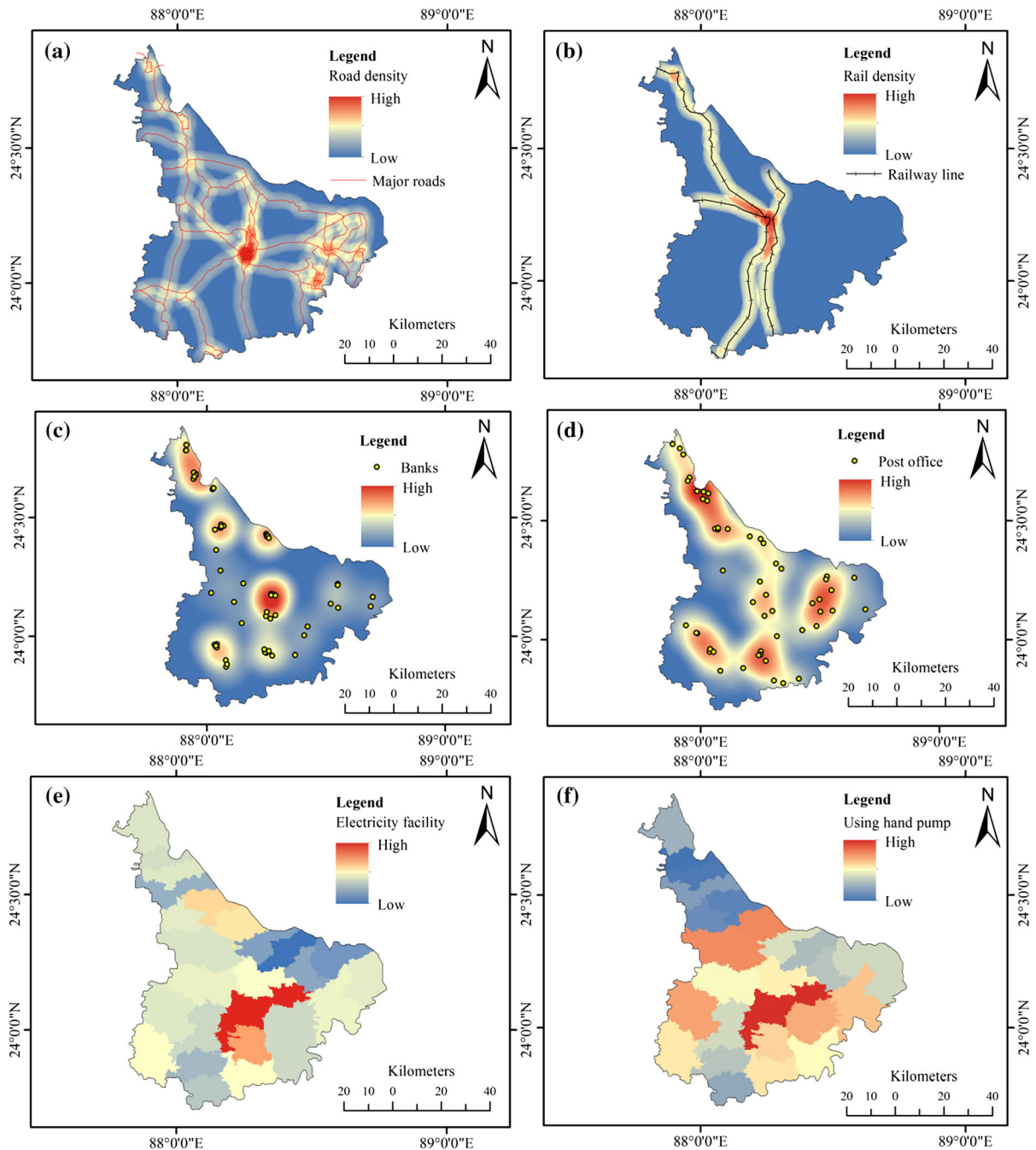
Fig. 3 Selected physical infrastructure and services available: **a** Road density, **b** Rail density, **c** Availability of Banks, **d** Availability of post offices, **e** Households having electricity, **f** Households using hand pump and tube well

Moreover, these all features are located in and nearer to the urban centers which are more develop a place in comparison to another farer area. That's why the high density of recreational sites was ranked as low

backward areas and vice versa for showing the backward areas (Fig. 6).

As far as the study design and methodological tree are concerned for analyzing the spatial extension of backwardness, the selection of parameters was the first
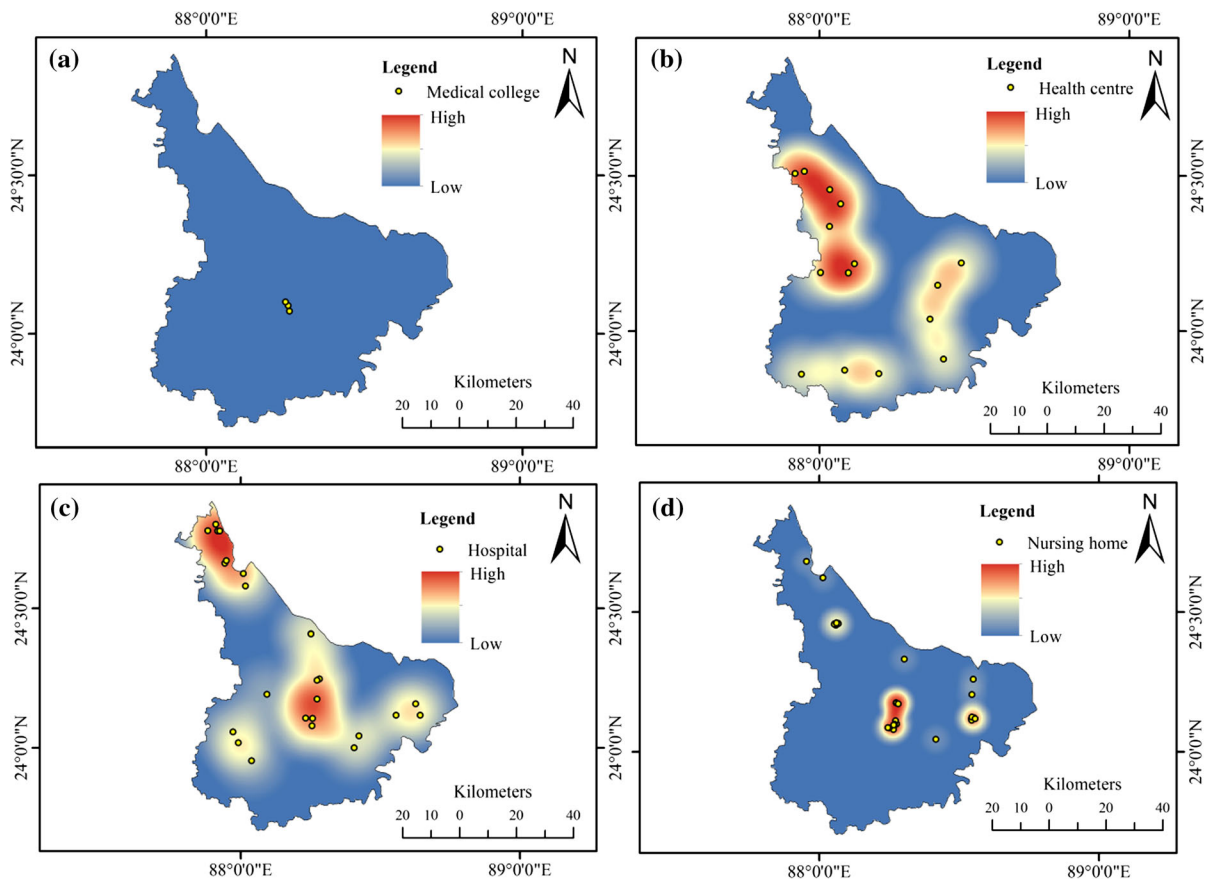
Fig. 4 Selected medical infrastructure and services available: **a** Medical college, **b** Primary health center/Dispensary, **c** Hospital, **d** Nursing home

or data selection stage followed by data preparation. Kernel density estimation that discussed above was the applied technique for data preparation that supports from the preparation of geo-database to the output of the final layer for showing the spatial backwardness. Data selection and preparation followed by data analysis which was illustrated through weight sum model for rating, classifying and preferring more weighted factors that responsible for the backwardness of Murshidabad district.

Weight sum model

It is required to take several conflicting objective into account for real-life problems optimization. In this regard, decision making is considered as the best solutions (Kaddani et al. 2017). There are different techniques of multi-criteria decision analysis (MCDA) which help decision-maker to take decision

accordingly (Velasquez and Hester 2013; Ginting et al. 2017; Jasri and Rahim 2017). Decision making is a systematic task for evaluating the complex relationship and decision problems. This involves dividing the decision problems into the smaller understandable part, judging every part and integrating each into a systematic structure in order to produce a significant solution (Malczewski, 1999). The fundamental functioning principle of any MCDA method is a same i.e. selection of relevant criteria, selection of suitable alternatives or sub-criteria, selection of aggregation, methods and ultimately choose the best alternative based on weights or outranking (Majumder 2015).

Among different techniques of multi-criteria decision analysis, weight sum model (WSM) is commonly used simple method and have the ability to offer to prefer ranking from the selected alternatives which are used for further analysis and in various field of application (Budiharjo et al. 2017; Handoko et al.
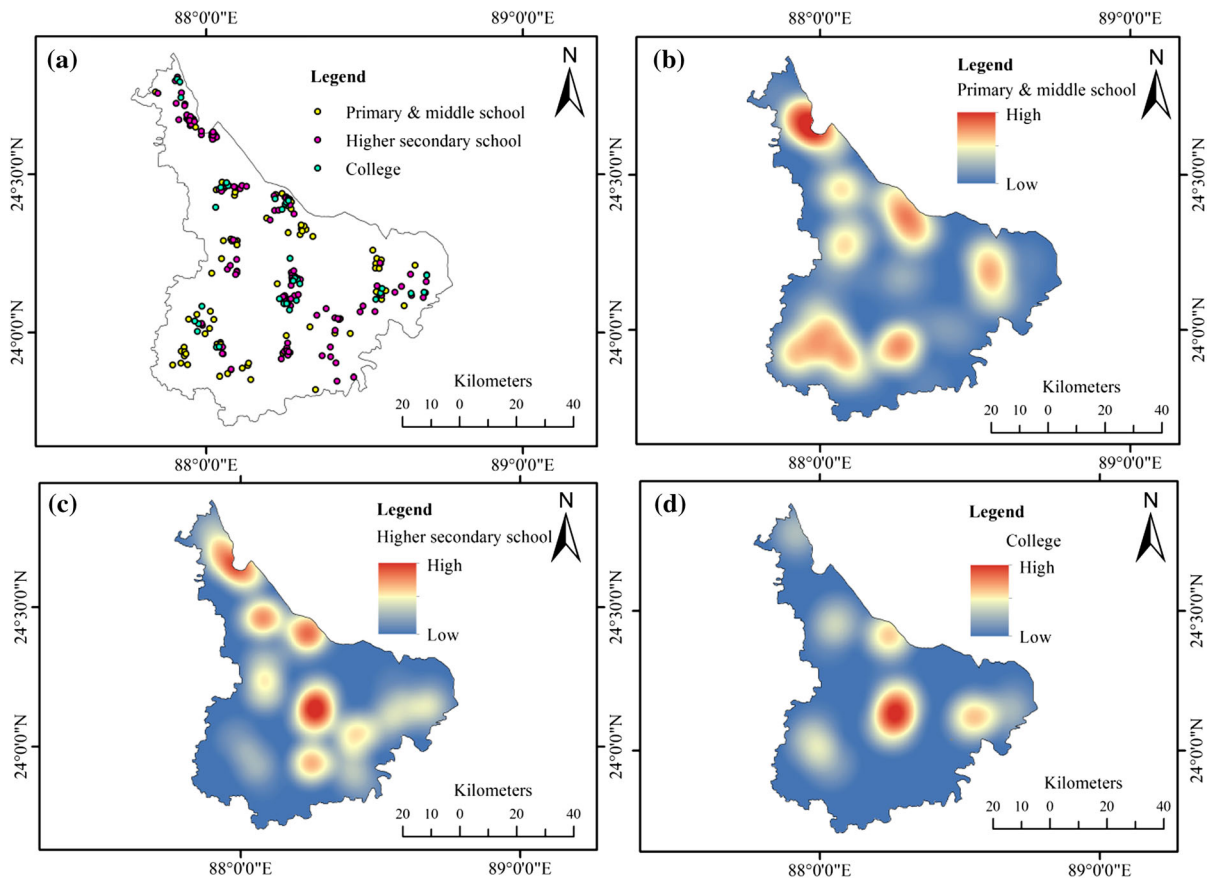
Fig. 5 Selected educational infrastructure and amenities: **a** Location of selected features, **b** Primary and middle school, **c** Higher secondary schools, **d** Colleges

2017). This method combines the different criteria and weights corresponding to those criteria to offer a single score for each alternative to make them comparable (Kim and de Weck 2005). The weighted sum is the easiest method that provides a good result that has a set of alternative criteria based on decision making (Karande et al. 2016). Looking towards the study criteria, the present study used WSM to derive preference value and backwardness rank of selected criteria. Thus, first of all, the comparison matrix was formed to normalize the given score of selected criteria, which can be expressed as:

$$\bar{X}_{ij} = \frac{X_{ij}}{\sum X_j}$$

where X_{ij} = particular criteria, ΣX_j = sum value of all criteria.

Upon calculating the normalized value using a linear normalization sum method, the weighted normalized decision matrix (WNDM) has to prepare using the following equation:

$$P_{iWSM} = \sum_{j=1}^{n} W_j X_{ij}$$

where X_{ij} = is the preference value of each cell, W_j = weight of each criterion (here, equal weight is assigned i.e. $1/n$, n is the number of selected criteria).

Now, to calculate the preference score, the row sum value of the weighted normalized decision matrix is taken, which is defined as:

$$P_i = \sum (Xij_1 + Xij_2 + Xij_n)$$

where Pi = preference score, Xij1 … Xijn = row value of normalized weight. Here, the highest value of Pi is considered as best alternatives and vice versa.
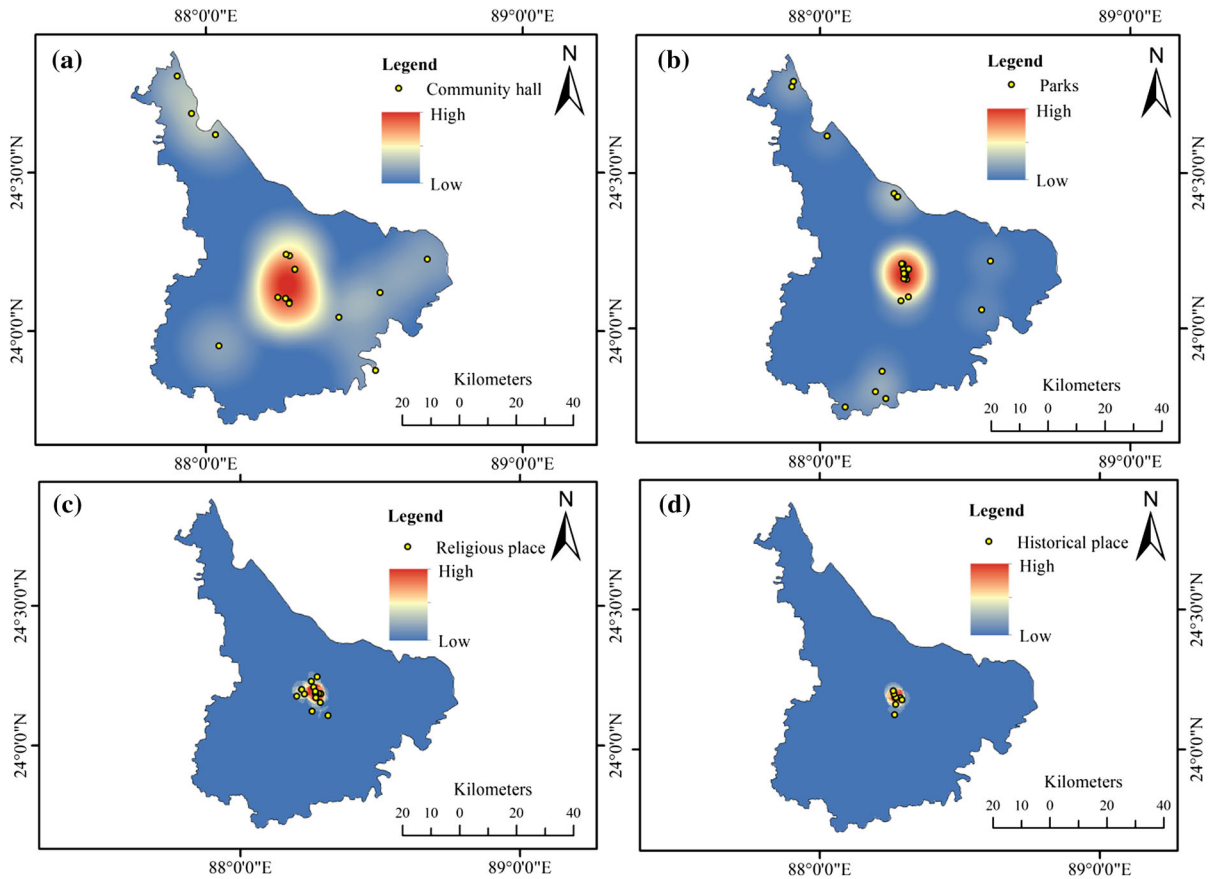
Fig. 6 Selected recreational infrastructure available: **a** Community hall, **b** Parks, **c** Gathering places/religious places, **d** Historical sites

Estimation of spatial backwardness

There are numerous factors and various techniques used by researchers to calculate backwardness index in different geographical location (Barsby 1969; Borooah and Dubey 2007; Baruah 2010; Planning Commission 2014). Instead of applying these types of method, quite a different effort was made in the present study by using geospatial database and GIS technique that hardly found in the literature. The geospatial technique has great efficiency to define different research problems and accurately estimate solutions (Weber 2006; Panigrahy et al. 2012; Rawat et al. 2013; Ali and Ahmad 2019b).

To calculate the spatial backwardness in the present study, separate raster layer of all four selected parameter was created first and weighted linear combination (WLC) technique was run based on preference value calculated through weight sum model. A weighted linear combination is an accepted

and commonly used technique for evaluating multi-criteria decision-making approach to find a spatial result that was also previously applied in various researches (Jeefoo et al. 2010; Hasekiogullari and Ercanoglu 2012; Ali and Ahmad 2018). The integration of different selected infrastructural facilities was done to find a single layer of spatial backwardness based on the weighted overlay, which is expressed as:

$$\text{BI} = \sum_{j=i}^{n} \left(P_j p_{ij} \cdots + P_n p_{in} \right)$$

where P_j is the preference value of selected parameter p, p_{ij} is the preference value of alternatives i of selected parameter p, and n is the number of selected decision criteria.

Result and discussion

Backwardness is ever seen in Murshidabad in comparison to another district of West Bengal is due to not only economic and social factors, the infrastructural facilities and basic amenities are also partially responsible. The lack of Govt. policies, facilities and program implementation are also a significant factor that left the district behind the development. The cause of such instances is a different discussion. But the present study has only emphasized to identify the spatial extension of backward areas and recommend plans for development and policy execution. For the same, a decision tree was prepared through multi-criteria analysis in which 17 indicators related to infrastructure were selected initially. These indicators were categorized into four parameters naming physical infrastructure, medical infrastructure and services, educational amenities and recreational facilities. Then kernel density estimator was applied to estimate the spatial density of these selected infrastructural features and a single raster layer was created. Finally, weight-based preference value was calculated using the weight sum model by putting inter-criteria rank of 1–5 (5 = high and 1 = low). Here, the inverse ranking system applied i.e. high density of infrastructural facilities reversely indicated low backward areas and low density of infrastructural facilities reversely indicated high backward areas (Table 2).

The study classified infrastructural facilities systematically into four categories i.e. physical, medical and health, educational and recreational looking towards major indicators of infrastructure for social and economic development like transportation, energy, water, electricity, safety and resilience, health and education, public space, culture, and environment, etc. The physical infrastructure refers to the basic amenities and physical structure required for the economic development of a society. Thus, six indicators or decision criteria comprising road density, rail facilities, availability of banks, availability of post offices, electricity facilities in household and hand pump and tube well used for drinking water source were taken in physical indicators. After preparing the spatial map of these features, infrastructural density and backwardness rank was put using 5 point scale of ranking. The high infrastructural density of selected feature was taken as a low backward area to show the areal extension of backwardness. Then inter-criteria

rank was given to six decision criteria of physical infrastructure using same ranking scale i.e. 1–5 and expert-based opinion for calculating preference (Pi) value and identifying most reasonable criteria responsible for backwardness (Table 3). The comparison matrix of physical infrastructure reveals that household-level electricity facilities and drinking water sources having the highest Pi value of 0.2702 and 0.2419 respectively. The road density, rail density, and availability of bank all have a Pi value above 0.10 indicating responsible for backwardness. Instead, only availability of post office has a Pi value less than 0.10, which is not a reasonable factor in measuring backwardness. These Pi values were used for map overlaying to display the areal extension of backwardness based on physical infrastructure available in Murshidabad district (Fig. 7a). The Pi value calculated by WSM shows that availability of electricity, source of drinking water and transport communication are significant physical amenities for a region to measure backwardness.

Likewise, the comparison matrix of other selected parameters i.e. medical and health infrastructure, educational amenities and recreational facilities were formed using the same ranking scale to calculate the Pi value. Four decision criteria or indicators of medical and health infrastructure like medical college, primary health center/dispensary, availability of hospital and nursing homes were considered to map the areal extension of backwardness (Table 4). The result reveals that the location and availability of nursing home and hospital are considered an important factor to define an area as developed or backward. In general, primary health center/dispensary is located in less developed and rural areas, but nursing home and hospital are located in urban or peri-urban areas. Same as three indicators of educational amenities and four indicators of recreational facilities were considered for spatial backwardness mapping. Thus, the comparison matrix of availability of primary and middle school, higher secondary schools and colleges in educational facilities and locality to the community hall, parks/play grounds, gathering places/religious place, historical sites in recreational facilities were prepared to calculate the Pi value (Tables 5, 6). The WSM based weighted map overlay was performed using Tables 4, 5 and 6 to show the spatial backwardness of Murshidabad district in term of medical and health

Table 2 Decision analysis and hierarchical structure for analysing spatial extension of backwardness

Infrastructure and amenities	Decision criteria	Inter-criteria rank	Density	Backwardness
Physical Infrastructure and services	Road density	5	High	Low
	Rail density	4	Moderate	Moderate
	Availability of Banks	3	Semi-high	Semi-low
	Availability of Post offices	1	Low	High
	Households having electricity	3	Moderate	Moderate
	Households using only hand pump and tube well	2	Semi-high	Semi-low
Medical Infrastructure and facilities	Location of Medical College	5	High	Low
	Location of Primary health centre/Dispensary	2	Semi-low	Semi-high
	Location of Hospital	3	Moderate	Moderate
	Location of Nursing homes	4	Semi-high	Semi-low
Educational amenities	Availability of Primary and middle school	2	Semi-low	Semi-high
	Availability of Higher secondary schools	3	Moderate	Moderate
	Availability of Colleges	5	High	Low
Recreational infrastructure	Locality to Cinema/community hall	3	Moderate	Moderate
	Locality to Parks/play grounds	2	Semi-low	Semi-high
	Locality to Gathering places/religious places	4	Semi-high	Semi-low
	Locality to Historical sites	5	High	Low

Table 3 Comparison matrix of selected criteria on physical infrastructure and services

	DC1	DC2	DC3	DC4	DC5	DC6	Pi	Pi (%)	Importance to backwardness
DC1	5	0.25	0.33	1	0.33	0.5	0.1009	10.09	2
DC2	4	4	0.33	1	0.33	0.5	0.1389	13.89	3
DC3	3	3	3	1	0.33	0.5	0.1630	16.30	4
DC4	1	1	1	1	0.33	0.5	0.0848	8.48	1
DC5	3	3	3	3	3	0.5	0.2702	27.02	6
DC6	2	2	2	2	2	2	0.2419	24.19	5

7-1 indicates high to low importance of decision criteria towards backwardness

Pi = preference value, DC1 = Road density, DC2 = Rail density, DC3 = Availability of Banks, DC4 = Availability of Post offices, DC5 = Households having electricity, DC6 = Households using only hand pump and tube well

infrastructure, educational services and recreational facilities available (Fig. 7b, c, d).

Now, GIS integration was performed with individual raster layer of WSM based overlay of selected parameters. The expert-based decision was considered and the rank was given accordingly to selected parameters to analyze the areal extension

backwardness. Weigh sum model proved that among all four main decision criteria, educational amenities and facilities has the highest significance in considering an area as backward with Pi value 0.3119 out of 1.0. Medical service and physical infrastructure have moderate significance with Pi value 0.2803 and 0.2202 and recreational facilities have the least significance in
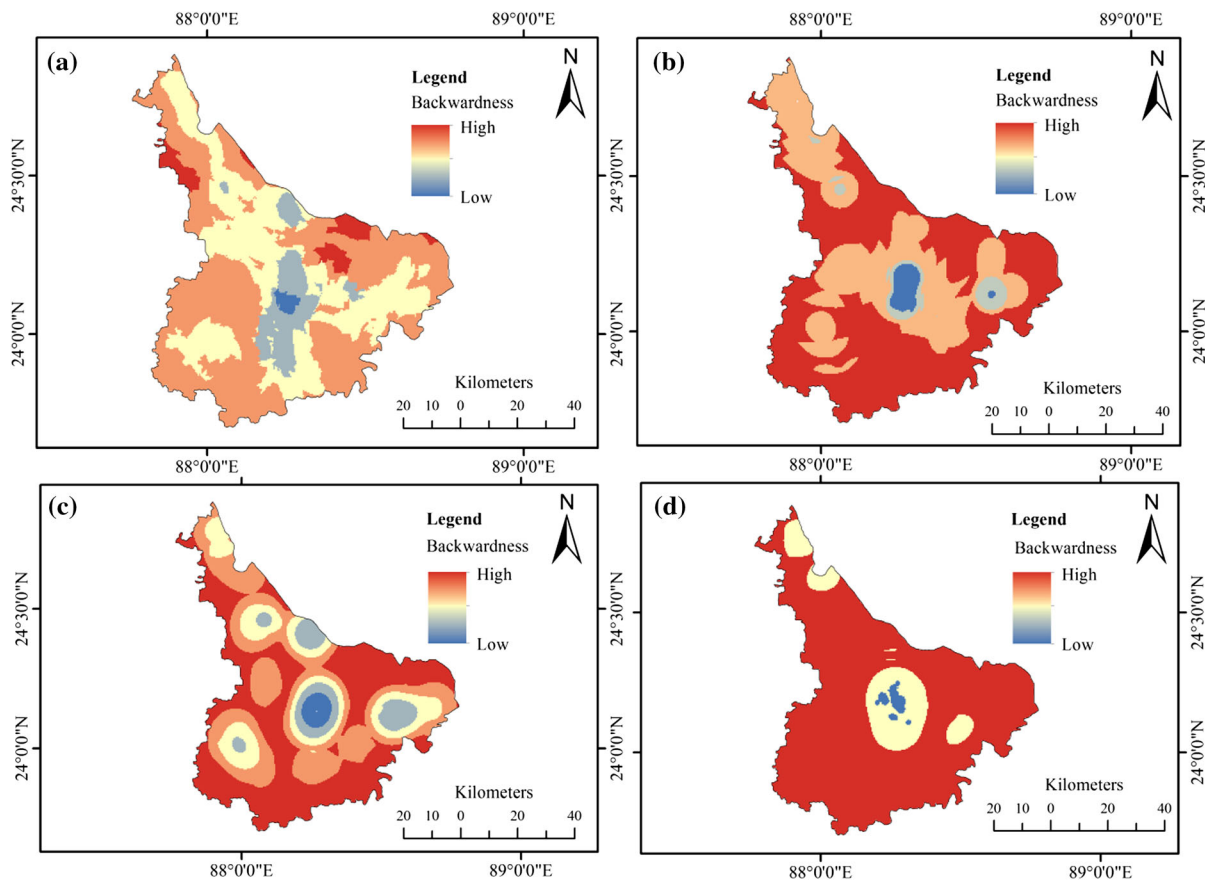
Fig. 7 WSM based overlay of selected parameters, **a** spatial extension of backwardness based on physical infrastructure and services, **b** spatial extension of backwardness based on medical infrastructure and facilities, **c** spatial extension of backwardness based on educational infrastructure and amenities, **d** spatial extension of backwardness based on recreational infrastructure

Table 4 Comparison matrix of selected criteria on medical infrastructure and facilities

	DC1	DC2	DC3	DC4	Pi	Pi (%)	Importance to backwardness
DC1	5	0.5	0.33	0.25	0.1264	12.64	2
DC2	2	2	0.33	0.25	0.1123	11.23	1
DC3	3	3	3	0.25	0.2435	24.35	3
DC4	4	4	4	4	0.5176	51.76	4

4-1 indicates high to low importance of decision criteria towards backwardness

Pi = preference value, DC1 = Location of Medical College, DC2 = Location of Primary health centre/Dispensary, DC3 = Location of Hospital, DC4 = Location of Nursing homes

estimating an area as backward with Pi value 0.1872 (Table 7). These WSM based Pi values were multiplied with the individual raster layer to estimate the multi-criteria decision support based areal extension of backwardness of Murshidabad district (Fig. 8). The output result shows that major areas of Bhagwangola-

II, Ramnagar, Raninagar-II, Nawda, Bharatpur-II, Bharatput-I and Burwan have high backwardness. Concomitantly, eastern partion of Suti-I, western partion of Khargram, Nabagram, Sagardighi, Raghu-nathjang-I, Suti-II and Farakka have also high back-wardness. But major areas of Berhampore,

Table 5 Comparison matrix of selected criteria on educational infrastructure and amenities

	DC1	DC2	DC3	Pi	Pi (%)	Importance to backwardness
DC1	2	0.333333	0.2	0.0922	9.23	1
DC2	3	3	0.2	0.2323	23.23	2
DC3	5	5	5	0.6752	67.51	3

3-1 indicates high to low importance of decision criteria towards backwardness

Pi = preference value, DC1 = Availability of Primary and middle school, DC2 = Availability of Higher secondary schools, DC3 = Availability of Colleges

Table 6 Comparison matrix of selected criteria on recreational infrastructure

	DC1	DC2	DC3	DC4	Pi	Pi (%)	Importance to backwardness
DC1	3	0.5	0.25	0.2	0.0799	7.99	1
DC2	2	2	0.25	0.2	0.0947	9.47	2
DC3	4	4	4	0.2	0.2725	27.25	3
DC4	5	5	5	5	0.5527	55.27	4

4-1 indicates high to low importance of decision criteria towards backwardness

Pi = preference value, DC1 = Locality to community hall, DC2 = Locality to Parks/play grounds, DC3 = Locality to Gathering places/religious place, DC4 = Locality to Historical sites

Table 7 Comparison matrix of selected decision parameters for overlay to analyse areal extension backward areas

	PIS	MIF	EA	RI	Pi	Pi (%)	Importance to backwardness
PIS	5	0.33	0.5	1	0.2202	22.05	2
MIF	3	3	0.5	1	0.2803	28.03	3
EA	2	2	2	1	0.3119	31.19	4
RI	1	1	1	1	0.1872	18.72	1

4-1 indicates high to low importance of decision criteria towards backwardness

Pi = preference value, PIS = Physical Infrastructure and services, MIF = Medical Infrastructure and facilities, EA = Educational amenities, RI = Recreational infrastructure

Hariharpara, domkal, Beldanga, Murshidabad-Jiaganj, Lalgola, Samserganj and Farakka have low to very low of backwardness.

Accuracy assessment

Accuracy assessment is a vital step for any kind of study on geospatial analysis. The spatial analysis offers result based on input vector or raster and it has not such ability to identify human biases and wrong input because spatial analysts can predict only what can be seen from various locations. Thus, to judge, how far the result of the spatial analyst is correct;

accuracy measurement of the result is truly crucial to make the study more reliable and reasonable. There are various developed techniques used globally for measuring accuracy of study findings based on study objectives; including viewshed delineation algorithm (Maloy and Dean 2001), error matrix (Wu et al. 2012), root mean square error (Ali and Ahmad 2019a), area under curve (AUC), success rate (SR), prediction accuracy (PA) etc. (Chung and Fabbri 2003; Mondal and Maiti 2013). Prediction accuracy (Pa) was applied in the present study for measuring the accuracy of the study result by using sampled villages located on the output layer of backwardness estimation. Prediction

Fig. 8 Backward areas appraised using WSM and GIS-based kernel density estimation
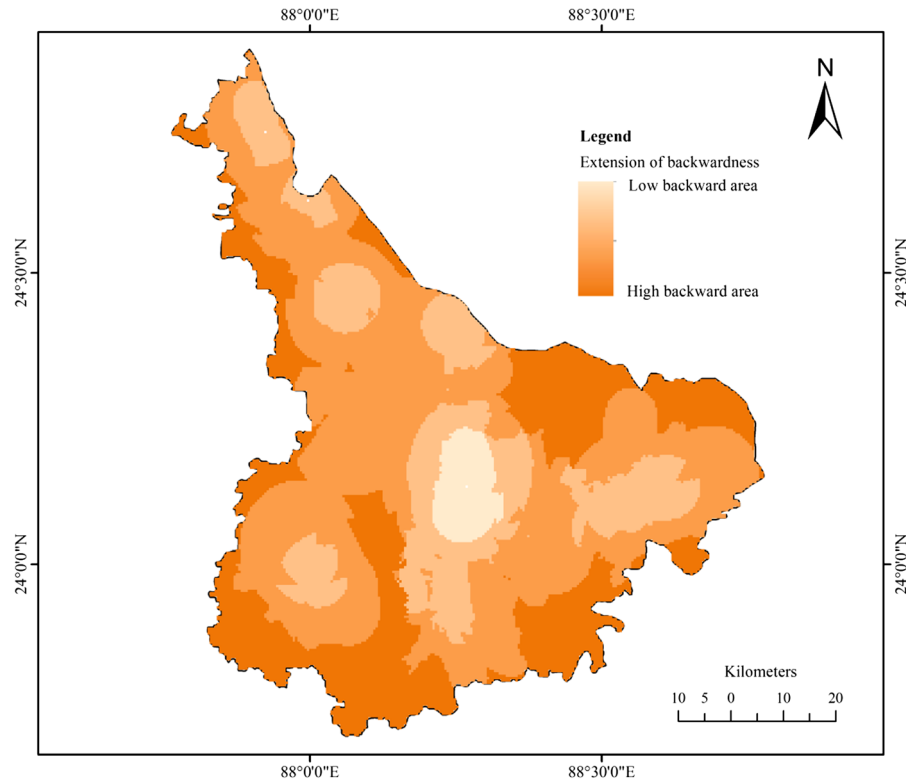
accuracy can be applied to those geospatial based studies, where actual locations of ground sampled points are possible to collect, which is expressed by the following equation:

$$Pa = \frac{\sum_{i=1}^{n} al_i}{\sum_{i=1}^{n} tl_i}$$

where Pa is the prediction accuracy, al_i is all sampled villages overlaid with high backward areas of a single unit; tl_i is total sampled villages of a single unit area.

If the result of accuracy is absolutely 1.0, it defines 100% accuracy of the analysis and the value above 0.70 can be considered as accurate prediction (Ali et al. 2019). Thus, for measuring the accuracy of the present study, initially, 150 villages were selected as more backward based on the proportion of scheduled caste, scheduled tribe and literate population to total population. Villages with a lower proportion of the literate population and higher schedule caste and schedule tribe were considered as backward villages. Then, GPS coordinates of these 150 backward villages were marked and merged with the final overlay map of the backward area (Fig. 9).

The accuracy result reveals that out of a total of 150 sampled backward villages, 123 are correctly overlaid on the high backward area (Table 8). Among 5 sub-division of the district, the prediction accuracy of Kandi and Domkal show perfectly accurate with Pa value 1.0 and 0.90 respectively, Jangipur and Lalgola also have high accuracy with Pa value 0.78 and 0.82 respectively. Differently, only Behrampore Sadar shows a moderate accuracy with Pa value 0.50, it is because of that the villages surrounding the district capital city also develop from less to large extent in comparison to another area. Moreover, the overall prediction accuracy signifies 82% ($Pa = 0.82$) which validates the weight sum model (WSM) and kernel density estimator (KDE) applied in areal extent analysis of backwardness in Murshidabad district of West Bengal, India.

Conclusion

Mapping of backward areas are required for better policymaking and implementing developmental strategies. The spatial analysis is gaining great

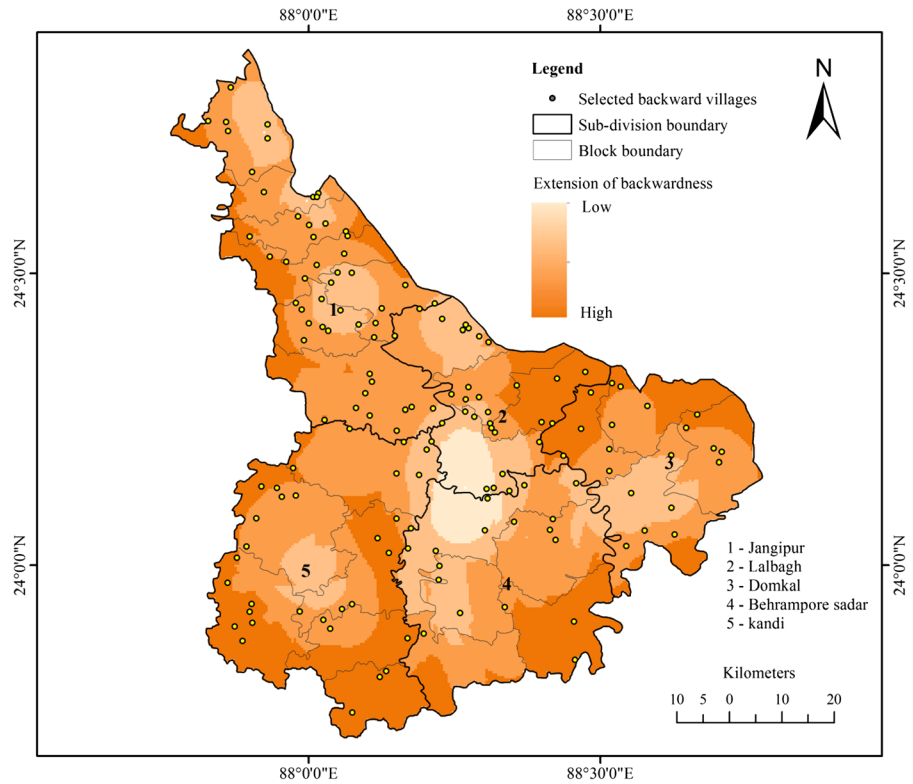**Fig. 9** accuracy assessment of retrieved result on backward areas

Table 8 Validation of the result measured suing prediction accuracy

Sub-division	Total Blocks	al_i	tl_i	Pa
Jangipur	7	51	40	0.7843
Lalbagh	5	28	23	0.8214
Domkal	4	20	18	0.9000
Behrampore Sadar	5	18	9	0.5000
Knadi	5	33	33	1.0000
Total	26	150	123	0.8200

al_i = No. of Sampled villages taken, tl_i = sampled villages overlaid with high backward areas, Pa = prediction accuracy

implication for this type of requirement. Thus, the effort was made to assess the infrastructural facilities and available amenities for analyzing the areal extension of backwardness in Murshidabad, a backward district of West Bengal, India. Instead of gathering and calculating manual data on available resources to analyze backwardness index, the present study used the geospatial database on infrastructural facilities to show the spatial extension of backward areas. The study evidenced that GIS can perform spatial integration and weight-based overlay. Previous research showed that many studies used numerical data on infrastructural amenities like road, rail, electricity, school, college, health service, etc. to measure backwardness in any region. But the application of GIS and geospatial analysis for zonation of backward areas is a new invention and new approach in this field. With the development of GIS technology, research interest has been increasing towards social science including visual representations of population data, household distribution, land use, social degradation, crime distribution, political issues, etc. along with spatial interaction between each other variables. Similarly, work out in this study to find spatial pattern and distribution of backwardness.

It is always found a linear consequence between poor infrastructural facilities and backwardness of an area. But selection and application of the accurate method are essential for the reasonable and accepted result. Looking towards the study objective, multi-criteria decision analysis and geospatial technique were used for analyzing the spatial extension of backwardness. Weight sum model (WSM) as multi-criteria decision approach was used for preferring

weighted factors toward backwardness. The main advantage of weight sum model is that it combines the different criteria and weights corresponding to those criteria to offer a single score for each alternative to make them comparable by providing good result. So initially, the present study focused on four infrastructural amenities available in the study area including physical, medical and health, educational and recreational. These infrastructural criteria were subgrouped into suitable decision alternatives that are inter-connected and closely associated with economic advancement or backwardness of a region. These data were collected and analyzed through GIS modeling for spatial analysis. To reach the aim of this study, GIS integration was performed based on calculated weight through the model applied. Based on spatial analysis, the result from the present study reveals that educational amenities and facilities have the highest significance in measuring an area as backward or develop. Consequently, medical services and mode of transport communication have also the greatest role to determine a region as backward. To generalize the result and make weight the methodology applied this study to analyze, the accuracy of spatial analysis has also been carried out which signifies 82% accuracy of the result which validates the use of WSM and KDE for analyzing the spatial backwardness of the defined study area. Along with, this study also recommends the application of the same GIS model in spatial analysis of define problems, especially in no data region.

Data availability So, for this study, the compliance with ethical standards is not applicable since only the spatial data on available infrastructural facilities was collected from GPS and Google earth open software and ground-level information regarding on basic amenities was collected from different households of the district for decision making.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical statement The present study confirms that the objectivity and transparency are followed in this research along with acknowledged principles of ethical and professional behavior. The present research endorses.

Human and animals rights Human participants or any kind animals were not engaged in the present study.

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