

PREDICTION OF INDUSTRIAL LAND USE USING LINEAR REGRESSION AND MOLA TECHNIQUES: A CASE STUDY OF SILTARA INDUSTRIAL BELT

SHEIKH MUSTAK^{1*}, NARESH KUMAR BAGHMAR², SUDHIR KUMAR SINGH^{3*}

^{1,2} School of Studies in Geography, Pt. Ravishankar Shukla University, Raipur-492010, Chhattisgarh, India

³ K. Banerjee Centre of Atmospheric and Ocean Studies, IIDS, Nehru Science Centre, University of Allahabad, Allahabad-211002 (U.P.), India

*Correspondence: sudhirinjnu@gmail.com; mustak.sk5@gmail.com

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Abstract

The Siltara Industrial belt is an important industrial pocket of Chhattisgarh state located in the northern part of the Raipur city, which is rapidly growing. In this process spatial, cultural, political and administrative factors are controlling its rate, direction and pattern. The Simple Linear Regression (SLR) and Multi-Objective Land Allocation (MOLA) techniques, which are embedded in SPSS and Idrisi Kilimanjaro software respectively, and have been used for the estimation of future scenario of the industrial growth. In this model, a suitable platform has been prepared in which future industrialization has been estimated by integrating physical, social, cultural factors and land acquisition policy. In this article, results have revealed that industrialization has occurred very fast during last one decade. The industrial land was 6.15 km² in 2001 and 18.725 km² in 2011 and estimated as 31.30 km² in 2021 and 43.87 km² in 2031 using SLR. The rapid industrial growth is very critical issues for agrarian society and fresh environment. This model very accurately estimating (overall accuracy=95.39%, K_{no}=97.24%, agreement=98.63 %) the future growth of industrial land. This work will be useful to the planners and policy makers of private and government sectors to regulate the sustainable planning practices and smart decision-making.

Keywords: GIS, Multi-Objective Land Allocation (MOLA), Simple Linear Regression (SLR), industrial belt growth

1. Introduction

Industrialization is the process of the expansion of industrial area, which was arising, with the advancement of human civilization through economic growth. This scenario gives birth to the urbanization which jointly termed as industrialization-urbanization process. The dynamics of this process was triggered through the economic demand to sustain the rapid population growth in one side and enhancing the alarming change in agricultural land into industrial land uses and healthy environment into polluted environment is the another side (Downing et al., 1999; Chaitanya, 2007; Lu et

al., 2011; Singh et al., 2016). In this regards, the China and India experiencing sole giants in the rest of the countries of the World (FAO, 2006). Recently, this scenario is a challenge to the existence of the human society in response to food security and climate change (Li et al., 2011; Rutten al., 2014). Besides, Chhattisgarh is one of the rapid industrialized states in India which spread over various spatial pockets. The Siltara industrial belt is an important industrial pocket of this state located in the northern part of the Raipur city and experiencing several changes in landscape and its surrounding environments. During last several decades it was observed

that the several simulation models like Cellular Automata (Batty, 1997; Clarke and Gaydos, 1998; Li and Yeh, 2000), Markov Chain (Lo'pez et al., 2001; Weng, 2002; Wu et al., 2006), CA-Markov (Memarian et al., 2012; Ahmed and Ahmed, 2012; Singh et al., 2015), MLP-Markov (Tewelde and Cabral, 2011; Ahmed and Ahmed, 2012; Megahed et al., 2015) have been used by the researchers for simulation of land use and land covers however none of them were ever conducted the study on the integration of statistical model like Simple Linear Regression with the Spatial model like MOLA for the simulation. This article aims to identify the present and

future scenarios of industrial growth through advance geo-simulation model namely Multi-objective Land Allocation (MOLA) and Linear Regression. MOLA is a spatial overlay technique that converts statistical entity into spatial entity and Linear Regression which extract statistical entity based on causally two interdependent variables. This advance geo-simulation model may enhance the result as compared to traditional methods and thus it will be very fruitful to various landscape and economic planners in government and private sectors for policy making and implementation.

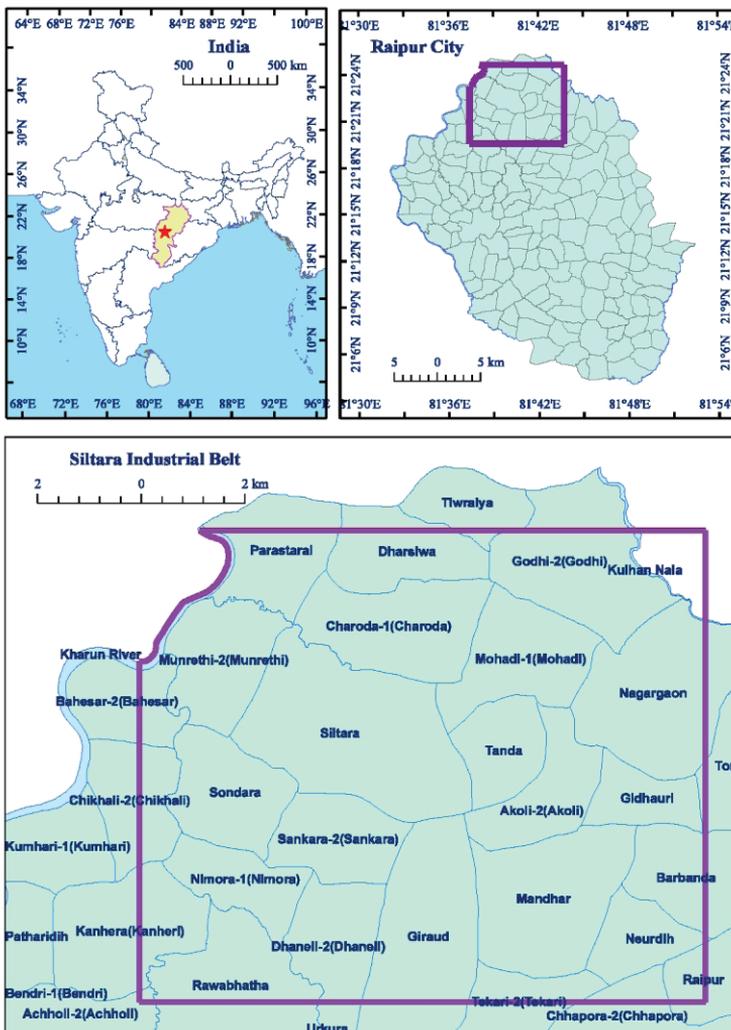


Fig. 1. Location of Siltara industrial belt

2. Study area

The Siltara industrial belt is located in the northern part of the Raipur City, India and extends in between 21°19' N to 21°24' N latitude and 81°37' E to 81°43' E longitude covering with an area of 99.38 km² at 280 m height from above mean sea level (Fig. 1.). The Kharun is the main perennial river which flowing from south to north in the western part of this industrial belt. The Bilaspur-Howrah national highway (NH-200) and Howrah- Nagpur rail line connects the industrial belt with Kolkata and Mumbai metropolitan cities for trade and commerce.

3. Database

This article is based on the application of high resolution earth observation satellite datasets such as IRS-1C (LISS-III, GSD 23.5 m, dated- 2001), IRS-1D (PAN, GSD 5.8 m, dated-2001) and Cartosat-1 (PAN, GSD 2.5 m, dated- 2011) and Resousesat-1(LISS-IV, Multispectral, GSD 5.8 m, dated- 2011). These datasets have been collected from National Data Centre (NDC), National Remote Sensing Centre (NRSC), Hyderabad (A.P).The Survey of India topographical sheets (64G/11 and 64G/12, 2005 modified) have been collected from the Survey of India, Regional office, Raipur, India. The details of satellite datasets are given in table 1.

The referenced datasets such as Bhuvan Geoweb data collected from the website of National Remote Sensing Centre, Hyderabad, India (2011), the Google earth satellite

imageries (2011) and field survey data (ground truthing) using GPS.

4. Methods

This study has been carried out through several steps that explained in Fig. 2.

Pre-processing

The pre-processing of satellite imageries such as the geometric correction (UTM projection, zone-44north, datum WGS84) has been carried out using Indian topographical sheets, 64G/11 and 64G/12. The radiometric correction has been done using the Improved Dark Object Subtraction Approach (Mustak, 2013) and the image fusion has been done using the Wavelet transformation. All these pre-processing tasks have been carried out to enhance the spatial and spectral information for the better interpretation and accuracy. However, subset and mosaicking have been carried out for the delineation of area of interest. The whole pre-processing tasks have been carried out using Erdas Imagine 9.1 software.

Thematic mapping

The onscreen visual interpretation technique has been adopted for the preparation of land use maps of 2001 and 2011 using satellite datasets of 2001 and 2011 by incorporating with the referenced datasets such as survey of India topographical sheets (64G/11 and 64G/12, 2005 modified), Bhuvan Geoweb data (2011), Google earth

Table.1. Satellite imageries and referenced datasets, 2001-2011

Satellite datasets			Referenced datasets	
Satellite/Sensors	Spatial Resolution (metre)	Year	Data types	Year
IRS-1C (LISS-III)	23.50	2001	Topographical sheet 64G/11 and 64G/12	2005
IRS-1D (PAN)	5.80	2001	Bhuvan Geoweb data	2011
Cartosat-1 (PAN)	2.50	2011	Google Earth satellite imageries	2011
Resousesat-1 (LISS-IV)	5.80	2011	Ground truthing using GPS	2011

Multi-Objective Land Allocation

MOLA has capability to allocate the land on space based on the competitive land use demands and numbers of spatial suitability and constraints in which conflicts that has derived in the simulation process are automatically resolved by this model (Houet and Hubert-Moy 2006; Eastman, 2012). In this model, industrial land, which has been predicted for future using SLR, has been used as an input in MOLA to fulfil the competitive land use demands during simulation. This model has been calibrated through several steps. Firstly, criteria and constraints has been defined in this simulation. In this process, the criteria which are termed as driving forces that provides suitable spatial allocation environments while constraints are strict limiting space in which allocation of land in future is strictly prohibited. In this article, suitable criteria are industrial Euclidian distance, road Euclidian distance, vacant land/layout, barren land and fallow land (Fig. 3) while constraints are residential land, transportation land, main river proximity (500 m), other waterbodies proximity (20 m) and main waterbodies (Fig.4).

Secondly, criteria weight optimization has been carried using Analytical Hierarchy Process (AHP) through Matlab programming. This step is very important for the land suitability analysis in which judgement has been made on several criteria based on Saaty's 9 point rating scale to derived criteria weights (Saaty, 1980; Mustak et al., 2015). In this judgement, the results is very consistent as defined having Consistency Ratio as 0.0152 ($CR < 0.10$ acceptable, $\lambda_{max} = 5.0681$, $n=5$) because for consistent matrix $\lambda_{max} = \text{order of matrix } (n) \text{ or } \lambda_{max} \geq n$ (Saaty, 1980; Memarian et al., 2012). Thirdly, criteria layers standardization has been carried out in this study which is very important for the land suitability mapping. In this process, different criteria layers have been standardized at scale of 0-255 using monotonically decrease and

user-defined fuzzy membership functions which are pre-requisites for the simulation process. This process has been carried out in Idrisi Kilimanjaro software, Clark Lab, USA.

Fourthly, land suitability and suitable rank mapping has been carried for future land allocation of industrial land. The land suitability mapping has been done using the Multi-criteria Evaluation (MCE) module, which integrated with the Weight Linear Combination (WLC), and Boolean Intersection (BI) algorithms of Idrisi Kilimanjaro Software. The index of land suitable map varies in between 0 to 255 in which 255 explained highest suitability while 0 explained lowest suitability. Such land suitability map is an input for the rank suitability mapping. The Rank module of descending order algorithm has been used to prepare rank suitability mapping (Fig. 5.) using Idrisi Kilimanjaro Software.

The index of rank suitability map explained that the lowest value represents high suitability while highest value explained the less suitability.

Finally, competitively land allocation has been carried out using MOLA module, which embedded in Idrisi Kilimanjaro Software. In this process, the MOLA is spatially allocate the land of different categories (objectives) based on number of objectives, objective weights, rank suitability map and area statistics (Eastman, 2012). In this study, for each future decade (such as 2021, 2031), single objective, existing rank suitability map with objective weight equal to 1 and predicted industrial land (estimated using Simple Linear Regression) have been used as the input in MOLA for the future industrial land allocation by resolving the several land allocation conflicts. Thus, industrial growth of the Siltara industrial belt has been predicted for the decade of 2021 and 2031 by integrating Simple Linear Regression and MOLA simulation model.

Accuracy Assessment and Model Validation

The accuracy is a standard parameter used to measure the consistency of results, how close to actual scenario. In this article, 65 to 70 GPS points were collected from field verification using hand handled GPS to check

thematic accuracy. The thematic accuracy was calculated using Kappa coefficient method and result is consistent (Overall Kappa =90%) (McCoy, 2006) as per guideline of National Urban Information Systems (National Remote Sensing Agency, 2008). The simulation results has been validate

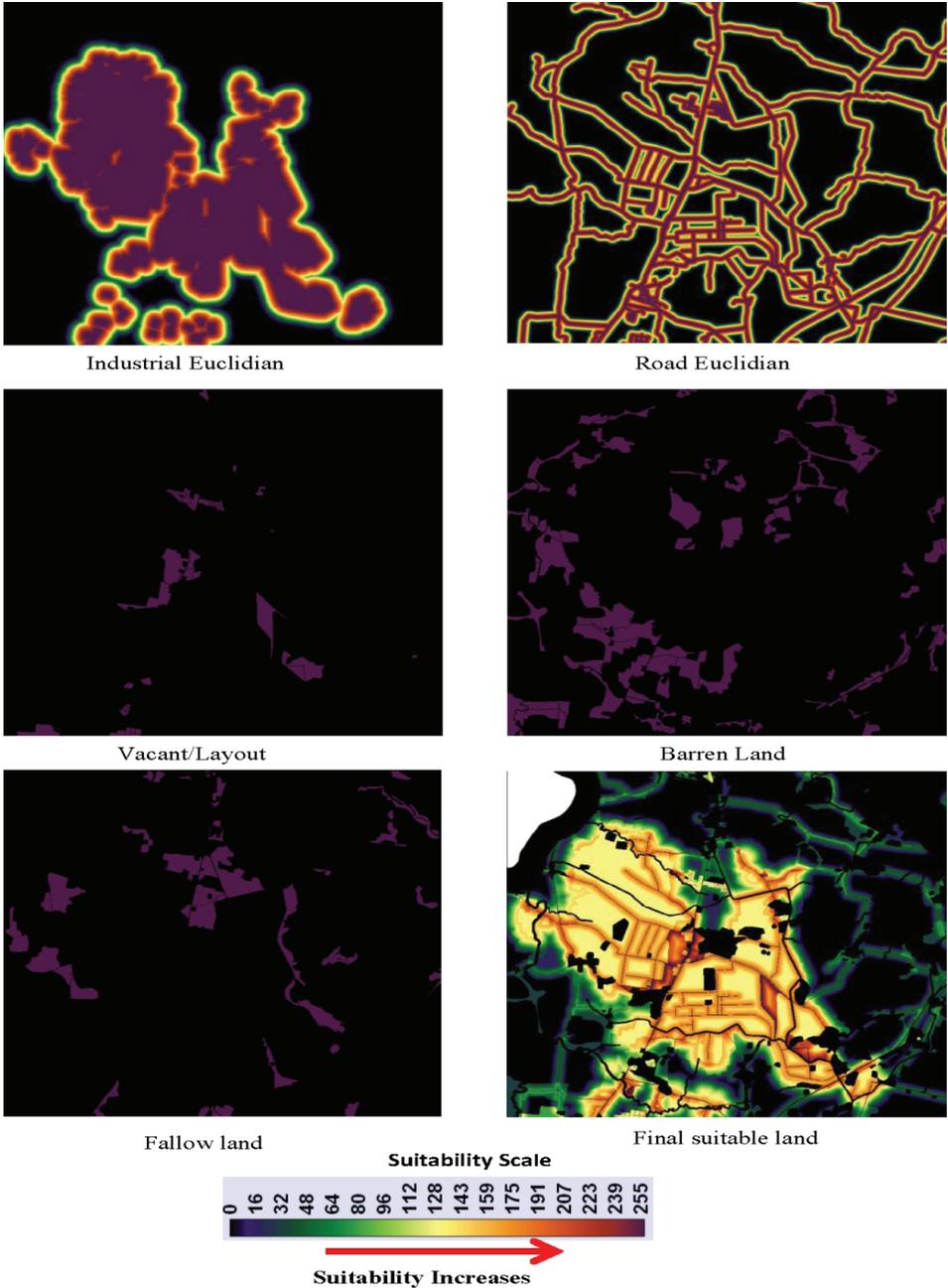


Fig. 3. Land suitability for future industrial growth

using validate and cross tab modules of Idrisi Kilimanjaro software to check the simulation powers of MOLA technique. The results showing that, MOLA has high capability of simulation powers is as 95.35% overall accuracy (K standard or overall accuracy)

and locational (K location) accuracy and Kno is 97.24% (Overall Kappa index of no information) (Fig. 6.).

However, this model satisfied 98.63% simulation agreement and 1.37 % simulation disagreement at class level (Fig. 6.).

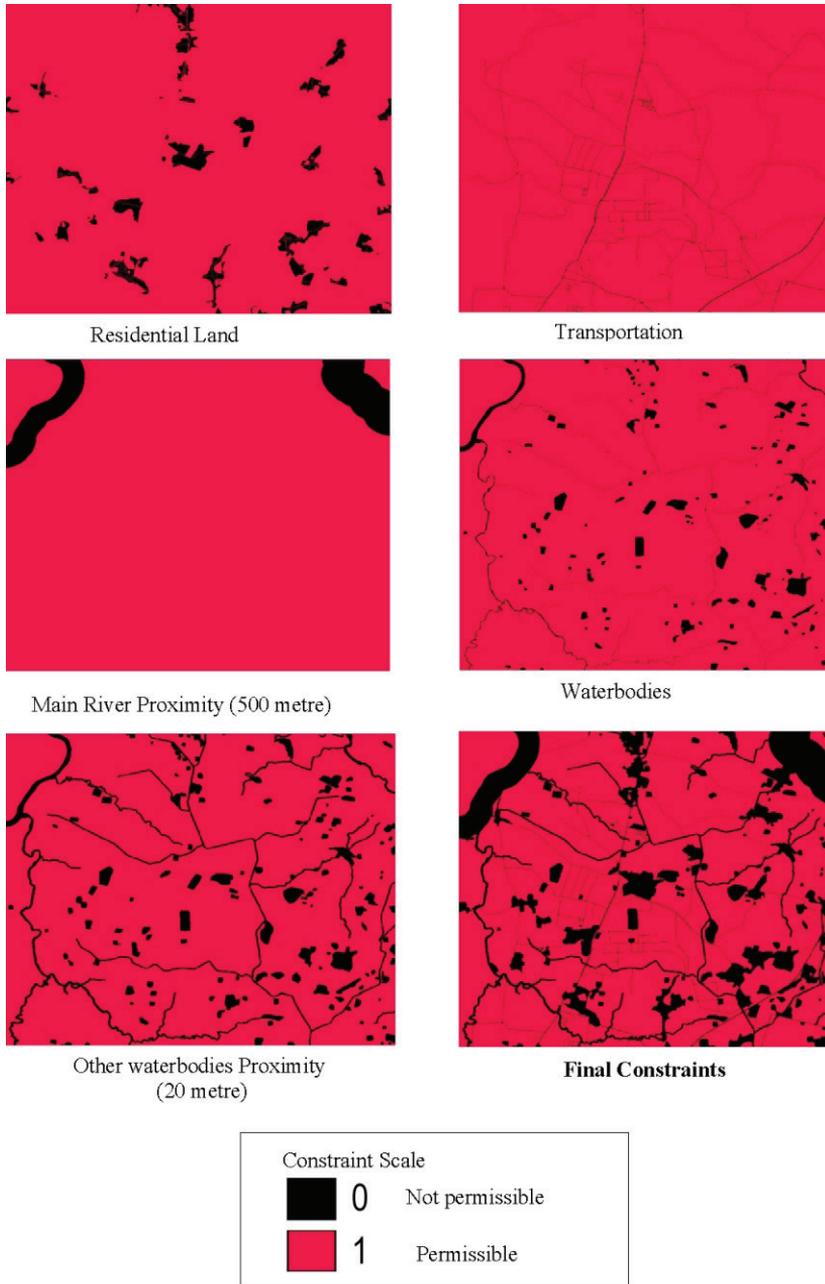
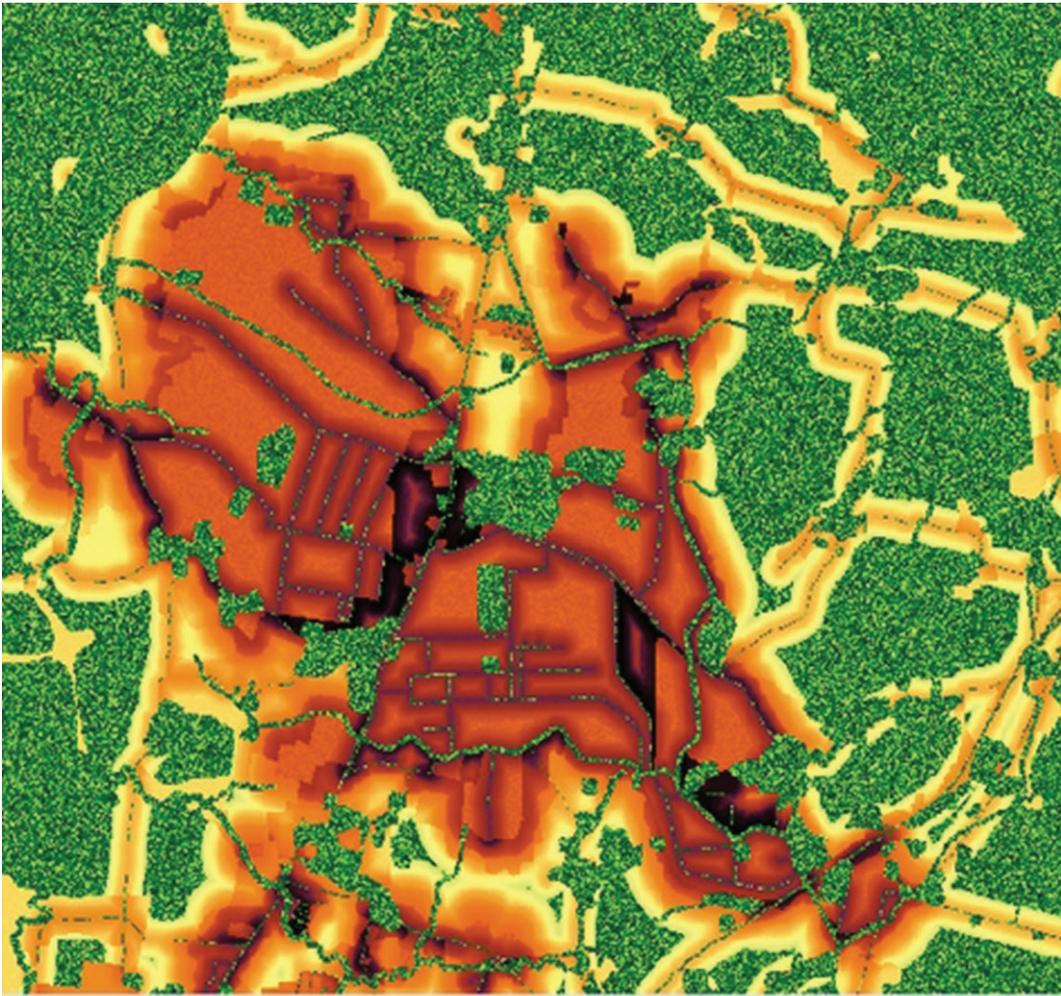


Fig.4. Constraints for Future Industrial Growth Simulation, 2001-2031



Rank Suitability



Suitability

Fig. 5. Rank Suitability for Future Industrial Growth Simulation, 2001-2031

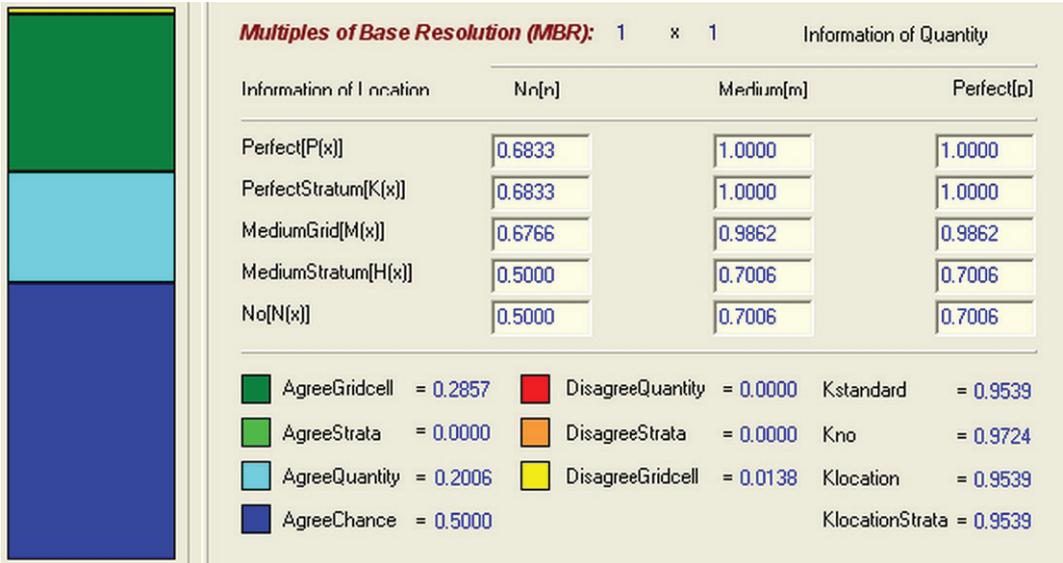


Fig. 6. Validation of simulation result using existing industrial land (2011) and predicted industrial land (2011) using validate module of Idrisi Kilimanjaro Software

5. Results and Discussions

The results of this research work have revealed that the growth of industrial land during past decades was observed more linear than the non-linear and hence SLR model has been applied to predict the future growth of industrial land. This trend of growth showing that the growth of industrial land was very fast as in 2001 was 6.15km² but is 18.725km² in 2011 and similarly 31.30 km² in 2021, 43.87km² in 2031 due to wide range of suitable condition for industrial setup in terms of physical and cultural suitability (Table 2, Fig.7., Fig. 8.). Although, such suitable conditions are existing in this area yet several political and administrative interferences and land acquisition policy makes it dynamic. In this study area, the land transformation processes are handled by government, industrialist and businessman who are directly or indirectly purchased the

agricultural land from the farmers in very cheap rate and transformed into industrial land. Once industries are established in the land surrounded by cropland gradually makes unfertile due to rapid accumulation of industrial dust, polluted materials on such cropland, which rapidly converted into either fallow or barren land with advancement of time.

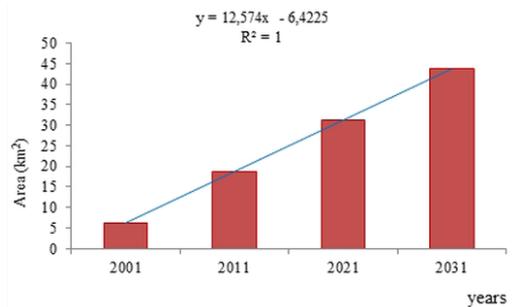


Fig. 7. Growth of industrial land derived using SLR, 2001-2031

Table 2. Growth of Industrial land derived using SLR, 2001-2031

Industrial Land (X)	2001	2011	2021	2031	Total
No. of Pixel (Y)	983974	2995852	5007730	7019608	16007164
Area in sq.km	6.15	18.725	31.30	43.87	100.04
$Y=a+bX, a=782786.20, b=201187.8$					

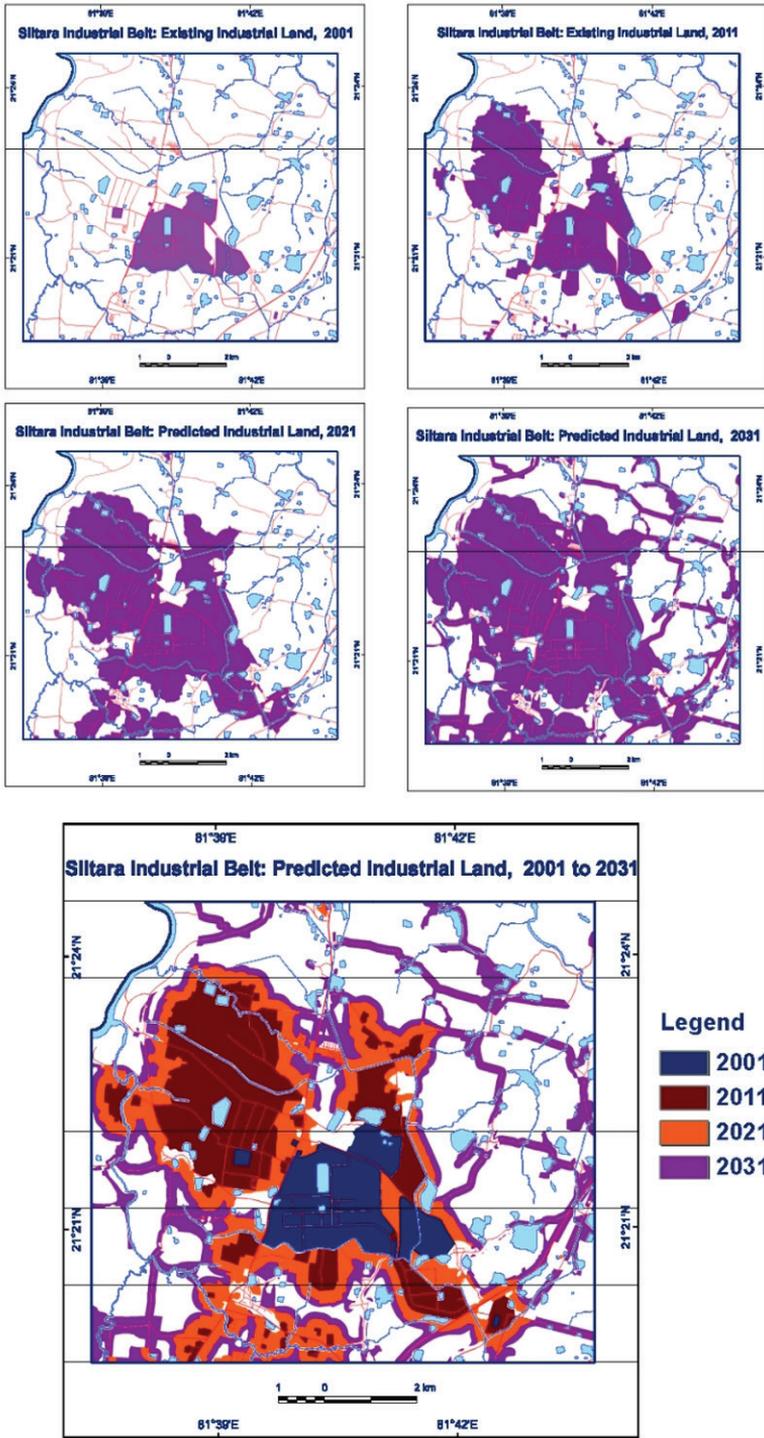


Fig. 8. Simulation of future industrial growth integrating SLR and MOLA, 2001-2031

However, vegetated areas and other grazing land are also affected by the dust coming out from the industrial chimney and reduced its natural growth. The farmers being dissatisfied by the benefits from cropping land they finally sell such unfertile cropland to the businessman or industrialists. Consequently, the growth of industrial land has been rapidly expanding with time.

This, article has noble characteristics because, its reconnects the statistical model with the spatial land allocation model for the future growth simulation of the industrial land without making any conflict. However, this article is incorporated with the high-resolution satellite imageries, advanced decision-making algorithms such as AHP, Fuzzy Membership, MCE, WLC and Boolean Intersection (BI) etc. in the simulation modelling. In this study, the Kappa coefficient and Validate algorithms have been used to assess the accuracy of the model at class level, which resulted that the model has provided very accurate simulation results. Therefore, in this study it has been observed that the integration of SLR and MOLA for the simulation of industrial land has provided real scenarios and better accuracy as we expected for the future growth of the Siltara industrial belt.

6. Conclusion

Results of this work have revealed that industrialization is very rapid in the region after declaration as the state capital because initially the industrial land was 6.15 km² (2001) and 18.725 km² (2011) and estimated as 31.30 km² (2021) and 43.87 km² (2031). It is concluded that the accuracy of the model is varied depending on the quality of the data because good data produces better results whereas poor data produced worse results. Therefore, application of this simulation model is not only limited to the forecasting of industrialization but has also wide application on dynamic features, which have spatial characteristics. This model will provide the better opportunities to the

planners and policy makers to carry out sustainable development plans and resource management practices through reconnecting various policy interventions.

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