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New methodological approach for biomass resource assessment in India using GIS application and land use/land cover (LULC) maps

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ABSTRACT

India has a high potential for technically recoverable biomass, sufficient to meet part of its increasing energy needs, promote energy access in rural and remote areas, create economic opportunities at the national scale, and reduce indoor pollution. Effective utilization of surplus biomass resources is often challenged and hindered by seasonal availability, extensive distribution over vast and distanced areas, and the embedded socio-cultural factors associated with its use. Therefore, the development of reliable maps for the assessment of available/surplus biomass resources is the first key step toward the creation of a new supply chain for cost-effective bioenergy production, particularly in developing countries. In this paper, a new methodological approach that combines primary and secondary data sets, social factors, remote sensing data, and software, such as GIS applications, has been developed. The main goal is to create high-quality, land use/land cover (LULC) maps for agricultural and wastelands in India. With an acceptable level of accuracy assessment, the paper also determines the surplus biomass resources in wastelands and municipal solid waste (MSW) distribution in three Indian states: Madhya Pradesh, Maharashtra, and Tamil Nadu. These states were selected due to the high level of agriculture production and thus high agro-biomass potential, the presence of large industrial agglomerations, and the high interest in bioenergy development in these states. The maps show that the highest surplus biomass from wastelands exists in Madhya Pradesh, while high MSW potentials exist in Maharashtra state. The developed maps considered the existing uses of biomass in order to calculate the surplus biomass resources. The presented maps are a useful tool to optimize the locations of biomass-based and/or co-generation power plants in the surveyed states.

Contents

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1. Introduction

In recent years, renewable energy and bioenergy technologies have witnessed a resurgence in capacity installations in response to supportive public policies, incentivization measures, the negative publicity of coal-fired power generation, and the Fukushima nuclear disaster in 2011 [1–4]. According to the International Renewable Energy Agency (IRENA), new renewable power capacity installations globally were 1829 GW by the end of 2014, around 1000 GW higher than in 2000, as both solar and wind technologies experienced remarkable growth [4]. Bioenergy remains a key component of renewable energy targets due to high agro-biomass potential in developing countries, the environmental friendliness of the product (nearly carbon neutral), and the availability of mature and nearly-commercialized bioenergy technologies that can thermo-mechanically and/or biologically transform biomass into useful forms of energy [1]. According to IRENA statistics, about 14 GW of bioenergy capacity was installed by the end of 2014, with India accounting for 6% of the newly installed capacity (Fig. 1) [4]. Moreover, the World Bioenergy Association has estimated the potential of agricultural residues for energy to be between 13.1 and 122 EJ [1]. However, effective utilization of surplus biomass resources is often challenged and sometimes hindered by seasonal availability and by climate factors (precipitation), extensive distribution [5–7], and by embedded and often neglected socio-cultural factors associated with traditional fuel choices and uses [8]. Therefore, the creation of maps for the assessment of available and surplus biomass resources, while accommodating socio-cultural factors, is a quintessential step toward the creation of a new supply chain for cost-effective bioenergy production. In doing so, only surplus biomass would be utilized without jeopardizing the biomass-based livelihood of poor people and soil fertility conditions, particularly in developing countries with a high agricultural dependency.

Currently, Geographical Information Systems (GIS) and remote sensing technologies, such as aircraft or space-borne satellite sensors, UAV-LiDAR, and hyperspectral mapping are undergoing remarkable changes as a result of plummeting costs, expanding systems memory, and the scale of their applications in daily life. Webster and Dias, [9] cited the use of LiDAR applications in engineering, food risk mapping, coastal processes, and groundwater infiltration. Most recently, GIS applications have been deployed in disaster management, crime statistics, archeology, and transportation. In renewable and bioenergy sciences, GIS applications have evaluated the potential of livestock manure for biogas production at a regional scale [10], the availability of degraded land for biofuels production [11], estimated solar radiation and solar farm selection [12], wind energy potentials and suitable locations [13], and tidal stream power potentials [14].

India has a requirement to feed and power about 17% of the global human population and 15% of global domestic livestock [15]. The economy and population of India are both growing rapidly, which underscores the huge challenges required to meet the expanding demand for energy and quality-electricity, particularly in rural villages and remote areas [16]. Through the Ministry of New and Renewable Energy Sources (MNRES), India has established policy frameworks necessary to navigate the pathway toward energy independence and security, rural electrification, and towards harnessing local renewable and bioenergy resources [16]. India is primarily an agricultural country with high production capacities for cereals (rice), pulses, and oilseeds (sugarcane). Therefore, surplus agricultural residues are considered a valuable source for a new and modern energy supply chain, although it remains a largely untapped renewable energy resource [16].

As a pretext to enhance biomass utilization and to foster bioenergy development in India, a number of scholarly studies investigated in biomass resources assessment and distribution [17–20]. The estimated biowastes resource in India is approximately 565 million tonnes (MT) per annum, of which 189 MT can be used either to fully provide for the transportation requirements of the country or deliver a potential 18,000 MW of power generation [17] A further one MT of non-edible oils are available each year to meet the biodiesel requirements of the diesel-based railway network [17]. Another study by Kumar et al. [18] estimated that India has about 500 MT of surplus agricultural and forest biomass available for energy production each year. A study by Hiloidhari et al. [19] estimated the Indian biomass resources from 26 crops at 686 MT gross crop residue biomass on an annual basis, of which 234 MT (34% of gross) are estimated as surplus for bioenergy generation, which is equivalent to 17% of India's total primary energy consumption. The study also showed that at the state level, Uttar Pradesh produces the highest amount of crop residues. Moreover, Hiloidhari and Baruah, [20] employed GIS applications and validated Linear Imaging and Self Scanning Sensor (LISS) to estimate the rice straw residue in the Lakhimpur district of Assam. The study estimated that approximately 51,000 t (equivalent to 788 TJ) of surplus rice straw is available in the Lakhimpur district annually, which could generate about 5 MW_e at a continuous generation with 20% overall conversion efficiency. Using the same methodological approach, Hiloidhari et al. [21] further evaluated the potential use of rice straw as an alternative renewable energy fuel for tea drying and found that rice straw is

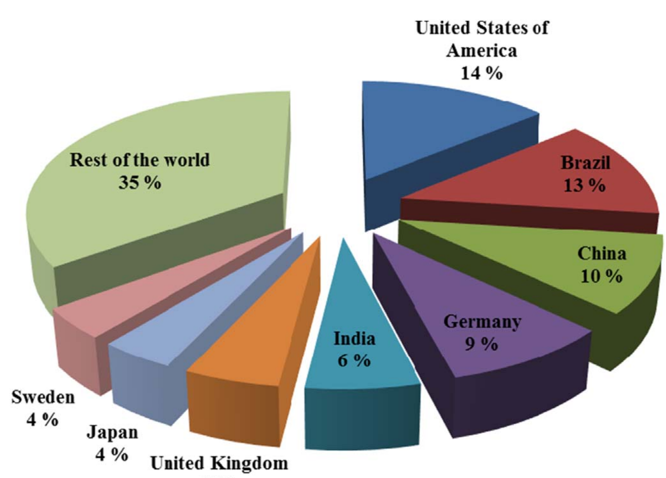

Fig. 1. Share of Global installed cumulative bioenergy capacity by the end of 2014 [4].

economically competitive with coal as a source of thermal energy and may increase the farmers' income.

Biomass potential for energy production in India is not only limited to agro- or forest biomass resources. For instance, biomass and biofuel production on wastelands, and the considerable share of biodegradable materials technically-recoverable from Municipal Solid Wastes (MSW) are of great importance and offer numerous decentralized economic opportunities. A newly published study by Edrisi and Abhilash, [11] employed GIS application and data products from various agencies to re-classify 20 sub-types of wastelands in India into either “total marginal land” or “potential marginal land” suitable for bioenergy production. The study estimated the total area of wasteland in India at approximately 46.67 Mha, of which 39.24 Mha could be exploited for biomass and biofuel production. According to a field study by Annepu, [22] the total MSW generated in urban India is 68.8 million tonnes per year (TPY) or 188,500 t per day (TPD). The study also suggested that urban India will generate 160.5 million TPY (440,000 TPD) by 2041.

Many of the studies mentioned above contain a number of shortcomings. Some studies have focused only on one biomass resource, such as agriculture biowastes. Other studies have relied solely on field data collection or secondary sources of data, which might be outdated or not fully reliable. More importantly, these studies are considered as mainly technical studies and have omitted, during the biomass resource estimation process, important socio-economic, cultural and environmental factors associated with existing biomass use and choices at the household level. A more reliable estimation of biomass resources requires identification of the degree of biomass use at the household level, in order to avoid conflict of interest between biomass use for energy production and the livelihood of farmers. In their resource assessment study in three India states, Natarajan et al. [7] calculated the estimated surplus biomass in six districts at 387,000 t in Bhopal, 834,000 t in Indore, 572,000 t in Thane, 1,364,000 t in Pune, 160,000 t in Kanchipuram and 202,000 t in Coimbatore. These resource estimation figures were calculated after taking into account the existing uses of biomass at the household level. The study also emphasized that the share of biomass consumption and surplus biomass availability varies considerably geographically, and depends on factors, such as crop productivity, crop types, seasonal variations and available energy infrastructure (e.g. access to and availability of Liquefied petroleum gas (LPG) cylinders) [7]. Other studies that have focused on fuel (biomass) choices and the socio-economic and cultural factors associated with its consumption have conceded that income, the time needed to collect a certain amount of fuel, the availability and price of commercial alternatives, family and household size, stove ownership, and season are commonly cited factors determining household fuel choice. Furthermore, cultural characteristics, such as religion or caste, cultural preferences and traditions, and lack of knowledge on the adverse effects of low-quality fuels among less educated people can have a pronounced influence on energy (biomass) consumption in India [7,23–26].

Since farmers (biomass producers) are the cornerstone of any biomass supply chain, their ability and willingness to supply surplus biomass largely influence biomass availability for energy production [16,27–30]. In India, a recent study on the ability and willingness of farmers to supply surplus biomass for energy production found that farmers are very willing to engage in and supply their surplus biomass for energy production, especially through contracts and without the involvement of “middlemen”. The farmers also viewed the new biomass supply chain as a source of income and as improving the local economy. However, the study found that transportation logistics and middlemen complications were crucial factors in the biomass supply chain in India [16].

Since social factors are a crucial element of the biomass resource assessment procedure, it is therefore imperative to develop new methodological approaches that consider social factors (i.e. existing biomass use) in technical studies that employ GIS applications. In this study, primary field data, secondary data, remote sensing data, mathematical equations, accuracy assessment, and land use re-classification procedures were combined to produce a reliable estimation and distribution of the biomass resources in three selected Indian states.

2. Materials and methods

2.1. Study area

The study area was focused on three states of interest (Fig. 2). The selected states were Madhya Pradesh, Maharashtra and Tamil Nadu. Both Madhya Pradesh and Maharashtra cover an area of more than 300,000 km^2 and Tamil Nadu more than 130,000 km^2. The study area covers nearly 25% of India and more than one fifth of the total population lives within these states. The states were selected due to their high biomass potential, their strong interest in developing a biomass-to-energy industry, and to the presence of large industrial agglomerations that might be interested in utilizing the heat from the biomass-based or co-firing power plants. Six cities (districts) were selected for a pilot-level study from the three states: Bhopal and Indore (Maharashtra), Thane and Pune (Madhya Pradesh), and Chennai and Coimbatore (Tamil Nadu). The selected cities are considered the largest in each state. The pilot area covered the city and the surrounding rural areas. The pilot areas were delineated by the Landsat 8 image border. Each of the above mentioned cities were used as the center point when looking for satellite images.

To map the available biomass resources in the pilot areas, data was retrieved from (a) field surveys with farmers, (b) secondary data sources, such as the Resource Atlas of India and from each state's agriculture and forestry databanks, and (c) from literature review. The survey tool consisted of several sections aimed at identifying the production capacities of the farmers, existing biomass use in order to calculate surplus biomass [7], and the ability and willingness of the farmers to supply surplus biomass for energy production purposes [16]. The questionnaire study was conducted in the rural areas of each pilot area. The survey was translated into Hindi, Marathi and Tamil for the pen-and-paper based survey. A sample size of 75 farmers was determined across the selected districts. During preliminary discussions with the stakeholders, it was acknowledged that farmers within the different socioeconomic categories were likely to have different patterns of production, use and supply. Hence, farmers were divided into three categories of small (less than 5 acres), medium (5–10 acres) and large farmers (more than 10 acres). An equal sample of 25 was drawn from all three categories. Subsequently, these samples were divided across various and villages to provide a wide representation of the geographical area in each district. Following this stratification, households in the villages were randomly surveyed. The questionnaire data was analyzed to calculate per hectare production and consumption of agro-biomass, and total surplus biomass for agriculture land use. The surplus biomass values were later used in the biomass mapping stage. Further insights into the survey methodology can be found in relevant studies [7,16].

Secondary sources of biomass data included the Biomass Resource Atlas of India from which the district-level information was acquired because it was the best combination of spatial detail and data reliability. Taluk-wise information was avoided because there were many differences between the administrative taluk

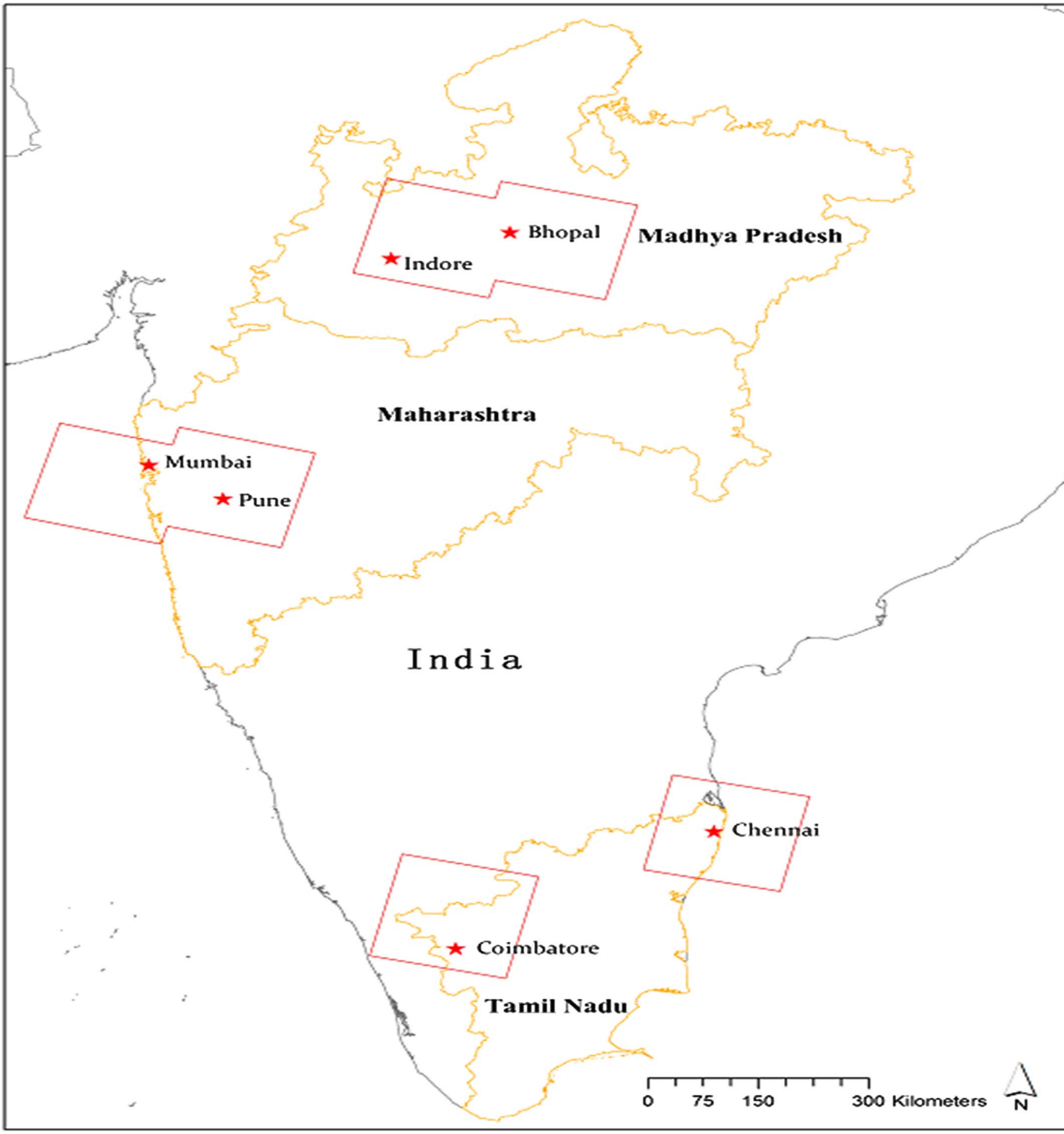

Fig. 2. State-level study regions and selected pilot cities including the mapped pilot region.

Table 1
Metadata for Landsat 8 images used in pilot area LULC classification.

Location	Image ID	Path/ Row	Data type	Date acquired	Cloud cover (%)
Chennai, Tamil Nadu	LC81420512013137LGN01	142/51	L1T	17.05.2013	0.07
Coimbatore, Tamil Nadu	LC81440522013279LGN00	144/52	L1T	06.10.2013	13.54
Bhopal, Madhya Pradesh	LC81450442013142LGN01	145/44	L1T	22.05.2013	0.00
Indore, Madhya Pradesh	LC81460442013133LGN01	146/44	L1T	13.05.2013	0.05
Pune, Maharashtra	LC81470472013108LGN01	147/47	L1T	18.04.2013	2.93
Mumbai, Maharashtra	LC81480472013115LGN01	148/47	L1T	25.04.2013	0.50

border layer used and the Atlas' taluk division. District-level biomass surplus and production figures were used for the agriculture, forest and wasteland land use classes. The area of specific land use within each district was used to calculate biomass quantities per hectare, which were later used in map production. Other secondary sources included a study conducted by Tamil Nadu Energy Development Agency (TEDA) and the Institute for Energy Studies (IES) and a comprehensive study on MSW resources in India by Annepu. [22]. The MSW per land use cell was calculated by dividing the total MSW by the amount of cells in a settlement class within each state. Finally, the power production potential in each district was calculated based on surplus biomass availability after taking into account biomass production capacities (from existing field level, plantation crops, agro industry, non-irrigated wasteland), and utilization (basic, domestic and industrial). The study also evaluated the potential for biomass production through energy plantations on non-irrigated wastelands.

2.2. Remote sensing data

The land use/land cover (LULC) classification for the pilot areas was determined using Landsat 8 OLI imagery (Table 1). The original imagery was downloaded from the USGS website as Level 1 GeoTIFF Data Product [31]. Table 1 describes the metadata for the individual Landsat 8 images. The Landsat 8 images are medium-resolution (30 m), 16 bit images with 11 bands. Only bands 2–7 were selected for further processing. All the images were set in WGS84 Universal Transverse Mercator (UTM) coordinate system. The images were selected so that they would be from the same year and same season. All the acquired images were from April to May 2013, except one image that was from October, due to cloud cover in the previous months. While this image still had a considerable cloud cover (~13.5%), it was the least cloudy image in recent years for that particular location. After downloading the Digital Number (DN), values of the images were transformed into Top of Atmosphere (TOA) reflectance values. The spectral and textural features were later calculated from the reflectance values.

2.3. Land use/land cover maps

A LULC classification map was required in order to generate biomass maps for the study area. Since the study area is large, ready LULC maps were used. The formally accepted LULC maps for India are generated annually in the National Remote Sensing Centre (NRSC), Hyderabad. The most recent LULC classification is the eight cycle and was made in 2011–2012 [32]. The LULC maps were generated using "Resourcesat AWiFS" satellite imagery, which classifies the whole of India into 19 land use classes. These original classes were re-classified into six classes for biomass mapping (Table 2). The re-classification was done to ensure that reliable biomass values can be determined for each class. The re-classification of wastelands was performed using the same class divisions as on the NRSC wasteland classification [33]. The LULC map was created at the scale 1:250,000, which produced a cell size of approximately 55 m that varied slightly from north to south.

Table 2
NRSC LULC original land use classes and reclassified classes.

Original class	Reclassified class
Built-up	Settlement
Kharif only	Agriculture
Rabi only	Agriculture
Zaid only	Agriculture
Double/triple	Agriculture
Current fallow	Agriculture
Plantation/orchard	Forest
Evergreen forest	Forest
Deciduous forest	Forest
Scrub/degraded forest	Wasteland
Littoral swamp	Wasteland
Grassland	Wasteland
Other wasteland	Wasteland
Gullied	Wasteland
Scrubland	Wasteland
Waterbodies	Water
Snow covered	Snow
Shifting cultivation	Wasteland
Rann area	Wasteland

2.4. Plot data

Two sets of plots were created for the LULC classification. The first set was prepared for the classification of the Landsat images as training data, and the other set was prepared for independent reference data set for accuracy assessment. The training data set for the classification was made with the ArcMap version 10.0 Image classification toolbox. The toolbox was used to create a number of polygons within each Landsat image, which represented the various land uses in the image. The polygons were all shapes and sizes, and there were always multiple polygons for all land uses. The training data was made separately for each of the images. After the reference polygons were created, they were combined with the image feature data set and a signature file was created using the Iso Cluster Unsupervised Classification tool. The signature file depicts the relationship between each of the classes and the image features. The selection and classification of the accuracy assessment plots were based on methodology created for the EU funded project, ReCover [34,35]. The plots were created inside each Landsat image covering each of the pilot areas. The plots were distributed as a systematic sample to cover all classes. In total, there were 864 sample plots and they were distributed between Madhya Pradesh (378), Maharashtra (259) and Tamil Nadu (227), respectively. The plots were square shaped and each of the reference plots coincided with a cell in the state-level map. This ensured that there were no mixed pixels. The pilot-level map was assessed with the same reference data set and, thus, the cells were not aligned, because the cell size of the pilot-level map was smaller than that of the reference data set. In that case, the map class was calculated from the LULC map as area-weighted median. The classification of the accuracy assessment plots was performed based on the reclassified LULC map classes, i.e. five classes used in LULC maps. The classification of the wasteland class was developed based on the instructions in the NRSC wasteland classification document [33]. The classification was carried out based on Google Earth and ESRI ArcGIS Online high-resolution imagery (2010–2013).

3. Methods and calculations

3.1. Classification and image features

For the purpose of producing a LULC map for the pilot areas, image features were extracted from the Landsat 8 reflectance images. The image features are spectral, textural as well as the direct image reflectance values. Three indices were calculated from all the images. The indices were: Normalized Difference Vegetation Index (NDVI) (Eq. (1)), Atmospherically Resistant Vegetation Index (ARVI) (Eq. (2)), and Modified Soil-Adjusted Vegetation Index (MSAVI) (Eq. (3)).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

$$ARVI = \frac{NIR - rb}{NIR + rb} \tag{2}$$

where,

$$rb = RED - \gamma(BLUE - RED)$$

$$MSAVI = \frac{\left(2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - RED)}\right)}{2} \tag{3}$$

In all the equations, NIR, RED and BLUE are the reflectance of near infrared (NIR), red and blue bands, respectively, and γ (gamma value) is a weighting function that depends on the aerosol type [36]. Furthermore, reflectance bands were used to calculate textural features in order to enhance the classification. The Haralick's textural features [37] were calculated from each of the images and consist of 13 features; angular second moment, contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, two information measures of correlation and maximal correlation coefficient [37]. The 13 features were calculated using NDVI and ARVI images, which gave a total of 26 image features. Since so many features were produced, a principal component analysis (PCA) was used to combine the information from the textural features and decrease the total amount of image features and help produce distinguished images. The first principal component explains the majority of the variation in the initial data, the second component explains the majority of the variation left unexplained after the first component, etc. In this research study, the amount of principal components was set to six components. In addition to the ratio and textural features, the direct reflectance values were included from Landsat 8 bands 2–7. This resulted in a total of 15 image features used in the classification. These 15 feature images were combined into one multiband image, which was given as input for the Maximum Likelihood classification.

3.2. Maximum likelihood classification

The Maximum Likelihood Classification tool is a supervised classification method [38,39] that uses user-defined input to define the classes beforehand, i.e. the signature file. The same image feature data set, which was used to create the signature file, was also used as the input imagery for the classification. An iterative process was used for each area. In the initial step, all cells in the area were classified. Secondly, a thorough visual checking of the classification was performed, the signature file was updated and the classification was redone, or the classification was accepted. The visual checking was performed against the Landsat 8 imagery and against ESRI high-resolution satellite imagery available from ArcGIS Online. Thereafter, and when each of the initial classifications were approved, the maps were reclassified into the same land use classes as in the state-level map, i.e. settlement, agriculture, forest, wasteland, and water. After reclassification, the LU maps were ready, the biomass distribution maps were produced and the LU maps could be assessed for accuracy.

3.3. Biomass mapping procedure

After the biomass values for each of the six land use classes were calculated and the LULC classification maps finalized, the biomass distribution maps were created using two datasets. The workflow for biomass mapping was the same for both the state-level and the pilot-level maps. The only differences were in the resulting unit size, and the fact that the pilot area LULC maps had cloud and shadow classes, which were absent from the state-level maps. In regard to the state-level maps, the mapping was done using two different result units, taluk-wise mapping and grid-wise mapping at a 5 km × 5 km cell size. Due to limited space, only taluk-wise maps are presented in this study. Pilot-level mapping was only performed grid-wise. For the grid calculations, surplus biomass and biomass production and consumption were calculated. Thereafter, the approximate area of the different land use class within the produced units was computed based on the number of cells and the cell size of the LULC map. The amount of biomass was determined by multiplying the area of each land use within a cell by the corresponding biomass value of that land use class. This resulted in initial biomass distribution maps. Under cloud and shadow, land use may not be well identified so further processing was needed, where it was assumed that the distribution in the final unit that cloudy class is the same as it is within the uncloudy part of the same unit. The cloudy part of the final unit was then distributed between the other classes (settlement, agriculture, forest, wasteland and water) and their biomass was adjusted according to following formula (Eq. 4).

$$B_i = B_{i\_init} + \left(B_{i\_init} * \left(\frac{A_i}{A_{tot} - (A_{cloud} + A_{shadow})} * \frac{A_{cloud} + A_{shadow}}{A_{tot}}\right)\right) \tag{4}$$

where B_i is the cloud cover adjusted biomass for class i, B_{i_init} is the initial biomass for class i, A_i, A_{cloud} and A_{shadow} are the areas of the class i, cloud and shadow, respectively, within the 5 km x 5 km result unit, A_{tot} is the total area the resulted unit. Finally, the accuracy assessment computed a level of reliability for each land use class and a conservative biomass estimate (CBE) was calculated for each class.

3.4. Land use/land cover mapping and accuracy assessment

The level of accuracy in the LULC classification at both state- and pilot-levels was determined by performing a cell-level accuracy assessment using independent reference plot data. The plot data was created to cover all of the pilot areas and to cover all land use classes to get an unbiased estimate. The reference plots were visually assessed to mark every plot with a reference class, which were compared to the classified classes using a confusion matrix. Using the confusion matrix, naïve and kappa statistics were then calculated. The confusion matrix is the most commonly applied method for the accuracy assessment of thematic maps [40] and the overall accuracy can be derived by considering all off-diagonal cells in the matrix as misclassifications [41]. Furthermore, the kappa index compensates for the effect of differences in class sizes in the sampled data (observations). The usual form of the kappa index (unweighted kappa) considers all errors as equally important. The kappa index can be calculated as described by [42]. The Kappa index gives a value between -1 and 1. If the kappa value is more than zero, the classification is considered to be acceptable.

4. Results

4.1. State-level Land use/land cover mapping

Due to limited space only the state-level maps are presented in this article. Furthermore, due to restrictions on use of the data, since land use mapping was developed through NRSC and ISRO, the original land use map is not shown in this paper and its classification accuracy was not calculated. Fig. 3 shows the state-level reclassification of land use. The map shows land use in Madhya Pradesh, Maharashtra, and Tamil Nadu. While the original LULC map had 19 classes, the reclassified map has only five classes with a high accuracy level overall. Table 3 shows the classification accuracy for the three different states. The overall accuracy in Madhya Pradesh, Maharashtra and Tamil Nadu was 78%, 55% and

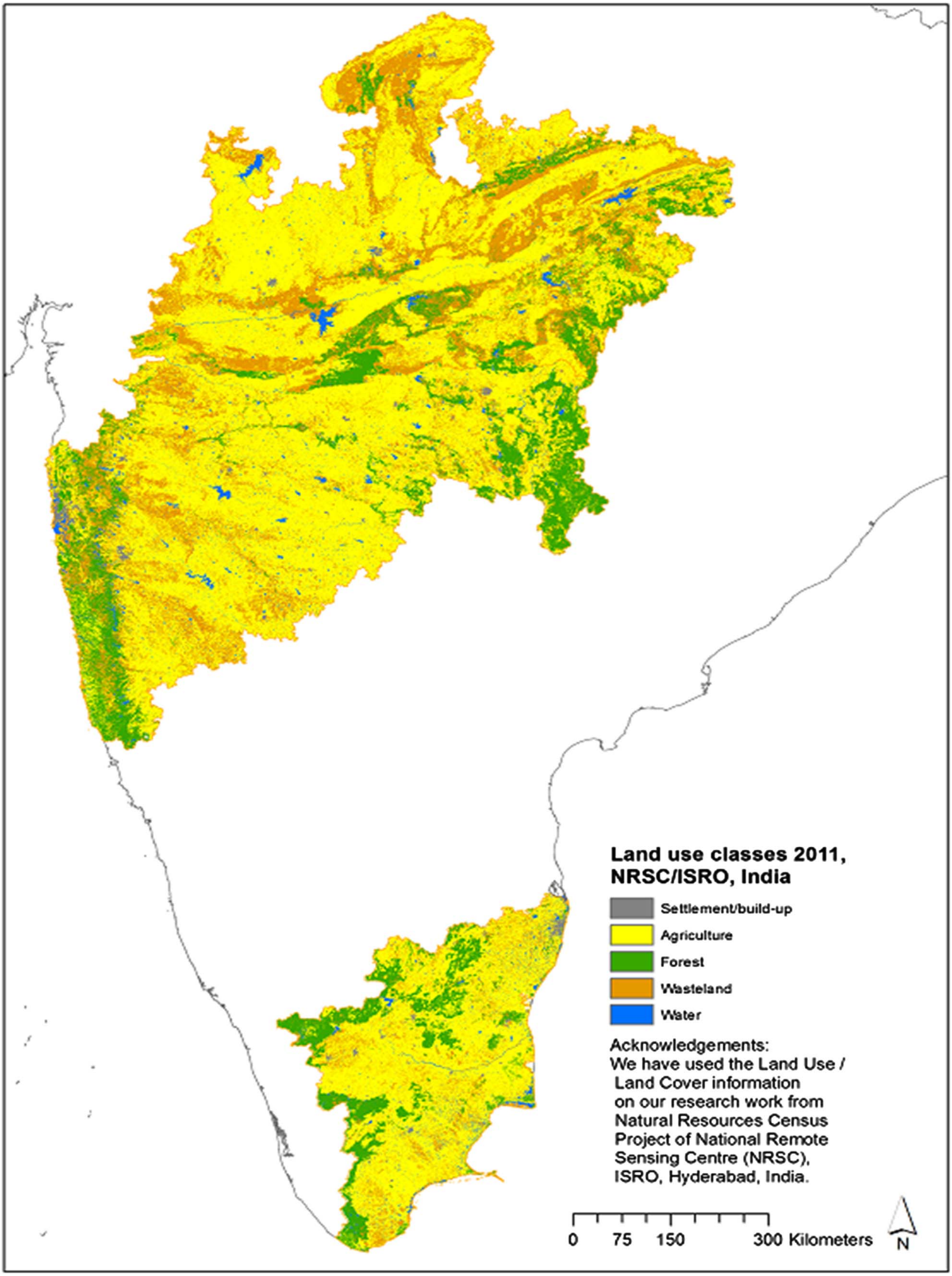

Fig. 3. Reclassified state-level LULC map for Madhya Pradesh, Maharashtra and Tamil Nadu.

Table 3
Accuracy assessment results for state-level LULC maps. Accuracy results are presented by state with overall, user's and producer's accuracy and confidence intervals.

MADHYA PRADESH									
Map	Reference								
	Settlement	**Agriculture**	**Forest**	**Wasteland**	**Water**		**User's accuracy (%)**	CI lower limit (%)	CI upper limit (%)
Settlement	9	0	1	2	0	12	75	46	104
Agriculture	5	227	2	27	2	263	86	82	91
Forest	0	0	5	1	0	6	83	45	121
Wasteland	1	21	19	52	0	93	56	45	67
Water	0	2	0	0	2	4	50	−12	112
	15	250	27	82	4	378			
Producer's reliability (%)	60	91	19	63	50				
CI lower limit (%)	32	87	2	52	−12				
CI upper limit (%)	88	95	35	74	112				
Overall accuracy (%)	78	**Overall kappa**	0.55						
CI lower limit (%)	74								
CI upper limit (%)	82								
MAHARASHTRA									
Settlement	17	1	0	3	0	21	81	62	100
Agriculture	8	66	7	23	5	109	61	51	70
Forest	0	3	12	10	0	25	48	26	70
Wasteland	10	28	8	33	1	80	41	30	53
Water	1	3	3	3	14	24	58	37	80
	36	101	30	72	20	259			
Producer's reliability (%)	47	65	40	46	70				
CI lower limit (%)	30	56	21	34	47				
CI upper limit (%)	65	75	59	58	93				
Overall accuracy	55	**Overall kappa**	0.37						
CI lower limit (%)	49								
CI upper limit (%)	61								
TAMIL NADU									
Settlement	12	2	1	3	0	18	67	42	91
Agriculture	19	69	35	14	2	139	50	41	58
Forest	0	2	23	0	0	25	92	79	105
Wasteland	3	17	3	9	2	34	26	10	43
Water	0	3	0	0	8	11	73	42	104
	34	93	62	26	12	227			
Producer's reliability(%)	35	74	37	35	67				
CI lower limit (%)	18	65	24	14	36				
CI upper limit (%)	53	84	50	55	98				
Overall accuracy (%)	53	**Overall kappa**	0.32						
CI lower limit (%)	47								
CI upper limit (%)	60								

53%, respectively, and the corresponding kappa values were 0.55, 0.37 and 0.32, respectively. One reason why the figures are relatively low could be that the LULC map itself had a slight misalignment when compared to the satellite imagery. The reason for that misalignment was unclear, although NRSC does mention that the thematic accuracy is within 1–3 pixels. Since the accuracy assessment was done on a pixel-by-pixel basis, the misalignment of even one pixel, therefore, can result in the misallocation of a class to a specific area. Furthermore, the wasteland class in all states had the lowest user accuracy. This might be due to a misclassification of wastelands as agricultural lands, as in the case in Madhya Pradesh where some forest and/or degraded forest areas were misclassified as wastelands. The difficulty to accurately distinguish wastelands from other land use classes remains a very challenging task for researchers. Another challenging issue was the partial or complete cloud cover, which was evident in the Coimbatore region in Tamil Nadu, and resulted in less accurate land use maps and biomass values. However, this is a regional problem and did not affect the majority of the study area.

4.2. State-level wasteland mapping

Fig. 4 shows the wasteland classes represented in the three selected states. There were six different wasteland classes presented. The majority are scrub/degraded forest, scrubland or other wasteland. In addition to the major classes, there are three minor classes that are present only in very local cases. The majority of wastelands in Madhya Pradesh are scrub/degraded forest and a mix of scrublands and other wasteland, while in Maharashtra and Tamil Nadu the wastelands are a mix of scrubland and other wasteland. Madhya Pradesh also has a minor aggregation of gullied wasteland in the northern part of the State. A new map was produced for the quantification and resource distribution of biomass availability from wastelands. Fig. 5 shows the distribution of biomass from wastelands in the selected states. Madhya Pradesh had the highest biomass share, which ranged from 50 to 140,000 t per annum. Tamil Nadu, which is prominent in rice production, had the lowest share of biomass on wastelands. The biomass resources assessment clearly indicates that the prospects of

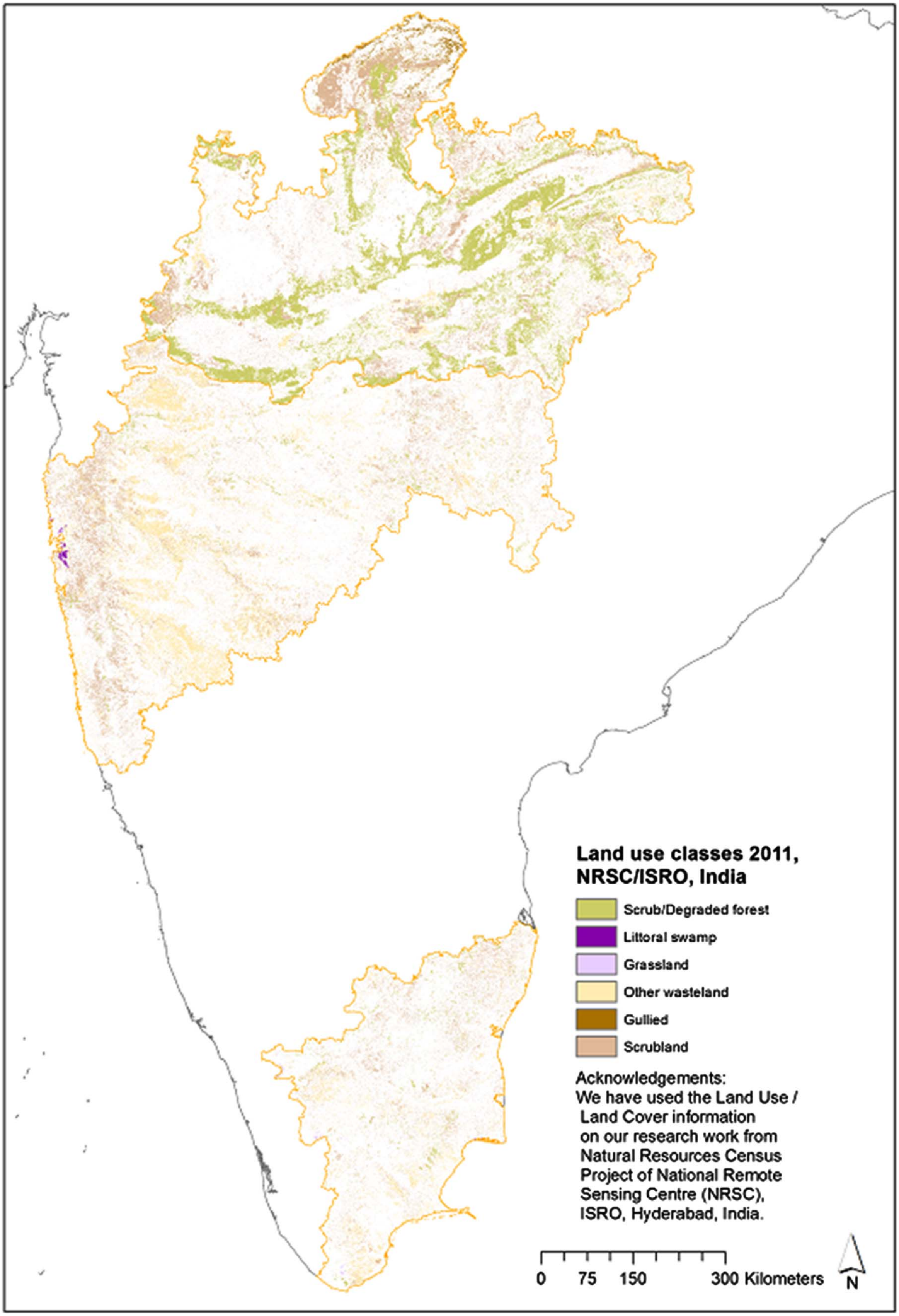

Fig. 4. State-level wasteland map for Madhya Pradesh, Maharashtra and Tamil Nadu.

bioenergy crop plantation for example, is not feasible in Tamil Nadu, and power plants seeking biomass for co-firing must consider Madhya Pradesh as a strategic location for biomass supply. The surplus agro-biomass and forest surplus resources and the corresponding energy potentials have been calculated and reported in Natarajan et al. [7]. Based on the study by Annepu, [22], a

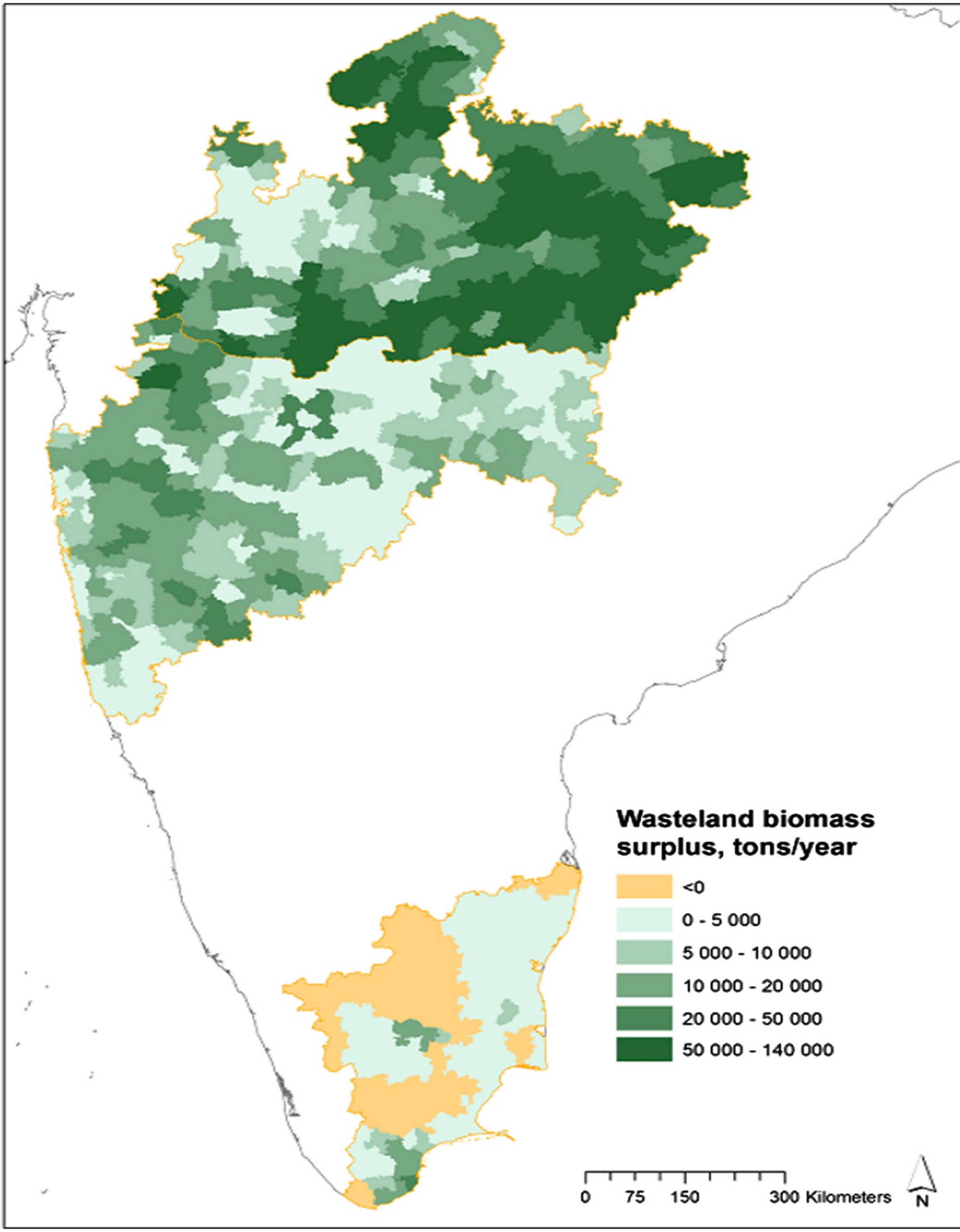

Fig. 5. State-wise wasteland biomass distribution map for the three selected states.

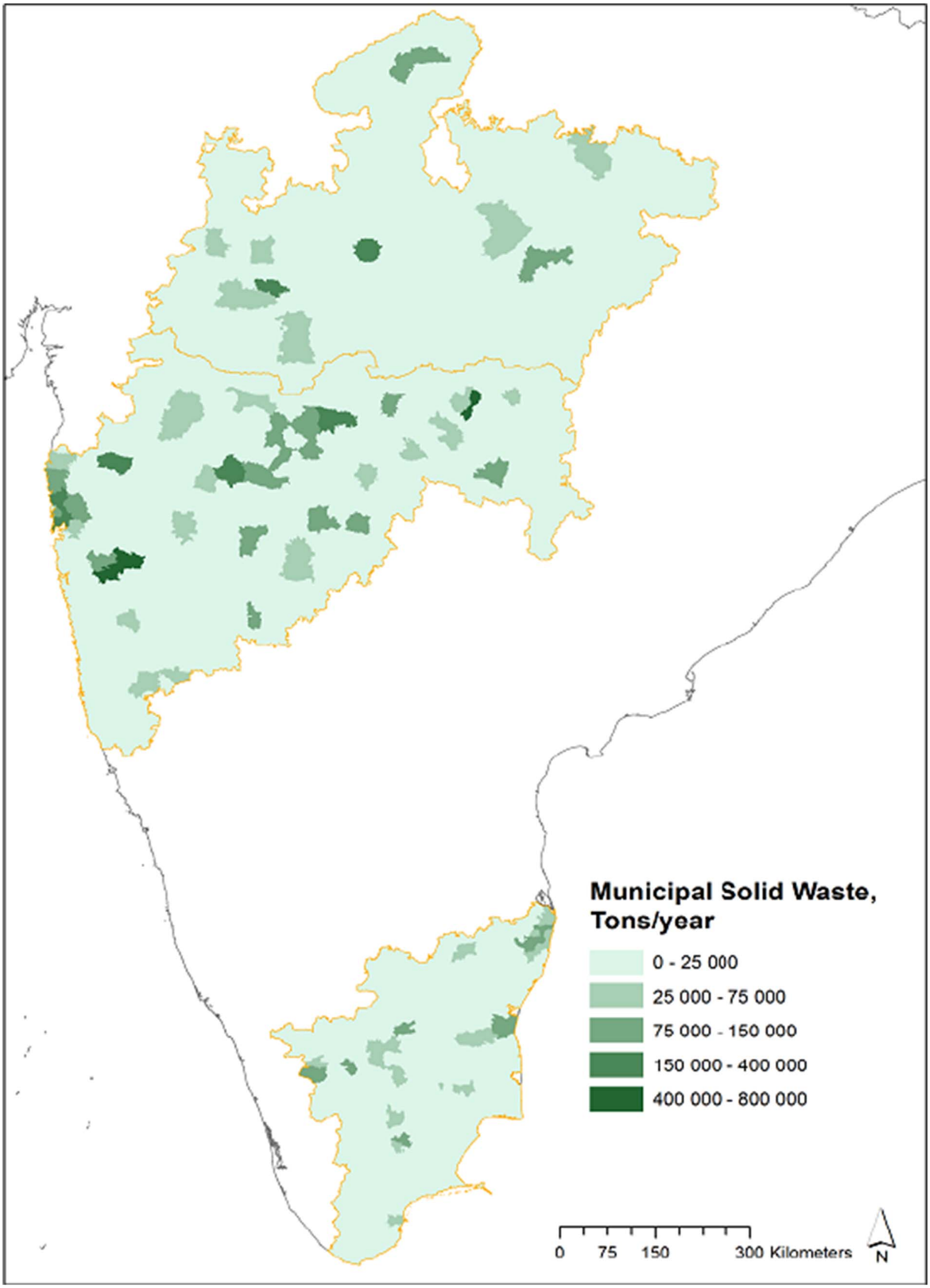

Fig. 6. State-level municipal solid waste biomass distribution map for the selected states.

distribution map of MSW potentials was generated (Fig. 6) and showed that Maharashtra had the highest MSW potential.

5. Remarks on the methodology used in this study

Three issues related to the newly developed method for biomass resource assessment in this study are presented. First, there are two main sources of error in the biomass mapping; the LULC classification can have misclassifications, and these misclassifications can affect the grid level map if the final unit is small. The level of error in the classification decreases when the size of the final unit is increased. The biomass values can have multiple sources of errors depending on how the values were generated. Second, the accuracy assessment computed a level of reliability for each land use class. It can be assumed that if a class has, for example, an error-level of 50%, then in the biomass map the "final unit" for that specific class may have 50% less area. In that case, the total biomass of that class within the result unit would be 50% smaller. Based on this premise, the CBE was calculated for each class and was calculated simply by multiplying the initial biomass with the classification accuracy of the corresponding class. This methodology does not, however, take into consideration that in the case of misclassification, the class would, in reality, be another class. Therefore, the CBE values are not summable between classes, meaning that a total CBE cannot be calculated. Third, the error levels for the biomass values cannot be fully assessed as a result of limited documentation and lack of data. The Biomass Resource Atlas of India lists a general level of accuracy. The values are taken from various sources and the quality of the data is highly variable. According to the Atlas, the biomass production figures have an accuracy of 5–25%. The biomass consumption figures on the other hand have an accuracy level of 20–40% [43]. The total accuracy of the surplus figures is not fully or adequately computed and cannot be calculated based on the given data. The accuracy level for the figures used for Tamil Nadu at the "state-level" are unknown, however it was assumed to be close to the level of accuracy in the biomass Atlas.

6. Conclusion

In this study, a set of primary and secondary data sets were processed in GIS applications to assess the biomass potentials from wastelands and MSW in three selected India states; Madhya Pradesh, Maharashtra, and Tamil Nadu. The objective was to develop a new methodological approach for biomass resource assessment with an acceptable level of accuracy. The new method sought to accommodate the socio-economic factors associated with biomass use that are often neglected in biomass, technical and GIS based studies. The newly developed method can be used for biomass resource assessment in other countries that are interested in developing their bioenergy resource. The maps present new classifications of land use and land cover and also highlight locations of high biomass potential from wastelands and MSW in the surveyed Indian states. Madhya Pradesh showed the highest biomass potential from wastelands, while Maharashtra showed the highest potential for MSW.

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