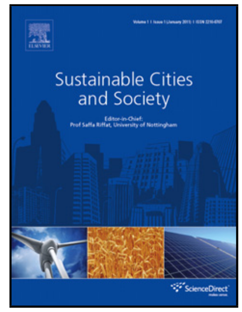

Multi-functionality and Land Use Dynamics in a Peri-urban Environment Influenced by Wastewater Irrigation

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PII: S2210-6707(20)30526-6

DOI: https://doi.org/10.1016/j.scs.2020.102305

Reference: SCS 102305

To appear in: *Sustainable Cities and Society*

Received Date: 28 May 2019

Revised Date: 29 May 2020

Accepted Date: 30 May 2020

Multi-functionality and Land Use Dynamics in a Peri-urban Environment Influenced by Wastewater Irrigation

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Highlights

- Peri-urban agriculture is dependent on the wastewater from urban centres in the developing world.
- The spatio-temporal land use change patterns of the peri-urban watershed analyzed using Google Earth data.
- Water availability is the main factor that often decides the fate of peri-urban agriculture.
- New built-up areas are pushing the agricultural landscapes with urban pressures.
- New agricultural plots and built-up areas are being developed in the peri-urban barren lands.

Abstract

Peri-urban areas are characterized by multifunctional land-use patterns forming a mosaic of built-up and agricultural areas. They are critical for providing food and other agricultural products, livelihood opportunities and multiple ecosystem services, which makes them transformative where urban and rural spaces blend. We analyzed land use changes in a peri-urban micro-watershed in Southern India by using Google Earth data to understand the micro-level spatio-temporal dynamics. This study aims at understanding the peri-urban agriculture and landscape changes as related to the change in use of wastewater and groundwater for irrigation. The temporal dynamics of peri-urban system including the changes in built-up, paragrass, paddy rice and vegetable cultivation, groundwater and wastewater irrigated areas in the watershed were evaluated. The detected changes indicate that, as a consequence of urban pressures, agricultural landscapes are being converted into built-up areas and, at the same time, former barren land is converted to agricultural plots. The mapped land use data are used in landscape change modelling for predicting the peri-urban agricultural dynamics and the driving factors in the watershed. Combined with the mapping and modelling approaches for land use change analysis, our results form the basis for integrated resources management in the wastewater influenced peri-urban systems.

Keywords

Peri-urban agriculture; Google Earth data; Change detection; Crop mapping; Micro-level changes; Land change modelling

1 Introduction

Peri-urban ecosystems are complex landscapes continuously influenced by diverse human-induced changes. Peri-urban spaces are multifunctional land use systems forming a mosaic of built-up and agricultural areas (Padgham et al., 2015). Urban or peri-urban system sustainability and land use changes are often looked at separately, which can lead to equivocal results and fallacious conclusions (Seto et al., 2012). Food security discussions nowadays focus on sustainable approaches to feed the increasing global population, but more attention needs to be paid to the fact that this population growth will be majorly associated with the urban centres (Filippini et al., 2019; Seto and Ramankutty, 2016). Urbanization and food security are strongly interlinked, and the much-needed focus should concentrate on urban and peri-urban agriculture to supplement the food supply to the urban agglomerations. Globally, it is estimated that around 456 Mha of total croplands are under urban and peri-urban agriculture cultivation (Thebo et al., 2014), and this could be further enhanced if efficient planning is practiced. These systems provide merits and showcase functions of multifunctional land use systems, which require integrated management approaches for achieving the social welfare and environmental benefits (Zhang and Schwärzel, 2017).

Urban and peri-urban agriculture is influenced by direct and indirect drivers, including the availability of water, and small-scale industries, land costs and land availability (Kurian et al., 2013; Kurian and McCarney, 2010). These drivers have a significant influence on local or regional land use change dynamics. Mapping the associated dynamics with water bodies and agriculture farms in urban and peri-urban systems using remote sensing based approaches can provide insightful details to the local policymakers, but often without ancillary data, remotely mapped locations can provide misinformation of the land use systems (Brown and McCarty, 2017). Improved accuracy in mapping the urban and peri-urban spaces helps local dwellers for improved land use management and for policymakers to develop effective policies. In the past two decades, technological advancements of remote sensing have resulted in high resolution satellite products that have helped to capture the multi-functionality of these transformative spaces. Google Earth's free and open source data provide the composite of several satellite datasets with a high spatial resolution up to 1 m for urban areas and selected test sites (Gorelick et al., 2017).

Google Earth, due to its user friendly accessibility, free access and high spatial resolution imagery, has increasingly been used in a scientific context for understanding social, earth system and environmental processes with anthropogenic impacts (Pulighe et al., 2016). Several studies explored the options to apply Google Earth in earth system science (Fisher et al., 2012; Yamagishi et al., 2010), urban agriculture (Taylor and Lovell, 2012), land use change and landscape processes (Huang et al., 2017; Hu et al., 2013), epidemiology (Chang et al., 2009), climate adaptation (Stocker et al., 2012), habitat quality (Benham et al., 2011), forestry (Dorais and Cardille, 2011; Ploton et al., 2012), biological and ecological applications (Al-Abdulrazzak and Pauly, 2014). Various case studies around the world utilized Google Earth as auxiliary support for training, classifying and validating land use/cover maps (Gbanie et al., 2018; Hu et al., 2013) and also as ground truth data to validate the Landsat, MODIS and PALSAR derived datasets (Dong et al., 2012; Dorais and Cardille, 2011). Irrespective of the high spatial resolution imagery of Google Earth, it was used as a primary data source for land use/land cover mapping only in few studies. Spatial and temporal dynamics of land use change can be assessed/mapped at different levels and scales using Google Earth, but the temporal resolution can be a challenge due to missing or unsuitable images in a time series.

The current study explores the micro-level land use change dynamics using Google Earth data in the peri-urban environment of Hyderabad city in India, which has been the focus of several earlier studies. Gumma et al. (2011) analyzed the urban and peri-urban agriculture dynamics and their impacts associated with the urban area of Hyderabad, in which regional level land use changes were well illustrated by using Landsat and MODIS imagery. For the city or regional level planners, this type of land use mapping can be quite helpful, whereas for local planning, mapping with higher spatial and temporal resolution is required (Gren and Andersson, 2018; Seto et al., 2012). Similar to the current study area, in many parts of the developing world, peri-urban agriculture is dependent on wastewater from urban centres for irrigation. In peri-urban Hyderabad, several authors investigated the wastewater irrigation opportunities (Buechler et al., 2002), food, water, health, energy nexus (Miller-Robbie et al., 2017), health risks, impacts on the local aquifer and salinity implications (Biggs and Jiang, 2009) among others. There is, however, still limited understanding of the land use change in peri-urban systems with wastewater irrigation influence.

The current study aims to evaluate the micro-level land use change dynamics of a peri-urban landscape system influenced by wastewater irrigation. We analyzed the micro-level changes including land use type, crop type and irrigation water type used for agriculture.

Understanding the temporal evolution of land use changes with a spatially explicit approach can help farmers and planners to better manage the natural resources in an integrated manner that are useful for food production, particularly for the peri-urban areas in developing countries where wastewater irrigation is a common practice. Further, this study will provide a basic understanding of peri-urban landscape evolution, which can provide opportunities to urban planners, to look for more sustainable food production within the larger city boundaries.

2 Materials and Methods

2.1 Study area description

Land use patterns of peri-urban Hyderabad are complex and mostly influenced by urban drivers, livelihood practices, wastewater availability and socio-economic conditions. Musi River passes through the Hyderabad city and characterizes the River basin into three large segments (Fig. 1). In the upstream, it is a source of drinking water supply. From the Hyderabad urban agglomeration, the partially treated or untreated wastewater is funnelled into the Musi River and serves as a potential irrigation supply source for the downstream peri-urban farmers. Wastewater from the Musi River is diverted to the peri-urban agricultural areas via a series of networked irrigation canals (Ensink et al., 2009). In the semi-arid peri-urban environment, wastewater is a potential livelihood opportunity for local farmers. Multi-cropping systems such as paddy rice (*Oryza sativa L.*), paragrass or fodder grass (*Urochloa mutica L.*) and vegetables are practiced in the peri-urban setting of Hyderabad city. Annual water abstractions on average, 70% of the wastewater and 30% of the groundwater accounted for water use for irrigation in the micro-watershed.

The current peri-urban study watershed, Kachiwani Singaram Micro WaterShed (KSMWS, Fig. 1), is located on the banks of Musi River, 15 km downstream of Hyderabad city. The micro-watershed comprises an area of 274 ha with both groundwater and wastewater irrigated areas. The mean annual rainfall and temperature are about 750 mm and 27 ^{O}C, respectively, representing a semi-arid climatic environment. Overall, the study watershed is a characteristic of multi-functional land use system, a mixture of agriculture, wetland, small-scale industry, barren and built-up areas, which is representative for several peri-urban areas in India, Asia and elsewhere (Binns et al., 2003; Jujnovsky et al., 2017; Nabulo et al., 2012; Nanninga et al., 2012; Padgham et al., 2015; Ullah et al., 2012).

2.2 Google Earth data and processing

The background images data were collected from Google Earth desktop version Google Earth Pro (https://www.google.com/earth/) for a 16 year period from 2000 to 2015. A total of 34 images are available from Google Earth database for the study period except for the years 2002, 2004 and 2007, where the data is not available (Fig. S1). Out of this available imagery on Google Earth, highest resolution (up to 1 m) images were selected for land use change analysis based on the quality of the image (clear visibility of land features and without cloud cover) for that particular year. To avoid any seasonal discrepancy and to ensure the precise classification of the different crop types, we selected only the images that are available in the months of April and May, where the images are available for a maximum number of years. A total of nine years (2000, 2003, 2006, 2009, 2010, 2011, 2013, 2014 and 2015) were considered for land use analysis over the 16-year period. The date and year of the Google Earth images used for the land use analysis are mentioned in Table S1. Land use features were manually digitized with visual interpretation of the images to assess the land use changes in the watershed. Using Google Earth tools, one can easily digitize land use features by using vectorial elements (point, line and polygon objects). These objects were finally saved as Keyhole Markup Language (KML) files (Frankl et al., 2013).

For accuracy, ground truthing was performed with periodic field visits, Global Positioning System (GPS) point data collection and farmers survey. The field data collection for ground truthing was carried out from 2010 onwards (every year between April to May for each agricultural plot and land use type in the watershed to identify the cropping patterns) to check the accuracy of the maps. The field observations included land use type, crop practice and irrigated water type used for agriculture of a particular plot of the watershed. The farmers in the watershed were interviewed in order to assess the past land use change patterns from 2000 to 2009, where ground truthing data is not available (Table S2). The questionnaire for farmers included questions related to practiced crop type and source of irrigation water used for agriculture for every year in the last decade. We used farmer's survey data for validation because farmers in the watershed area are practicing agriculture since a very long time (five decades), and they were aware of the historical land use types in the previous years (Table S2). Farmers´ responses and ground truth information were assigned to a particular agricultural plot of the Google Earth image. With the thorough mapping and the image validation process, we generated detailed land use maps for nine years between the years 2000 and 2015.

Land use and crop types were assigned based on Google Earth images following standardized procedures from satellite image interpretation (i.e. shape, shadow, tone/colour, texture, pattern, height/depth, site/situation/association). The image interpretation was exported as KML format polygons or polylines to ArcGIS 10.5.1 for further analysis. To avoid any spatial distortion of the exported Google earth images to ArcGIS, we georeferenced the images using GPS control points to the Universal Transverse Mercator (UTM) 44^{O} N World Geodetic System (WGS) 1984 coordinate system. At a later stage, these images were orthogonally rectified in ArcGIS. While mapping the images, we used a smaller scale (1:500) to delineate different land use classes and crop types. Even though we used zoom in and zoom out options to check out the neighbourhoods of the image, we maintained a constant scale in the entire mapping process. Based on the image classification, different land use types: agricultural, built-up and development areas were mapped (Table 1 and Fig. 2, upper panel). The unused land was assigned to barren land, defined as either empty land or with occasional grass patches depending on the season. In general, mapping different crop types using any available satellite imagery can be complex, but by using Google Earth's very high resolution imagery, we can easily identify and classify the crop types (Fig. 2, lower panel). It is easy to identify the crops like paragrass (light green), paddy rice (dark green) and vegetables (small plots with mixed green and brown patches), whereas mapping any other crops requires the support of ground truth data in the study area context. As vegetables are a perennial crop in the watershed area, the brown colour patches in the vegetable plots represent the crop cutting for those particular smaller plots in the imagery time (Fig. 2). Wetlands with reed pond or elephant grass area texture are also easy to identify in the Google Earth images. In general, over the years, the road networks remained constant in the watershed except for a new road, which was built alongside the canal in 2008 especially for crop produce transport and to gain easy access to the agricultural plots. All these micro-level changes over the 16 year period were mapped manually to create high accuracy maps for the peri-urban watershed.

Built-up, agriculture and development areas are classified under major land use dynamics and land use changes of the major crops in the watershed are classified under crop dynamics. Changes in the groundwater and wastewater irrigated areas are classified under irrigation system dynamics (Table 1). Groundwater irrigation and wastewater irrigation areas are mapped using field observations, farmers survey and attributes assigned to the mapped crop areas in the Google Earth images.

2.3 Land use change modelling

Land use change modelling requires different sources of information in addition to land use maps of different years. We integrated information such as Digital Elevation Model (DEM) (ASTER DEM 30 m), soil type, slope, geology, accessibility to the roads and accessibility to the canal (wastewater) as supporting input data (Table S3). Land use change modelling typically includes the following procedure: (1) land use change analysis between the given years, (2) determining the potential driving forces of the land use change, (3) modelling transition potential under different transitions or change influences, (4) prediction of future land use based on the given transitions, and (5) validation of the model for given year with observed data (Ibrahim et al., 2016).

The Land Change Modeler (LCM) of Terrset software version 18.0(https://clarklabs.org/) was utilized for analyzing the transitions between 2000 and 2010 and for future land use change predictions for the year 2030. The two raster files of 2000 and 2010 have the same specifications, such as colours, legends and spatial characteristics to observe and understand the nature of changes in the peri-urban micro-watershed. Before exporting the maps from GIS to land use change modelling platform, we converted the mapping results into raster format. These mapped changes were utilized to identify prevalent transitions and further generate the probability matrix and transition potential maps. The modelled transition maps between different land use categories were further used as inputs for land use change modelling prediction. Transition potential maps are critical inputs for land use change model prediction. Predictive variables such as DEM, slope, soil type, geology, wastewater (canal) accessibility and access to the roads are used in the modelling process.

Built-up and development areas are merged into the built-up area for transition modelling and model prediction as both represent the peri-urban built-up area. There are multiple models available for transition modelling: multilayer perceptron (MLP) neural network, logistical regression and simulation weighting (SimWeight). Here we used the MLP neural network model as it is a feedforward neural network and better suited for smaller study areas model prediction compared to other land use change models (Mas et al., 2014). The predictive power of modelled transition from 2000 to 2010 was used for predicting the land use map of 2015. Further, the original mapped data of 2015 using Google Earth was compared with the predicted map for validation. Model validation of observed versus predicted was calculated using percent error estimation for each land use type (Ibrahim et al., 2016). Following the successful validation of the land use map of 2015, the model transitions of 2000 to 2010 were used to predict the land use change scenario for the year 2030. The detailed flow diagram of the research methodological process for the study micro-watershed is depicted in Fig. 3.

3 Results and Discussion

3.1 Land use change analysis

The land use change analysis based on Google Earth data for the years 2000 to 2015 resulted in the identification of three types of key dynamic transformations in the context of the peri-urban watershed: major land use, crop and irrigation dynamics. In total, eight major classes of land use, namely, built-up area, development area, roads, wetlands, paddy rice, paragrass, other crops (commercial crops such as chilli and cotton) and vegetables were mapped using Google Earth images (Fig. 4).

3.1.1 Major land use dynamics

Built-up and development areas are continuously increasing in the watershed, and the observed peak in built-up and development areas in 2003 coincided with the expansion of the Greater Hyderabad city boundary, which raised the land prices and resulted in the conversion of agricultural landscapes into built-up areas (Gumma et al., 2011). The agricultural area almost remained constant over the 16-year period (Fig. 4). From the examined mapping details between the years 2000 and 2015, it was clear that barren lands were converted into new built-up and agricultural areas, compensating the losses to the built-up area (Fig. 5). The northern regions of the watershed were being developed faster than the other regions, being closer to a major road network. The major and moderate land use shifts were observed in the years 2003, 2006, 2010 and 2014. It was uncertain to track the reasons behind the shifts between built-up and agriculture land use, therefore we further looked at the details of crop and irrigation system dynamics.

3.1.2 Crop dynamics

Within the watershed, crop dynamics are significant, mainly between the crops paddy rice, paragrass and vegetables. The temporal change patterns of paragrass and paddy rice follow the same trend but showed an inverse relationship, where when paragrass patches increased, the paddy areas decreased. The decrease in paddy rice cultivation is associated with the salinity from long term irrigation with wastewater, which results in low crop yields (Biggs and Jiang, 2009). Increasing paragrass cultivation is linked with the demand for paragrass by the local dairy industry in the area, which supplies the milk to Hyderabad city (Buechler et al., 2002). Other factors that may be influencing the paragrass cultivation are high crop yields at shorter time intervals that result in quick profits, lower transportation costs and less labour requirement (Buechler et al., 2002). Thus, it can be expected that paragrass cultivation may increase in the future also due to quick economic returns and less labour requirement. Vegetable cultivation in the area started to boost around 2006 (Fig. 4, lower panel) to supply the food for urban markets, which yielded high profit margins for local farmers. Even though vegetables have a high profit and market value, decrease in the vegetable growing area after the year 2012 was associated with labour costs, continuous attention required for the crop cultivation and negative perception of consumers on using wastewater for agriculture. The risks of vegetable production with wastewater irrigation, especially leafy vegetables can be mitigated by practicing safe reuse approaches for irrigation (Nabulo et al., 2012; WHO, 2006).

3.1.3 Irrigation system dynamics

Wastewater availability for irrigation has a significant influence on agricultural land use shifts in the watershed. Two irrigation systems, wastewater and groundwater, exist in the watershed and both irrigation systems have unique characteristics. Wastewater irrigation has been practiced in the area since the last 40 years and groundwater irrigation has been practised in the watershed for more than 100 years. Both types of irrigated areas are almost constant over the years with minor shifts in the cropping area (Fig. 6). After 2003, there is a drop in wastewater irrigated area, which tends to imply the same shift in paragrass area from crop dynamics graph (Fig. 4, lower panel). Over the years of observation, only one shift is observed from agriculture to the built-up area, which is from paragrass to built-up area (Fig. 5). We are assuming that this shift may be associated with the increasing land costs, but it is difficult to track the original reasons behind the minor land use shifts because of the complexity of social dynamics and demography of the peri-urban systems.

3.2 Land use modelling

Resulting from the spatio-temporal mapping of land use and land cover, seven significant transitions were considered based on observed major land use shifts: paddy rice to paragrass, barren land to paragrass, barren land to paddy rice, barren land to vegetables, barren land to built-up area, paragrass to built-up area and paragrass to vegetables (Fig. 7). Accuracy assessment is provided for the case of the land use change modelling process due to the fact that we performed an exhaustive mapping of all the study area. Transitions from barren land to other land use types are inevitable with urbanization, which demands urban infrastructure and dwelling places. Other transitions, including paddy rice to paragrass, which is a farmers´

choice because of increasing soil salinity, and paragrass to vegetables or built-up area are also plausible choices. These seven transition submodels were used as input for the land use change prediction model, and all the individual transition submodels achieved a minimum accuracy of 70% with the MLP neural network approach. Predicted land use results for the year 2015 were validated with the observed land use results. The estimated error for model validation for each land use class is below seven percent. It is expected that the dominant land use classes are expressing higher errors compared to other land use classes (Han et al., 2015) (Fig. 8). The barren land and built-up areas are showing the highest errors with 6.11% and 4.65%, respectively, followed by paragrass and vegetables cropping areas showing errors of 1.11% and 1.01%, respectively.

After the validation of the model, the land use was predicted for the year 2030, which illustrates an increase in built-up areas (Fig. 9). Overall, the transition potential map explains that there is a huge potential for increasing both agriculture and built-up areas in the future. However, it seems that the land use prediction tends to result in increased built-up areas, which is a combination of both built-up and development areas. Between the years 2000 and 2015, the built-up and development areas together grew by ~150%, whereas agricultural areas decreased by 12%. If this growth rate of the built-up area continues, the predicted results would indeed hold true in the future. These changes are taken as the basis for the model predictions. It is clear that built-up areas are spreading over agricultural areas, and there is a moderate chance that the current irrigated lands can be also turned into built-up spaces for the peri-urban population. These changes are prompted by less attention to agricultural spaces and high land prices as progression of urbanization might be the reasons behind the big shift to built-up areas. The urbanization process can push people from the city to the peri-urban spaces or migrants who come looking for jobs can also occupy peri-urban spaces. This shift can be a threat to peri-urban agriculture in the future as it is a livelihood practice for the farmers and migrants in the region. Local governments are looking at policy options to improve and support the urban farms and peri-urban agriculture but institutional support for implementation is not in place. With the quantity of wastewater and groundwater that is available, peri-urban agriculture in the region can be easily sustained and can contribute to food security of the Hyderabad urban agglomeration.

3.3 Limitations of Google Earth data

Google Earth has some limitations with respect to large scale applications because of its inconsistent quality of images and intermittent data availability (Pulighe et al., 2016; Yu and Gong, 2012). Coincidentally, for the current study area, high quality images were available with Google Earth for observing micro-level land use changes in the peri-urban context. Even though Google Earth provides high resolution images especially in the urban and peri-urban areas, the reliability of these images raises questions due to horizontal accuracy and limited background information or metadata released by Google (Pulighe et al., 2016). The current study utilized the local farmers' knowledge and thorough ground truthing of the watershed over the years to overcome this situation, which might not be possible in every case for mapping micro-level changes as it requires a lot of field work and person hours for validation.

3.4 Implications of peri-urban agriculture

This study elucidated the shifts in land use and their interrelations with wastewater irrigation. As the peri-urban spaces are the most dynamic compared to urban or rural areas, future research should focus on sustainable land use planning by understanding the social and economic factors, which can support the transition to sustainable urban societies. Even though vacant lands in the peri-urban systems offer ample opportunities for agricultural activities, these opportunities are not visible as expected because of various factors including land costs, farmers disinterest, water accessibility, the conundrum with wastewater, etc. The health risks associated to food production with wastewater appear to be manageable in principle, but the issue of social acceptance remains. The second issue with wastewater irrigation is salinization, resulting in reduced soil fertility and productivity and environmental health. The observed shift from paddy rice to paragrass can be associated with this factor. This particular issue is quite site-specific, e.g. depending on soil characteristics and irrigation history. Whether the predicted shift to paragrass indeed would materialize depends on the actual salinization trajectory on single plots and many other, mostly socio-economic factors, which are not reflected in the land-use change model.

From the previous research, it was not clear what type of land use policy measures would be required to protect the peri-urban agriculture. Using sustainable irrigation practices for peri-urban agriculture may also improve the environmental conditions of urban agglomerations (Goldstein et al., 2016). As cities are the biggest consumers, shifting food production closer to the places of high demand (e.g. urban and peri-urban farms) can aid in reducing the food miles associated greenhouse gas emissions and mitigating climate change (Eigenbrod and Gruda, 2015; Filippini et al., 2019; Moein et al., 2018). The planning process in the urban and peri-urban areas should include agriculture as the priority in the vacant or abandoned places with the supporting policies to increase environmental sustainability (Asgarian et al., 2018; Oda et al., 2018). Developing integrated management plans for urban and agricultural systems in the nexus dimension considering reuse of wastewater, cost effectiveness and stakeholder interests can be a viable option for urban food production and also for land and water resources management (McClintock et al., 2016; Miller-Robbie et al., 2017). These study results provide insights into peri-urban landscape transformation, triggered by direct and indirect drivers, which can be converted to opportunities for more sustainable food production systems embracing city regions.

4 Conclusions

In this study, we provided an overview of the peri-urban land use system dynamics using high spatial resolution imagery of Google Earth and land use change modelling. The observed micro-level land use changes in the peri-urban watershed illustrate that there is an unintended competition between the built-up areas and agricultural areas. We conclude that with the increasing urban pressures, new built-up areas are spreading on to agricultural landscapes. On the other hand, new agricultural plots and built-up areas are being widely developed in the peri-urban barren lands. The availability of wastewater plays a critical role in continuing the agricultural activities despite the urban pressures. The crops produced find their way to the urban markets to feed the urban dwellers. No major changes are observed in the area under groundwater irrigation, but there is a shift in the choice of crops depending on the urban demands. Paragrass is the major crop in the watershed, and it is extensively irrigated by wastewater flowing into the Musi River from the Hyderabad city. Even though vegetables fetch a high price, fewer areas are being cultivated, due to negative impacts of wastewater irrigation. In fact, negative perception does not affect the paragrass cultivation as it is a direct feeder to the dairy industry, which further supplies the milk produced to the urban markets. Decreasing paddy rice cultivation over the years is linked with the salinity of the soils and low crop yields due to long-term wastewater irrigation.

The predicted land use change modelling for the year 2030 suggests that there is a greater chance of barren lands being converted to the development and built-up areas. Even though agricultural areas may exist in the future, built-up areas will likely be dominant because of the increasing land prices. The developed maps with micro-level changes can be useful for decision makers and farmers to decide on the future practices of peri-urban agriculture. These results are site-specific depending on factors like topography, proximity to the city, history of wastewater irrigation etc. and assuming similar developments in other peri-urban settings could be easily misleading. Other peri-urban systems can replicate this research methodology to observe the transformative changes for controlled peri-urban planning. Local decision makers should take necessary actions to preserve the peri-urban agriculture as it is directly aiding the sustainable food production for an increasing urban population and supports the livelihood of peri-urban farmers.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

MJ acknowledges the support from the TU Dresden Graduate Academy PhD Completion Grant. PA acknowledges the support from the CGIAR Research Programme on Water Land and Ecosystems (WLE).

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Figure Captions

Fig. 1 Location map of the Kachiwani Singaram micro watershed (KSMWS) in (a) Krishna River Basin of India, (b) in the context of peri-urban Hyderabad (c) with natural drainage and digital elevation model (DEM) in meters above mean sea level (amsl).

Fig. 2 Identification of different land use classes and crop classifications from Google Earth images for spatio-temporal mapping of the watershed.

Fig. 3 Flow diagram of the current study, leading to the assessment of peri-urban landscape dynamics.

Fig. 4 Land use change dynamics in the study micro-watershed. Upper panel is showing the spatial dynamics of the land use change for the years (a) 2000, (b) 2009 and (c) 2015. The white part of the watershed is empty land or barren land. The lower panel is showing temporal dynamics in different settings: (d) Major land use (three main use types) and (e) Crop (three main crop systems).

Fig. 5 Observed land use changes between the years 2000 and 2015, (a) and (b). The land use classes are shown here irrespective of the change detection observed between the classes. For example, there were no changes observed between the built-up area to barren land and barren land to the wetland. Observed percent land use changes in the watershed between the years 2000 and 2015, (c), (d) and (e).

Fig. 6 Irrigation system dynamics in the study micro-watershed. Upper panel is showing the spatial dynamics of the irrigation type land use change for the years 2000, 2009 and 2015. The lower panel is showing temporal dynamics of Irrigation system (Groundwater, GW vs Wastewater, WW).

Fig. 7 Mapped possible transitions between different crops and land use classes for future landscape change. Transitions maps showing; (a) Paddy Rice to Paragrass, (b) Barren land to Paragrass, (c) Barren land to Paddy Rice, (d) Barren land to Vegetables, (e) Barren land to Built-up area, (f) Paragrass to Built-up area, (g) Paragrass to vegetables. The colour scale range for the maps shown is from green to yellow to red, where green is a possible transition, yellow means transition may be possible or not possible, and red means either transition impossible or existing land use. White areas represent barren land or other land use types, which did not participate in the model transition.

Fig. 8 Estimated percent error for model validation of the observed land use from Google Earth vs predicted results from land change modeler for the year 2015.

Fig. 9 Land Use Change modelling (a) transition potential and (b) predicted land use for the year 2030. High (1) transition potential refers to possible for land use change and low (0) means transition of the land cover not possible.

Fig 1

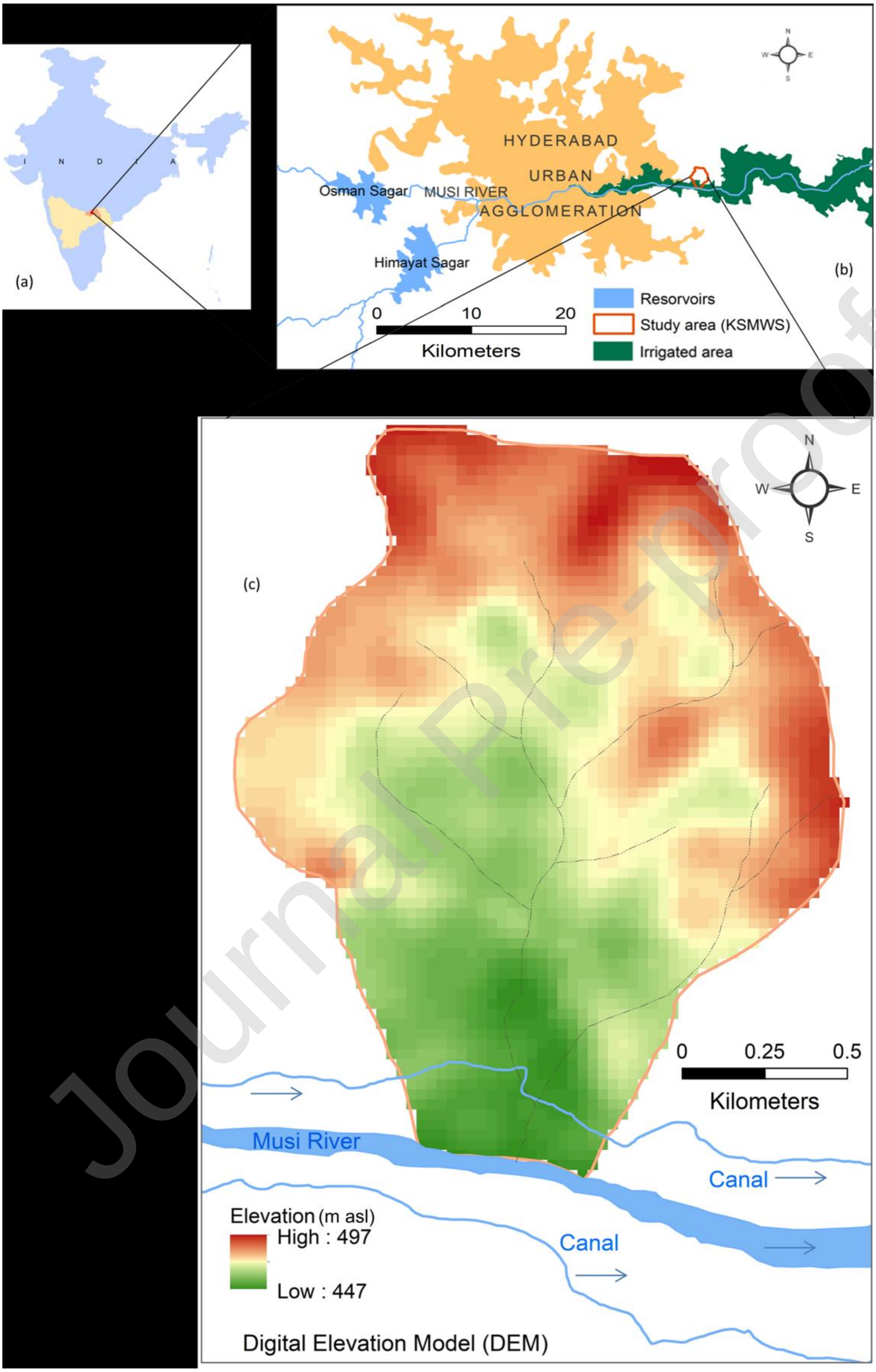

I N D I A
(a)
HYDERABAD
URBAN
AGGLOMERATION
Osman Sagar
MUSI RIVER
Himayat Sagar
(b)
0
10
20
Kilometers
Resorvoirs
Study area (KSMWS)
Irrigated area
N
W
E
S
(c)
0
0.25
0.5
Kilometers
Musi River
Canal
Canal
Elevation (m asl)
High : 497
Low : 447
Digital Elevation Model (DEM)

Fig 2

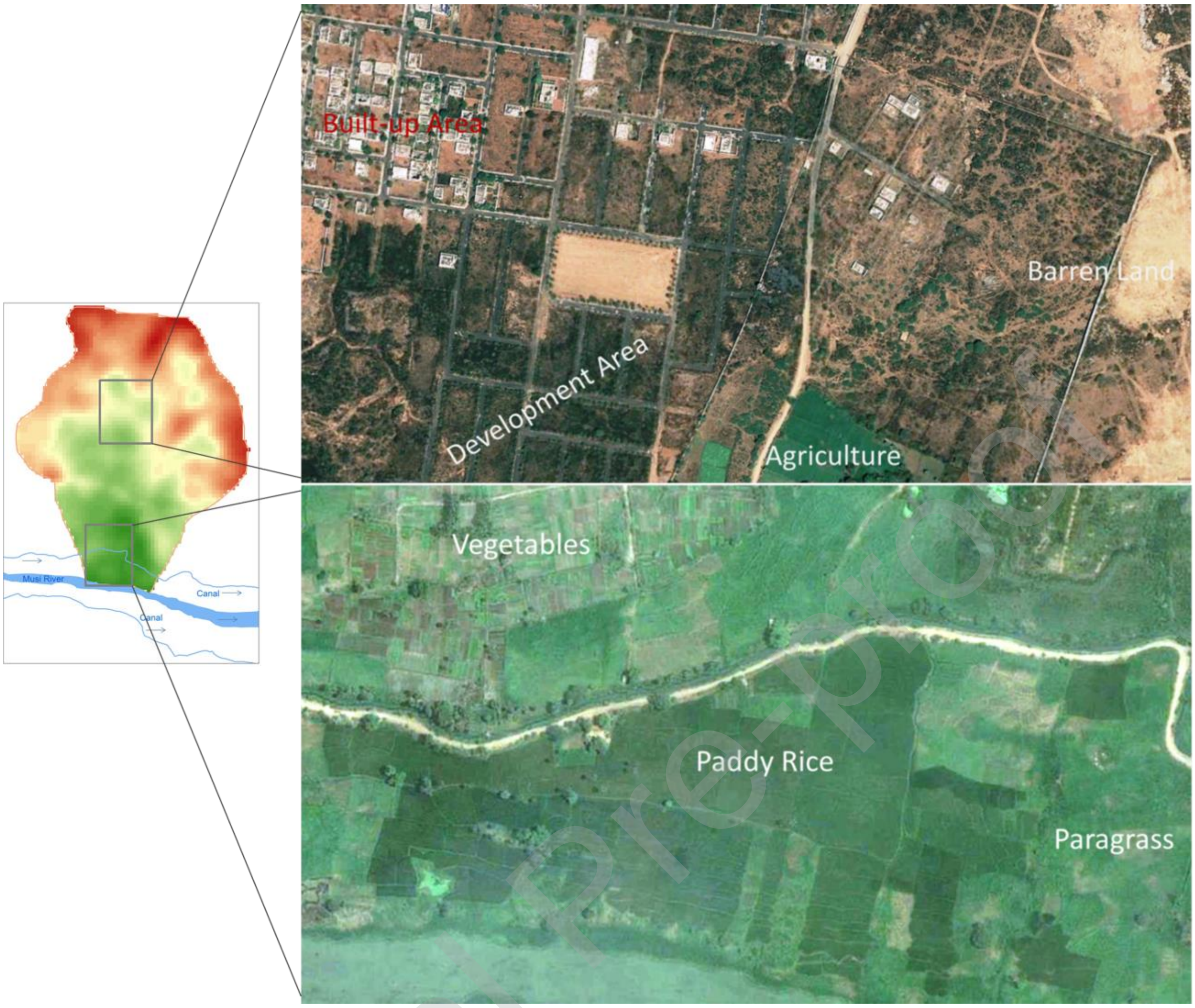

Built-up Area
Barren Land
Development Area
Agriculture
Vegetables
Paddy Rice
Paragrass
Musi River
Canal
Canal

Fig 3

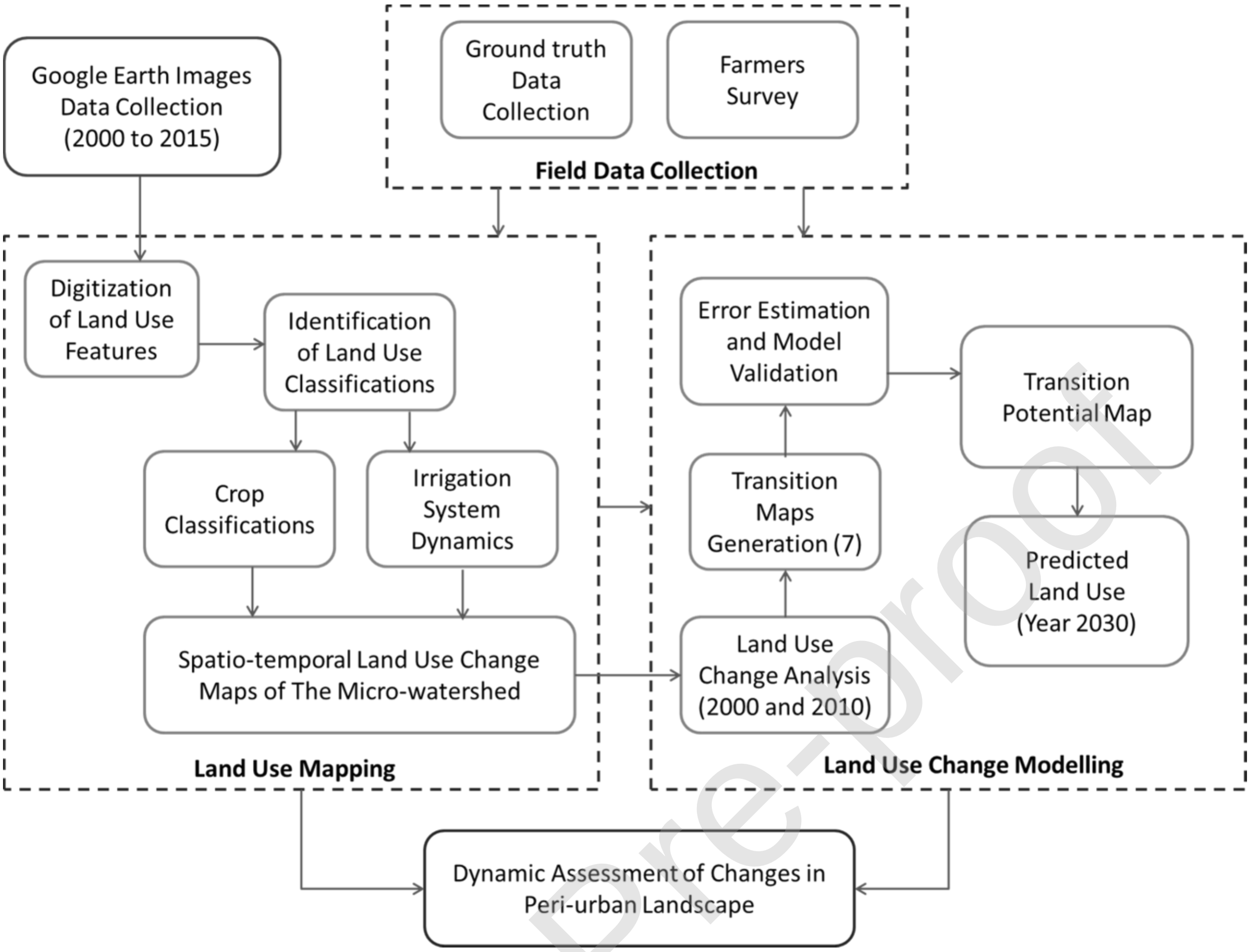

Google Earth Images Data Collection (2000 to 2015)
Ground truth Data Collection
Farmers Survey
Field Data Collection
Digitization of Land Use Features
Identification of Land Use Classifications
Crop Classifications
Irrigation System Dynamics
Spatio-temporal Land Use Change Maps of The Micro-watershed
Land Use Mapping
Error Estimation and Model Validation
Transition Potential Map
Transition Maps Generation (7)
Predicted Land Use (Year 2030)
Land Use Change Analysis (2000 and 2010)
Land Use Change Modelling
Dynamic Assessment of Changes in Peri-urban Landscape

Fig 4

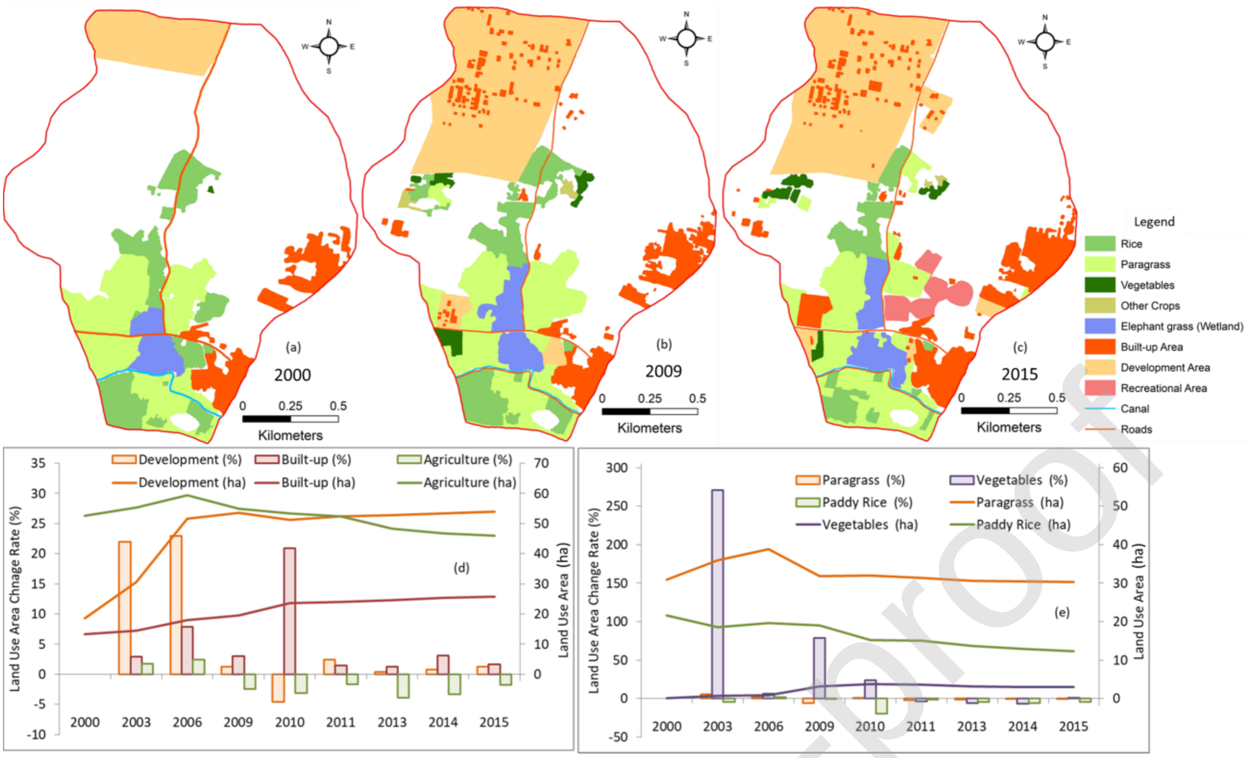

(a)
2000
(b)
2009
(c)
2015
0 0.25 0.5
Kilometers
Legend
Rice
Paragrass
Vegetables
Other Crops
Elephant grass (Wetland)
Built-up Area
Development Area
Recreational Area
Canal
Roads
Development (%)
Built-up (%)
Agriculture (%)
Development (ha)
Built-up (ha)
Agriculture (ha)
Land Use Area Chnage Rate (%)
Land Use Area (ha)
(d)
Paragrass (%)
Vegetables (%)
Paddy Rice (%)
Paragrass (ha)
Vegetables (ha)
Paddy Rice (ha)
Land Use Area Change Rate (%)
(e)
2000 2003 2006 2009 2010 2011 2013 2014 2015

Fig 5

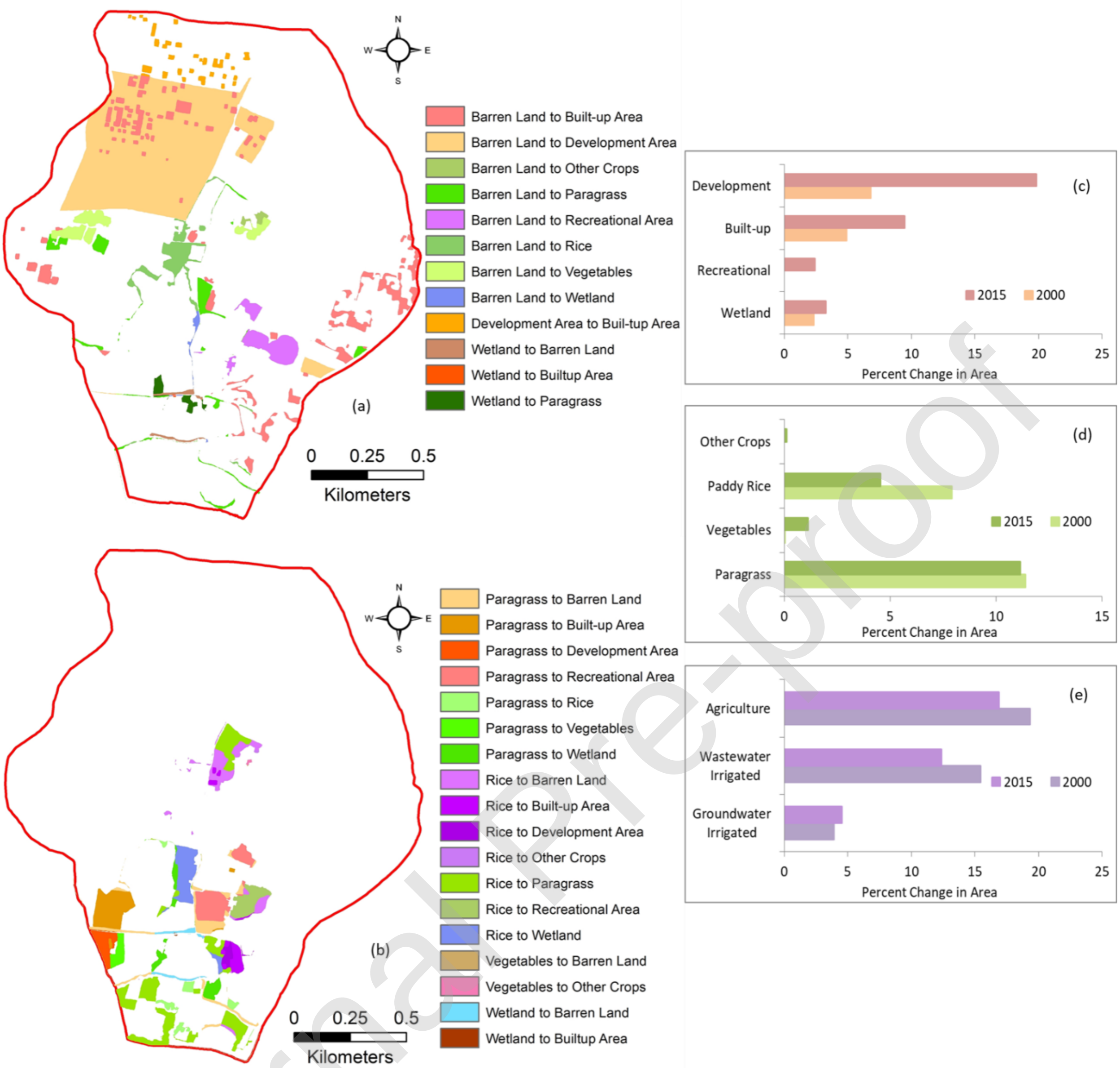
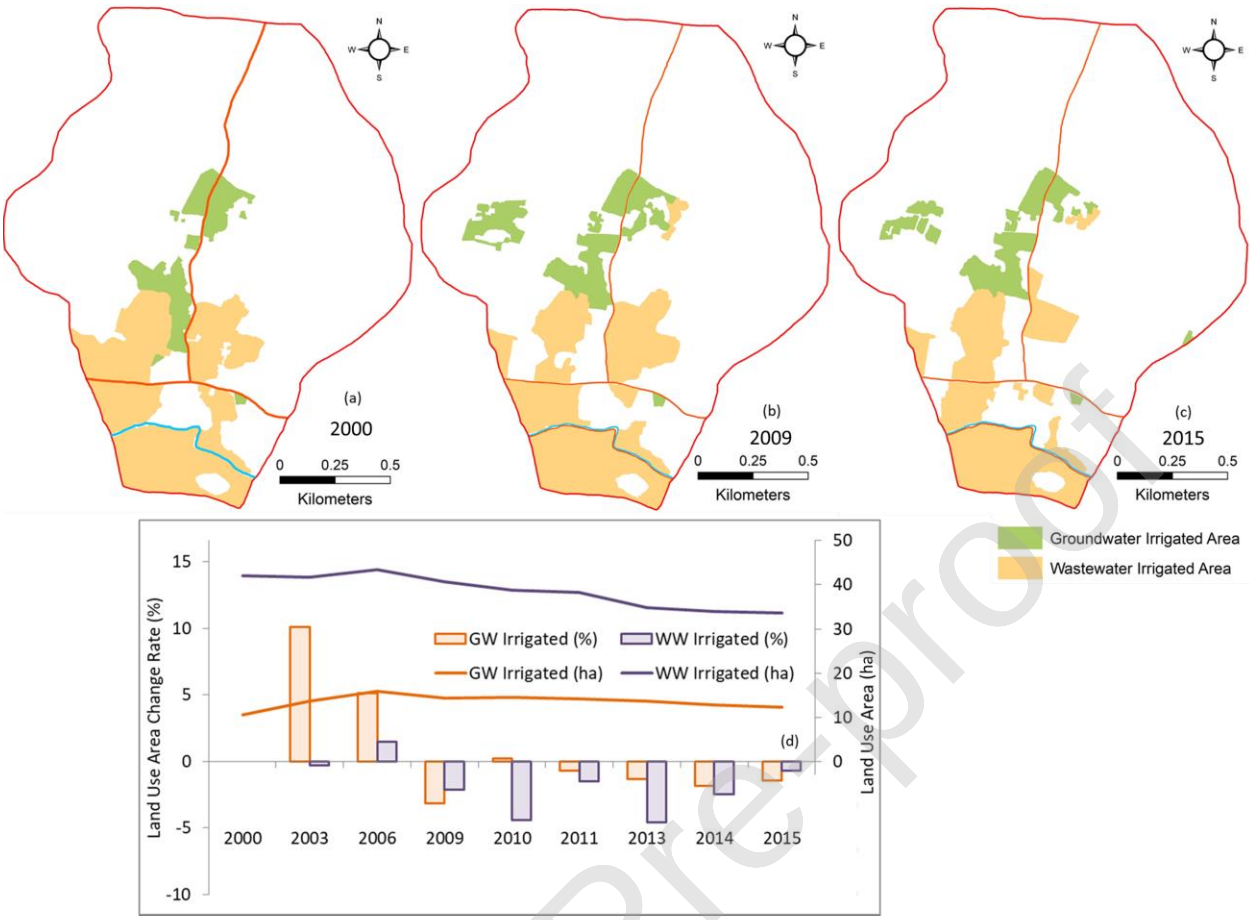

N
W
E
S
Barren Land to Built-up Area
Barren Land to Development Area
Barren Land to Other Crops
Barren Land to Paragrass
Barren Land to Recreational Area
Barren Land to Rice
Barren Land to Vegetables
Barren Land to Wetland
Development Area to Buil-tup Area
Wetland to Barren Land
Wetland to Builtup Area
Wetland to Paragrass
(a)
0 0.25 0.5
Kilometers
Development
Built-up
Recreational
Wetland
(c)
2015
2000
0 5 10 15 20 25
Percent Change in Area
Other Crops
Paddy Rice
Vegetables
Paragrass
(d)
2015
2000
0 5 10 15
Percent Change in Area
Paragrass to Barren Land
Paragrass to Built-up Area
Paragrass to Development Area
Paragrass to Recreational Area
Paragrass to Rice
Paragrass to Vegetables
Paragrass to Wetland
Rice to Barren Land
Rice to Built-up Area
Rice to Development Area
Rice to Other Crops
Rice to Paragrass
Rice to Recreational Area
Rice to Wetland
Vegetables to Barren Land
Vegetables to Other Crops
Wetland to Barren Land
Wetland to Builtup Area
(b)
0 0.25 0.5
Kilometers
Agriculture
Wastewater Irrigated
Groundwater Irrigated
(e)
2015
2000
0 5 10 15 20 25
Percent Change in Area

Fig 6



(a)
2000
0 0.25 0.5
Kilometers
(b)
2009
0 0.25 0.5
Kilometers
(c)
2015
0 0.25 0.5
Kilometers
Groundwater Irrigated Area
Wastewater Irrigated Area
Land Use Area Change Rate (%)
Land Use Area (ha)
GW Irrigated (%)
WW Irrigated (%)
GW Irrigated (ha)
WW Irrigated (ha)
(d)
2000
2003
2006
2009
2010
2011
2013
2014
2015

Fig 7

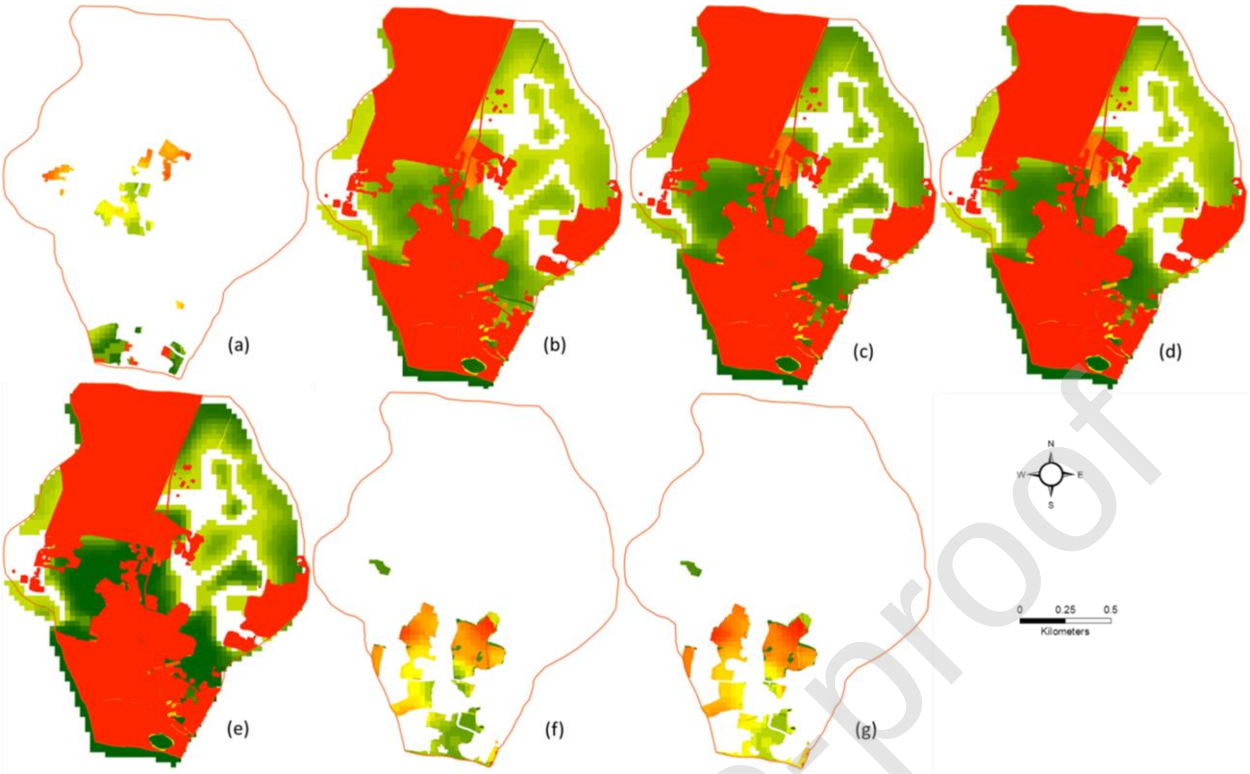
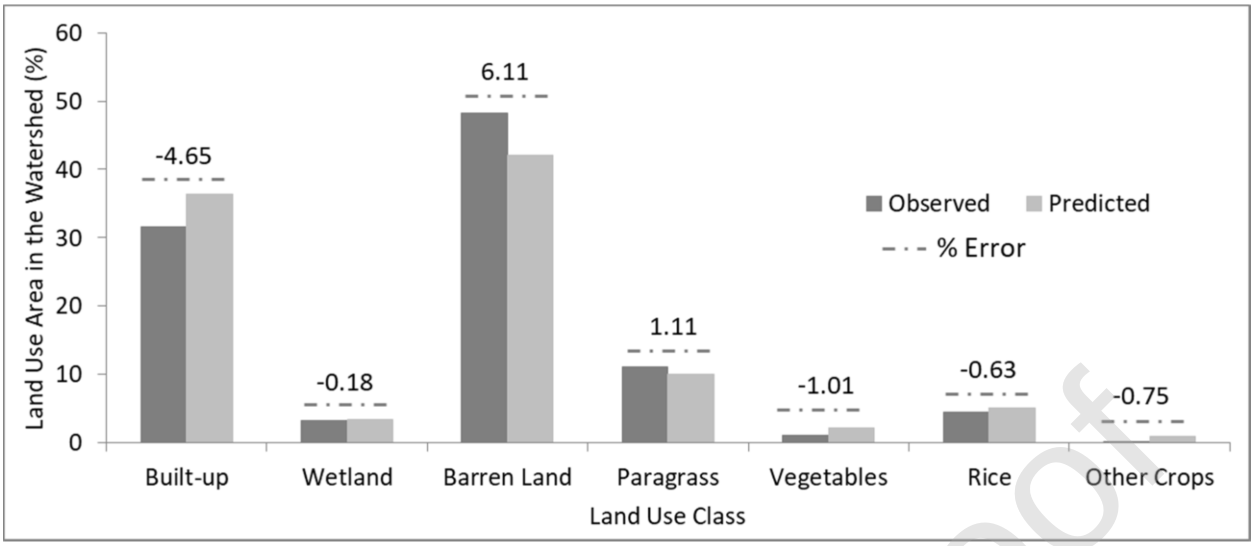
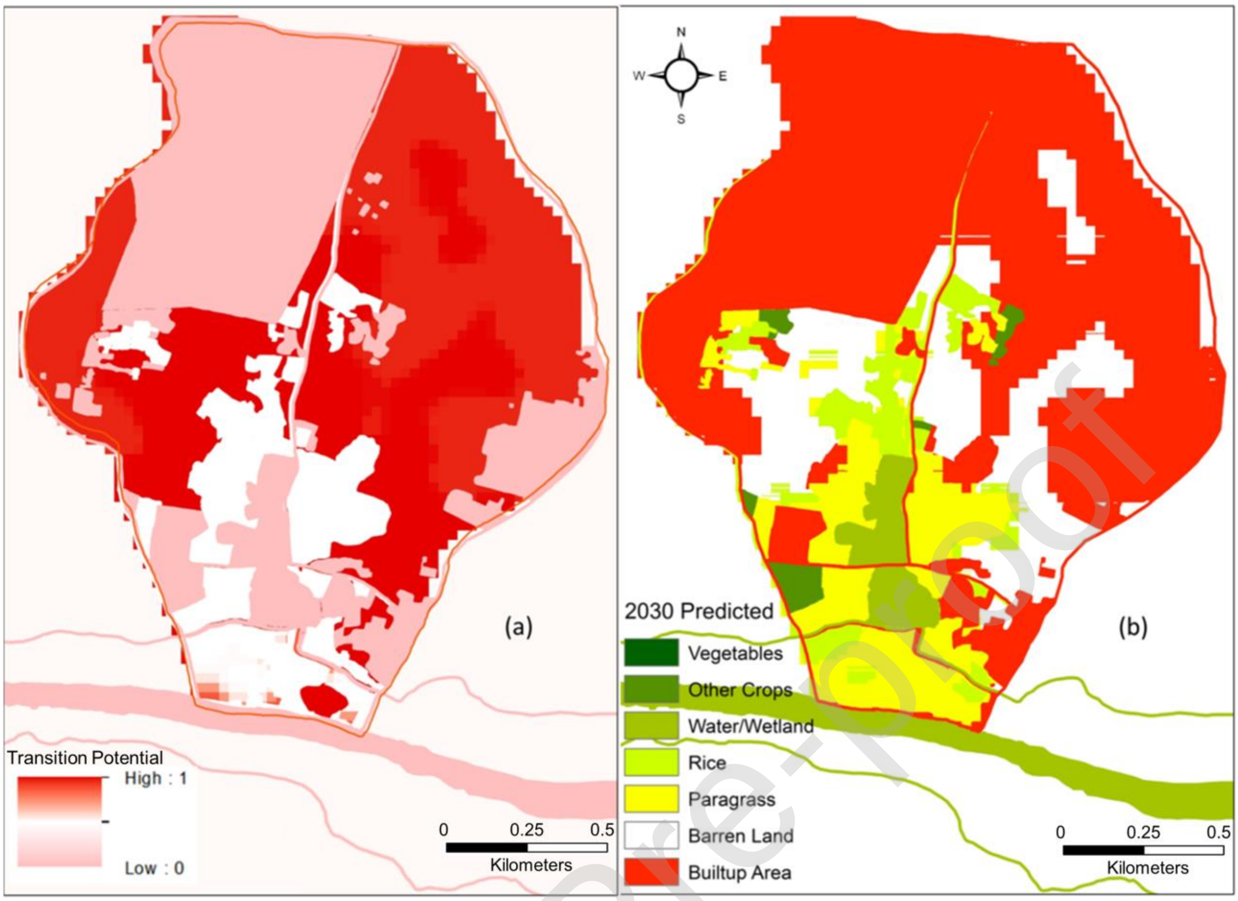


Fig 8



Land Use Area in the Watershed (%)
60
50
40
30
20
10
0
-4.65
6.11
1.11
-0.18
-1.01
-0.63
-0.75
Observed
Predicted
% Error
Built-up
Wetland
Barren Land
Paragrass
Vegetables
Rice
Other Crops
Land Use Class

Fig 9


(a)
Transition Potential
High : 1
Low : 0
0 0.25 0.5
Kilometers
N
W
E
S
(b)
2030 Predicted
Vegetables
Other Crops
Water/Wetland
Rice
Paragrass
Barren Land
Builtup Area
0 0.25 0.5
Kilometers

Tables

Table 1 Classification scheme of the land use changes in the watershed

Dynamics Category	Land Use Class Name	Description of the Land Use Class
Major land use	Built-up area	Existing housing and industrial infrastructure
	Development area	Planned plots for built-up area development
	Agriculture	Croplands irrigated with GW and WW
	Barren Land	Empty lands with occasional shrubs
	Wetland	Natural reed pond with elephant grass
Crop	Paragrass	Fodder crop and grows all around the year
	Paddy Rice	Food crop and grows ~300 days in the year
	Vegetables	Food crop and grows all around the year
	Other Crops	Commercial crops such as chilli and cotton
Irrigation System	GW Irrigated	Agricultural area under groundwater irrigation
	WW Irrigated	Agricultural area under wastewater irrigation