

Article

Two Decades of Land-Use Dynamics in an Urbanizing Tropical Watershed: Understanding the Patterns and Drivers

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Abstract: Java's Brantas River Basin (BRB) is an increasingly urbanized tropical watershed with significant economic and ecological importance; yet knowledge of its land-use changes dynamics and drivers as well as their importance have barely been explored. This is the case for many other tropical watersheds in Java, Indonesia and beyond. This study of the BRB (1) quantifies the land-use changes in the period 1995–2015, (2) determines the patterns of land-use changes during 1995–2015, and (3) identifies the potential drivers of land-use changes during 1995–2015. Findings show that from 1995 to 2015, major transitions from forest to shrubs (218 km²), forest to dryland agriculture (512 km²), and from agriculture to urban areas (1484 km²) were observed in the BRB. Responses from land-user questionnaires suggest that drivers include a wide range of economic, social, technological, and biophysical attributes. An agreement matrix provided insight about consistency and inconsistency in the drivers inferred from the Land Change Modeler and those inferred from questionnaires. Factors that contributed to inconsistencies include the limited representation of local land-use features in the spatial data sets and comprehensiveness of land-user questionnaires. Together the two approaches signify the heterogeneity and scale-dependence of the land-use change process.

Keywords: land-use; Brantas River Basin; tropical watershed; spatial trends; potential spatial drivers; perceived drivers; land-users



Citation: Wiwoho, B.S.; Phinn, S.; McIntyre, N. Two Decades of Land-Use Dynamics in an Urbanizing Tropical Watershed: Understanding the Patterns and Drivers. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 92. <https://doi.org/10.3390/ijgi12030092>

Academic Editors: Wolfgang Kainz and Godwin Yeboah

Received: 28 October 2022

Revised: 31 January 2023

Accepted: 20 February 2023

Published: 24 February 2023



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1. Introduction

Land-use is widely considered as a primary parameter of environmental change from local to global scales and is increasingly included in environmental change assessments [1,2]. Changes in land-uses may impact upon hydrology [3], biodiversity, water saving measures [4], and disaster risk [5]. Rapid land-use changes have often been associated with uncontrollable urban growth [6], farm loss [7], and deforestation [8].

The triggers or factors that lead to land-use changes or influence the process of land-use change are commonly termed “drivers” [9]. Studies show a broad range of drivers [10], which can be broadly categorized into biophysical factors (e.g., climate, soil, and terrain) and anthropogenic factors (e.g., population, technology, policy, culture, and economy) [11–15]. These drivers may be direct, such as a growing population [16] and increasing market prices [17]. Some others can be more complex, such as institutional and cultural settings [18]. It is widely accepted that changes, planned or not, are principally the consequence of human decisions [19]. Anthropogenic factors usually exhibit a more immediate impact than natural factors [14]. Studies show that drivers might interact with each other [20], and operate on differing scales, namely institutional, temporal, and spatial scales [9].

Information on land-use changes and their associated drivers is important for understanding the likely condition of future land-use and outlining land management strategies [21,22]. Relationships among drivers can be complex, and therefore it may be difficult

to identify and quantify the primary drivers operating in a particular landscape [23]. Approaches to quantifying the relationship between drivers and land-use changes include economic modeling, systems theory, and spatial modeling [9,14,24–26]. Some studies employ qualitative household-level surveys to understand what triggers land-use conversion [12,27,28]. While spatial modeling can provide insight about spatial variability of drivers at a regional scale, surveys can provide information about drivers at a land-user or household or local scale [14]. However, most studies have employed only one approach—either quantitative modeling or qualitative surveys [7,29–32].

Land-use change studies are commonly carried out at a watershed level due to the pivotal role of watershed land-use dynamics in water resource policy and planning. Such studies support understanding of how land-use change and its interaction with climate influence the watershed's hydrological functioning [33,34]. This is exemplified by several studies, such as those on the impact of climatic variability and land-uses on water resources [35,36], and the impact of increasing urban sprawl on water quality [37,38]. From an Indonesian context, urban sprawl has been considered a major factor in land-use change due to rapid population growth and it brings multiple consequences from ecological to socio-economic, which in turn affect the sustainability of the region and become a major consideration in land-use policy making [39].

Indonesia is a primary example of a tropical nation that continues to undergo rapid land-use changes marked with high extents of forest loss (0.31–0.69 Mha in 2000–2010) [40], massive urbanization [7], and associated environmental problems such as groundwater springs drying up [41]. Yet, research to support comprehensive understanding of land-use change in Indonesia and its impacts has been limited, scattered, inconsistent, and mostly focused on forest assessment studies outside Java. Relevant research has been conducted on the influence of population in shaping Java's land-uses [26], the role of policy in shaping Indonesian land-use [42], and quantification of forest loss in Sumatra [8]. However, research providing insight into the dynamics of land-use change, patterns, and drivers over different scales is lacking, especially in Java.

The period from 1995 to 2015 is marked by socio-economic and political reforms in major Indonesian sectors such as agriculture and economy and governance [43–47]. In particular, during 2004–2005 Indonesia underwent a major administrative power shift through the implementation of local autonomy, providing more authority for regional level decision making, and also saw the introduction of a new long-term development policy in East Java [48]. Many studies suggested that this new policy led to elevated deforestation, intensified urbanization, and agricultural decline [48–52]. The mid-point of this period, 2004–2005, was also considered globally as the turning point of global surface transition [52]. Similar results from local perspectives support this finding. During this period, intensified urbanization from agricultural conversion has been observed in China, resulting in consideration for ecological sustainability assessment [51,52]. Similarly, in Indonesia, the period 1995–2015 was marked by a major shift in deforestation for palm plantation [53], massive urban sprawl [39], and deterioration in watershed [54]. Land-use changes have also been linked to the climate change in this period. In Nepal, changes in climatic variability, despite insignificant, in this period have been observed that were considered partially due to changes in land-uses [55]. Massive landscape transformation as well as its global implications then apparently stimulated the necessity of land-use change studies [56].

This research was carried out to investigate land-use change drivers in the Brantas River Basin (BRB), a large tropical watershed in the island of Java, Indonesia. The BRB can be regarded as a typical tropical developing country watershed in the sense that land-use change is rapid due to varying factors related to the growing population and economic development [42]. While rapid socio-economic and ecological dynamics have been observed in BRB [41,57,58], empirical evidence on the type, patterns, and drivers of these dynamics is limited. This study therefore aims to contribute to understanding of inter-decadal land-use dynamics, patterns, and drivers in tropical and developing countries. As opposed to most

land-use change studies, our study combines geospatial regional scale modeling with local-scale questionnaires [7,29–32]. Using the two complementary approaches aims to allow a high degree of confidence in identifying principal land-use drivers. The study specifically aims to (1) quantify the land-use changes in BRB, (2) determine the patterns of land-use change in BRB, and (3) identify the potential drivers of land-use changes in BRB during 1995–2015 using two approaches: geospatial modeling and questionnaires.

2. Materials and Methods

2.1. Study Area

The BRB, with an area of 11,832 km², covers approximately 30% of the province of East Java (Figure 1). The basin (“basin” is the term typically used for a large watershed in Indonesia and so is adopted in this paper) is home to two major cities and 13 regencies. These 15 administrative boundaries have their own statistics with scattered data coverage. Most areas have their data starting from 2005, and 2005–2017 is the longest period where the 15 areas have the common and full coverage to district population level. The population grew from around 21 million in 2005 to 22.5 million in 2017, accounting for 54% of East Java’s population and 7.5% of Indonesia’s population. The information of population presented here is to provide an overview of the demography of Brantas watershed.

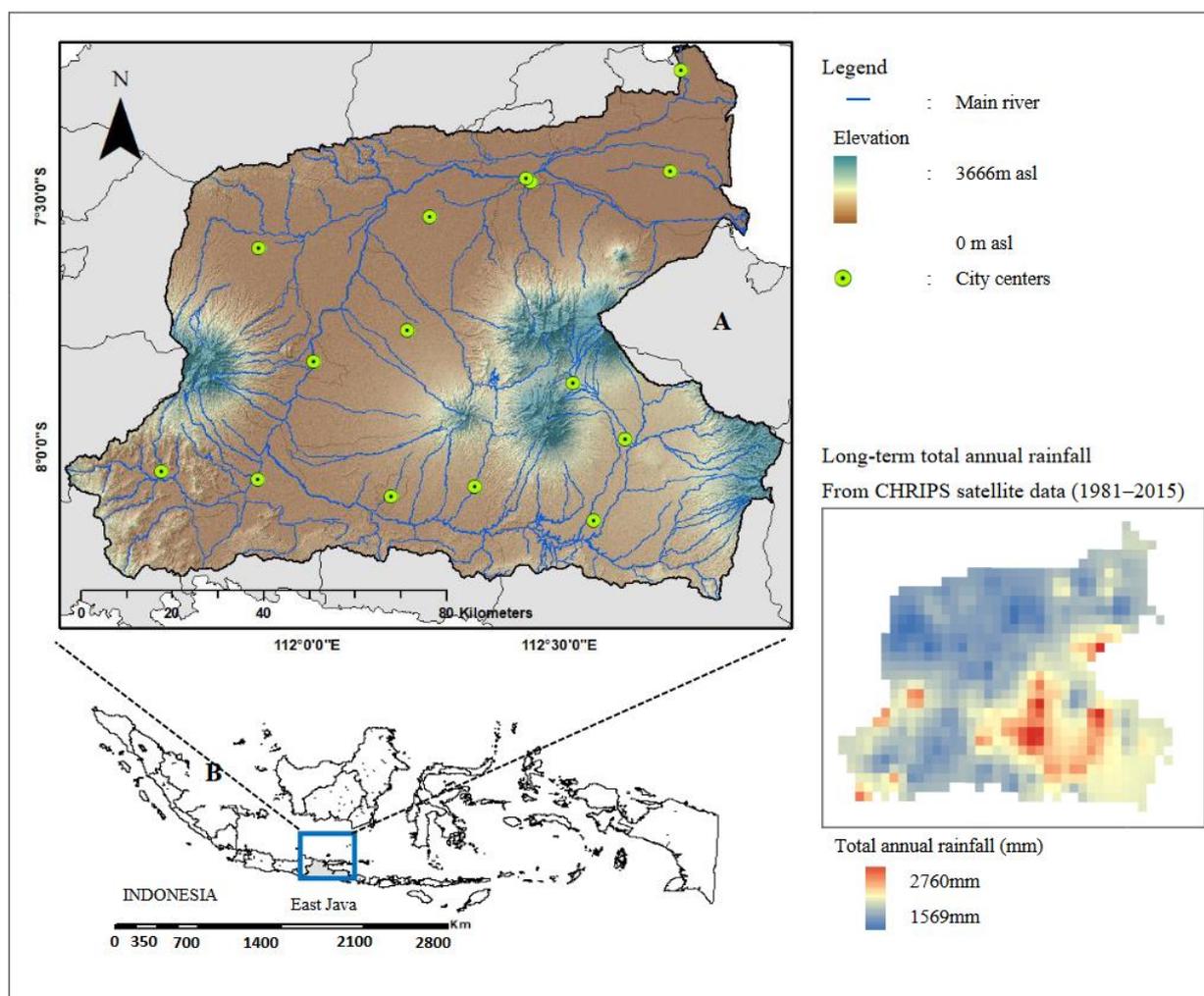


Figure 1. (A) The BRB within East Java. The blue lines show the main river network. The green dots are the largest cities in the BRB. (B) BRB orientation in Indonesia.

Seven mountains create large topographical variability. Elevation ranges from sea-level to 3663 m above sea-level. Geology is heterogeneous, shaped by alluvial processes, lahar deposition, volcanic formation, and tuff depositions. The BRB exhibits a typical tropical monsoon climate with two distinct seasons: a dry season (April–October) and a wet season (November–March) [59]. Recorded long-term annual rainfall (1995–2015) ranges from an average of 2000 mm/year to nearly 3000 mm/year at high altitudes.

The BRB represents a mixed rural and urban society, with potentially competing land-uses. Growing urbanization and industrialization have led to encroachment on remaining forests, especially in the upper basin. Due to this, the ecosystem functions of the upper BRB have been considered poor for at least two decades [60] and there is an increasing number of environmental reports particularly related to the increasing challenges of drought, floods, eutrophication, water pollution, and sedimentation [41].

2.2. Land-Use Mapping Using Remote Sensing

The research approach is presented in Figure 2. The BRB spans four Landsat scenes each with 30 m resolution (Path:118/65–66 and Path:119/65–66). There are several considerations for the selection of Landsat images: the long coverage, richness in spectral variety [61,62], and suitability for mapping complex landscapes [63,64]. The years 1995, 2005, and 2015 were selected due to the quality of images during these years, the turning points of ecological and political conditions, and because the increasing environmental issues associated with land-use have increased since the 1990s [41,65]. The already georeferenced and atmospherically corrected surface reflectance products from NASA [66] were used to minimize atmospheric effect variations, which is especially important due to the use of multi-temporal and multi-tiled images [65–68]. To overcome difficulties in creating mosaics, we utilized a Google Earth Engine (GEE)-aided platform from Climate Engine [69]. We removed the clouds and shadowed pixels from analysis using the QA band in GEE and we utilized all available images after the cloud and shadow removal. For example, for 1995, we retrieved all images available from 1 January to 31 December 1995, and then applied the cloud and shadow removal. In each year we had 23 scenes for each path/row. We derived average images from all spectral bands of Landsat-7 for 1995 and 2005, and from Landsat-8 for 2015. The average image was selected instead of the median image because: (1) throughout the years of 1995, 2005, and 2015, there were no perceived extreme climatic events that might cause large differences in the reflectance of the objects, and the presence of outliers is negligible, (2) similarity in median and mean image histograms, and (3) deriving the median image is more computationally heavy [70]. Screening resulted in 16 to 24 images per year. The generated seamless mosaics showed no visual signs of anomalies. Although analysis of phenology may be used to derive land-use maps [67], in this case we did not have the data to apply this approach or to validate phenology parameters before generating phenology-based land-use maps.

We adopted the land-use classification scheme from Indonesia's Ministry of Forestry [49]. The 13 land-uses classes pertaining to the BRB landscape were simplified into 11 classes as specified in Table 1. The decision to adopt this approach was for several reasons: (1) BRB covers 15 administrative boundaries making it suitable for a study at a regional scale with medium resolution dataset, (2) The objective of the study was to examine the role of general land-use classes without specifying the stages of the vegetation. The primary and secondary vegetation classes do not exhibit distinct differences in hydrological responses and are relatively similar under the medium resolution images. Regrouping the 13 classes into 11 classes (merging two forest classes and two mangrove classes) allows a synoptic view of the landscape condition pertaining to forest and mangrove general conditions and their roles to water resources and watershed management as well as policy making at a regional level.

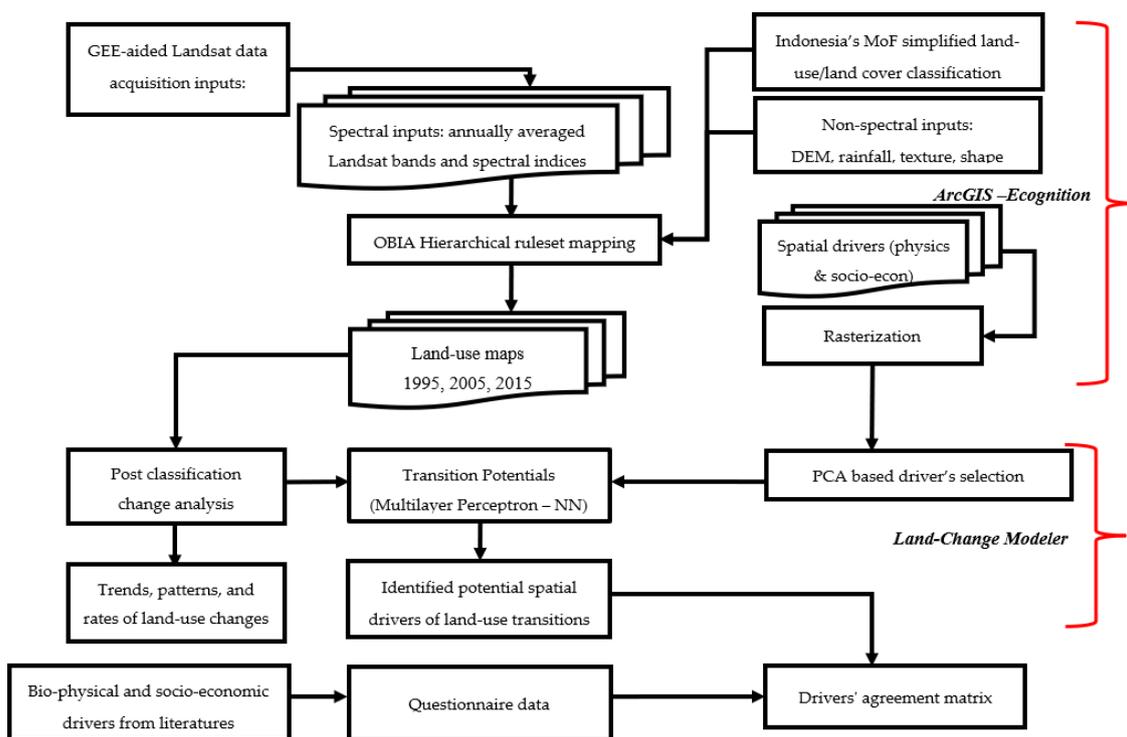


Figure 2. Methodological approach for the study.

Table 1. Land-use classification scheme (adapted from Indonesia Ministry of Forestry, 2021).

No	Land-Use or Open Water Class	Description	Combined Land-Use Class and Code
1	Water body	Open waters, including sea, rivers, lakes, reservoirs.	1. Water (WTR)
2	Primary dryland forest	Natural forests, which are grown and developed naturally, are stable, have never been exploited, and are free from waterlogging throughout the year.	2. Dryland forest (DRF)
3	Secondary dryland forest	Natural forests that have been grown following disturbance, have been exploited, with evidence of roads, remnants of burning and cutting/clearing, or that grow on degraded lands.	
4	Primary mangrove forest	Mangrove forest that is spread along the coastal areas and tidal influenced estuaries without signs of cutting.	3. Mangrove forest (MGF)
5	Secondary mangrove forest	Mangrove forest that is spread along the coastal areas and tidal influenced estuaries with signs of cutting and burning.	
6	Planted forest (industrial/estate forest)	Planted forests built to increase the potential and quality of production forests (already planted), including plantation reforestation and industrial plantations.	4. Planted forest (IDF)

Table 1. Cont.

No	Land-Use or Open Water Class	Description	Combined Land-Use Class and Code
7	Dry land farming	Agricultural activities on dry lands such as moors and fields.	5. Dryland agriculture (DRA)
8	Mixed dry land farming	Agricultural activities of dry land and gardens alternating with shrubs and bushes.	6. Mixed dryland agriculture (MDA)
9	Settlements, buildings	Land used for settlements, including urban, rural, industrial, public facilities, showing clear evidence of settlement/buildings.	7. Settlement and built-up (BUA)
10	Open field	Open land without vegetation (rock outcrop mountaintop, snowy peak, volcanic crater, sandbanks, beach sand, river deposits).	8. Bare land/sand (BRL)
11	Shrubs and bushes	Parts of Regrown Dryland Forest with few natural trees, dominated by short vegetation.	9. Shrubs and bushes (SHB)
12	Rice field	Overlay land for agricultural activities characterized by a bunding pattern.	10. Rice-field (RCF)
13	Ponds	Land for terrestrial fishing activities (fish/shrimp) or salt farming, which is characterized by a pattern, and usually flooded and located around the beach.	11. Ponds (PND)

We then performed object-based image analysis (OBIA) to map land-use using eCognitionTM software version 9.0 [71]. The OBIA and ruleset classifier were adopted based on several considerations: (1) it can better handle the issues of pixel-based mapping in that it can represent the complexity of shape, pattern, texture, context, and knowledge, which all are usually required to better define the land-use classes [72], (2) it reduces the salt-pepper effect due to spectral variations, (3) the use of ruleset and expert knowledge is useful in dealing with spectral limitations [73,74] and often results in a higher accuracy [75]. One drawback of the OBIA approach is the heavy computation and potential error propagation due poor segmentation [75,76]. There are no agreed rules in the segmentation and numerous studies applied shape and compactness scales on the basis of visual appearances of the segmented objects [77–79]. The segmentation parameters (shape and compactness) were reviewed in the current work by testing the values with 0.1 increments, finally choosing values of 0.2 and 0.7, respectively, that produced the visually most satisfactory delineation of objects while allowing OBIA to run relatively quickly. Association of land-use distribution and ecological factors were examined to help determine the hierarchical ruleset to classify objects [80]. The ruleset approach incorporated spectral and non-spectral features of an object such as elevation, distance, texture homogeneity, shapes, lengths, and width of objects, which is useful for mapping objects with similar spectral features [81]. In the OBIA-ruleset, we considered frequently used spectral indices in land-use mapping such as normalized difference vegetation index (NDVI) and normalized difference built-up index (NDBI), as well as non-spectral indices such as grey level co-occurrence matrix (GLCM) homogeneity and texture [81–83]. The threshold values used to separate objects were obtained from trials on a series of samples of objects with known land-use classes based on ground surveys, aerial photos, and Google Street View images. This approach reduces the possibility of misclassification that can arise from random sampling [84]. The thresholds were calculated from average values and visual optimization for the land-use class differen-

tiation. We acknowledge this approach introduces subjectivity to the ruleset; however, it is helpful in achieving computational efficiency by skipping complex non-linear optimization approaches.

In total, 52 aerial photographs were used to validate the 1995 map (823-point samples). For the 2005 and the 2015 maps, ground survey notes, Google Street View images and Google Earth (1776 points) were used. The maps were overlain with a 1 km × 1 km grid and the grid centroids were used as the sampling locations. Around each sampling location, a 30 m × 30 m square mimicking the Landsat resolution was generated, and observation was performed within this boundary. In cases where ground survey data validation data were not available in that rectangle, for example due to access constraints, but were available nearby in the same grid square, the sampling location was moved to the nearest point that provided ground survey data. Two validators were used. For assessing the accuracy of the maps, we used a contingency table [85]. A map with kappa accuracy above 80% was regarded as acceptable for use in land-use change modeling [31]. A pixel-based post-classification change detection was selected [86–88]. To minimize the presence of spurious change (1) radiometric correction and co-registration was applied before classification [89], (2) an OBIA approach was used to reduce the salt-pepper effect, contributing to avoidance of spurious changes [69], and (3) ancillary data and expert knowledge were used to check and, where necessary, modify the generated maps [83,84]. The spurious changes that could not be avoided were accepted as part of the associated errors of the maps.

2.3. Potential Land-Use Drivers from Spatial Modeling

The Terrset Land Change Modeler (LCM) was selected to model spatial drivers of land-use change. This platform has been widely applied in varying landscapes such as African grasslands [24] and Southeast Asian green space [31]. LCM quantifies the spatial drivers through change analysis, pattern analysis, calculation of change probability and performance reporting. Change analysis is conducted by overlaying two post-classification maps in LCM [13,90]. LCM is also equipped with a built-in module to examine spatial trends of changes. The pattern of change was modelled using a third order polynomial due to its suitability for mapping the changing patterns [91].

According to Eastman (2016) [91], the spatial pattern (also termed as trend of land-use change in LCM), was developed using a trend surface analysis (TSA) where polynomial equations for changes were calculated and interpolated. The generic equation fitted by LCM's TREND module is

$$Z(U, V) = \alpha_{00} + \alpha_{10} \cdot U + \alpha_{01} \cdot V + \alpha_{20} \cdot U^2 + \alpha_{11} \cdot U \cdot V + \dots + \alpha_{pq} \cdot U^p \cdot V^q \quad (1)$$

where Z is the distributed variable, in this case is the transition between two selected land-uses, α terms are the polynomial coefficients, and U and V are the locational coordinates. The TSA surfaces were then calculated by coding the pixels of a specific transition as 1 and pixels of no change as 0 and treating the values as if they were continuous values to which the surface Z is fitted [91,92]. The values of Z generated have no special significance but allow the degree and direction of transition trends to be mapped and can identify the hot spots of land-use changes [91,93]. Higher positive values of Z indicate areas with more transitions, lower negative values imply areas dominated by the opposite transition, while zero values indicate areas with no or few transitions [94–97].

In this study, our primary concerns are the biophysical and socio-economic drivers of land-use. Factors regarding land ownership and legal status might play roles in influencing the land-use dynamics. However, such data are unavailable in the BRB. We acknowledge this as one limitation in this modeling. In addition, recent observations show that there has been substantial agricultural occupation of national parks such as in Bromo Tengger Semeru national park and Taman Hutan Raya Suryo. This violation to the official land status implies the inability or inefficiency of land zoning plans in governing the land-use dynamics in the BRB. We generated 33 candidate spatial biophysical and economic drivers based on our best understanding of local and regional conditions, literature on Java and

other relevant landscapes [7,32,98–100], suitability, data availability and accessibility for research use. The candidate spatial drivers were generated from varying rasterized datasets such as elevation, roads, rivers, zonation plans, and digital climatic variables. To avoid correlated inputs and help interpret results, principal component analysis (PCA) [97] was used. The PCA results in the loading factors of each variable or driver. The drivers selected were all variables having high loading factors (>0.55 or <-0.55) in the PC and number of PCs included was that $>90\%$ of the variance was explained (Table 2).

Table 2. Twelve selected land-use change drivers from PCA analysis.

No	Driver	Definition	Data Source and Processing
1	DTR	Distance to national, provincial, and main city road networks	Vector road layer scale 1: 50,000 (Indonesian Geospatial Agency). Rasterized to 30 m grid in ArcMap. Calculated using Euclidean distance
2	RFL	Long term rainfall (1995–2015)	498 Rain stations in BRB (Indonesia’s Meteorology and Climate Agency). Rasterized to 30 m grid using IDW interpolator
3	DTC	Distance to city center	Distance analysis in 30 m grid using ArcMap. City center was defined using centroid from city boundary shapefile
4	ELV	Elevation/altitude (in m). Height from sea level.	USGS ASTER DEM 30 m
5	SLP	Slope of terrain (in degree)	USGS ASTER DEM 30 m. Processed from ASTER DEM using surface analysis in ArcMap
6	DTD	Distance to area designated as a high risk of disaster zone (volcanic hazards) *	East Java Province Spatial Planning (RTRW, 2011). Rasterized to 30 m grid in ArcMap. Calculated using Euclidean distance
7	DRD	Distance to regional development zone *	
8	DEA	Distance to economic zone A (designated areas for development centers for technology and industry as well as priority economy sector with local resource optimization) *	
9	DEB	Distance to economic zone B (designated areas for centers or “Agropolitan” and “Agroindustri” in East Java) *	
10	DAA	Distance to area designated as an annual agriculture development zone *	
11	DTC	Distance to area designated as a forest protection and conservation zone *	
12	DTT	Distance to area designated as a hardwood/tree development zone *	

* Refers to regional spatial planning policy of East Java Province [101].

LCM has the ability to quantify the relationship between a set of spatial explanatory drivers and a particular land-use transition type. In this study, land-use transition types were not grouped into “sub-models”. LCM determined primary land-use change transitions by excluding those with extents less than 0.5% of the total area. Then, LCM used a multi-layer perceptron (MLP)—an extended artificial neural network, non-parametric approach to model the specified transition type [102]. The relative contribution of a driver to the R^2 value defines its importance to the transition type. The overall importance of a driver was measured by summing its importance rank over all land-use transition types.

2.4. Potential Land-Use Drivers from Questionnaires

Questionnaires were distributed to two groups of land-users covering agricultural land-users (farmers) and urban land-users (housing residents) during fieldwork in December 2018–March 2019. The questionnaires were distributed in 10 of the 13 cities, each

of which provided 20–40 land users/respondents (total N = 280). The questionnaire was close-ended in the form of multiple choices. The drivers covered in the questionnaires were based on relevant published literature [7,32,98–100] and are listed in Appendix A. Questionnaire forms explored the land-users' points of view about land-use change; and represented local features as opposed to the broader-scale biophysical environment, and therefore cannot account for the interaction of variables over space [100]. The relative importance of a variable of driver group was measured as the proportion of responses identifying the particular variable as important. In this context, we used a qualitative approach to quantify the importance for the household-level responses. We considered the degree of dominance as a measure of a variable's importance. Whenever the percentage of response for each variable exceeded or was equal to the threshold, we listed this as a perceived driver. The threshold was quantified as 100% divided by the number of variables within a driver group (set to 50% for a driver group with only 1 variable). On the other hand, the relative importance of a spatial driver (driver used in LCM), was assessed using the relative reduction of R^2 when a variable was excluded. All variables showing no or negligible R^2 reduction were considered relatively less important. To evaluate the agreement between LCM-selected drivers and land-user-perceived drivers, an agreement matrix adapted from [14,77] was used (Table 3).

Table 3. Classes of agreement of a driver in geospatial and land-users approach.

Level of Agreement	Ranked as Important in LCM	Perceived as Important in Questionnaire
High	Yes	Yes
Low	Yes	No
Low	No	Yes

3. Results

3.1. Land-Use Change Quantification

The land-use maps produced for 1995, 2005 and 2015 were considered good with overall accuracy higher than 80% when it was aggregated over the 11 land-use classes (81.7%, 76.9%, and 81.2%, respectively). The relatively low-class accuracy values for sand, and shrubs (average: 78.4, 77.8, see Appendix B) may be attributed to the large variability of plant types and compositions in shrubs and bushes. We combined dryland forest classes (2 and 3 in Table 1) and dryland agriculture classes (7 and 8 in Table 1) into only dryland forest and dryland agriculture. This led to increased overall kappa accuracies of 87.3%, 83.1%, and 83.0% for 1995, 2005, and 2015, respectively.

Figure 3 portrays the land-use in the BRB in 1995, 2005, and 2015 (detailed information is in Appendix C). Over the study period, in 1995 the BRB was clearly dominated by agricultural land-uses (dryland farming and rice-fields), accounting for 77% of the total area, which declined to 68% in 2015 (Figure 4A). A decline was also observed in most other land-use classes, with varying rates (Figure 4B). Dryland forest showed the largest decline rates followed by rice-fields. Built-up areas almost tripled in extent from 1995 to 2015 (7.1% to 19.9%). Shrub and bush coverage increased by 1.5% from 1995 to 2015. Forest loss was higher in the period 1995–2005 and slowed down in the period 2005–2015. As opposed to this, rice-field and dryland agricultural losses were higher in the period 2005–2015. Over these two decades, around 29% of the BRB landscape changed.

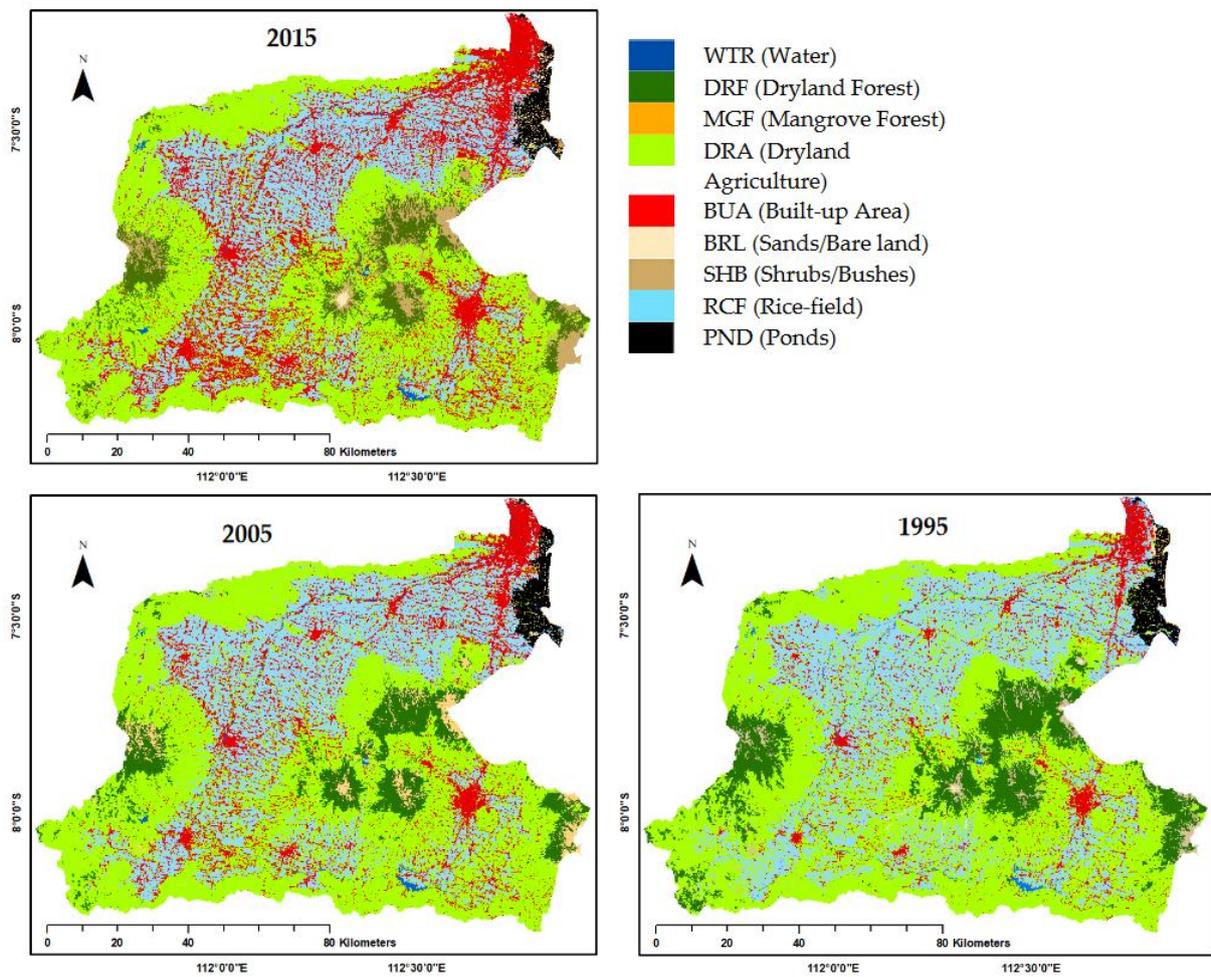


Figure 3. Land-use maps of Brantas River Basin in 1995, 2005, and 2015.

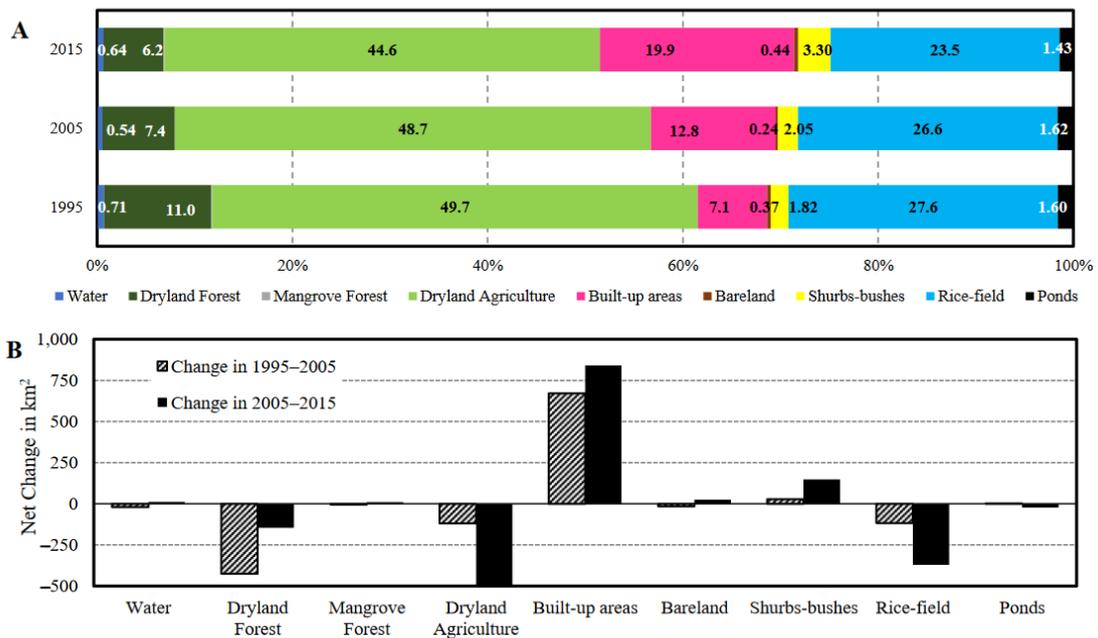


Figure 4. Comparison of changes over land-use classes by: (A) percentage of study area, (B) gains and losses of area in km².

The land-use changes in the BRB vary among cities (Figure 5). Urban expansion and agricultural decline occurred in all cities. The increases in built-up area ranged from 10% to 35%. A lower degree of urbanization (less than 15%) generally occurred in bigger cities than in smaller cities where agricultural land-uses are more evident. This might indicate bigger cities experience urban verticalization (leading to increasing population density without proportional increases in land-coverage).

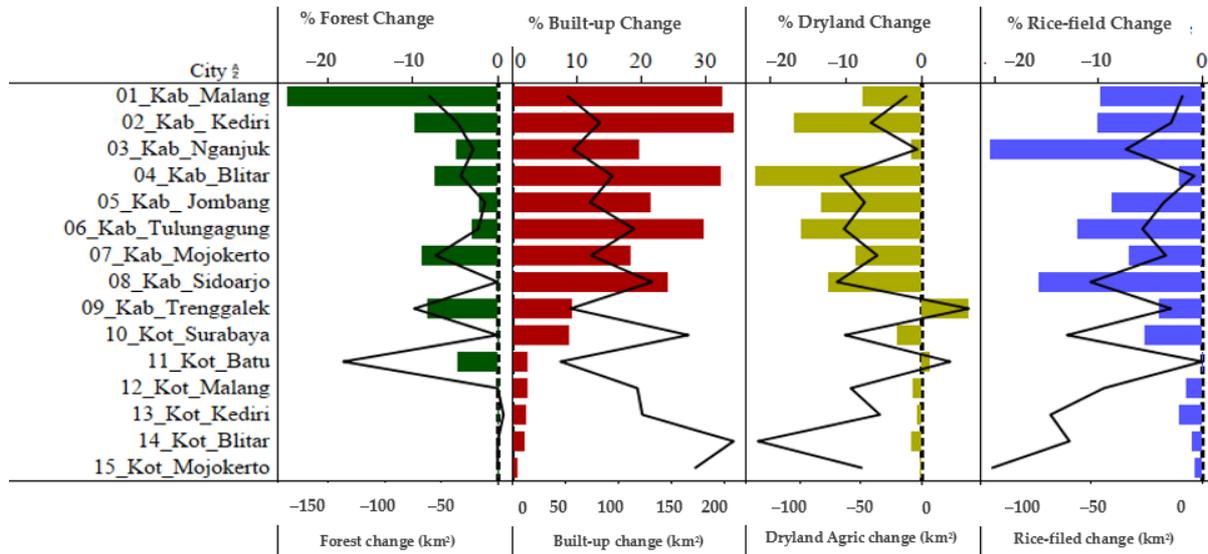


Figure 5. City-wise changes in land-use during 1995–2015. The black line is the change relative to the city’s size (%), and the bars are the magnitude of changes (km²). The cities are ordered based on their size.

Post-classification change analysis allows us to examine types of transition as well as the extents. Figure 6 shows that over the two periods the ten largest land-use transitions were relatively consistent. In the period 1995–2005, 413 km² of forest was converted to dryland agriculture. This extent dropped considerably in 2005–2015. Deforestation (including all land-use transitions from forest) and urbanization (all transitions to built-up areas) remain the largest transitions. Compared to rice-fields, dryland agriculture served as a bigger contributor to built-up areas. The most tangible transitions (>100 km²) are deforestation leading to shrubs and dryland agriculture, urbanization from rice-field and dryland farming loss, and the exchange from dryland farming to rice-fields and vice versa.

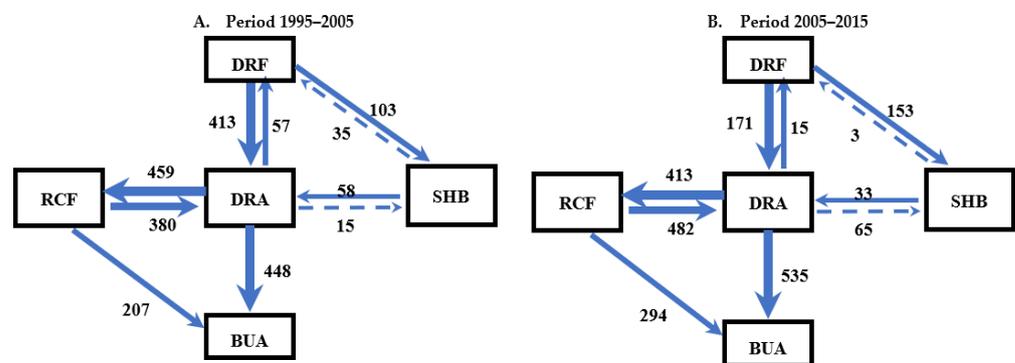


Figure 6. Primary land-use transitions and their magnitude (in km²) for period (A) 1995–2005, (B) 2005–2015, DRF: dryland forest, DRA: dryland agriculture, SHB: shrubs/bushes, RCF: rice-fields, BUA: built-up areas.

3.2. Land-Use Transition Spatial Patterns (Trend of Changes)

Figure 7 provides the spatial patterns of four major land-use transitions generated from the LCM in the periods 1995–2005 and 2005–2015. Figure 7 shows that the patterns of land-use transition were visually similar between the two periods, suggesting that the drivers of land-use changes did not change much. It is evident from comparing Figure 1 with Figure 7A,B,E,F that the hotspots of forest conversion are associated with mountain regions. Considering the values from the TSA raster, the period 1995–2005 showed intense deforestation in the Arjuno-Kelud, Ngliman, and Bromo-Semeru mountain complexes. This was indicated by the concentration of high positive values of Z (Equation (1)) up to 0.130 (yellow to red). In 2005–2015, forest loss lessened as shown by the lowering positive values (maximum positive values 0.081) and was mostly found in Arjuno-Kelud. The transition from dryland to shrubs/bushes was also focused on mountain regions. Given the important role of dryland forests as tropical biodiversity hotspots, the results in Figures 5–7 support the need for further investigations into changing biodiversity patterns in the region [78].

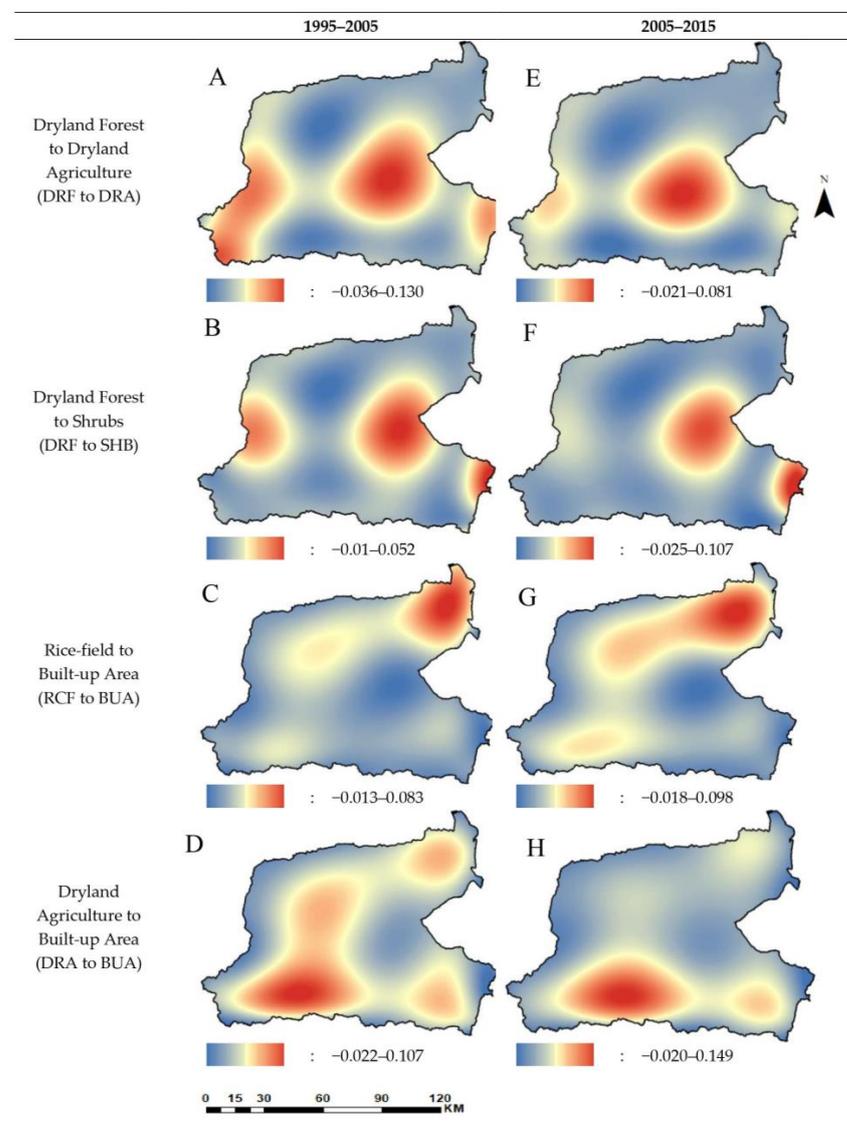


Figure 7. Spatial patterns of deforestation and urbanization for 1995–2005 (A–D) and 2005–2015 (E–H).

Spatial trends in land-use transition suggest that urbanization did not occur uniformly across the BRB. It was evident that maximum positive values of Z in the second period

increased from 0.083 to 0.098 for RCF to BUA and DRA to BUA, respectively. Spatially, the conversion of rice-fields to built-up areas was dominant in the northern part of the BRB, while dryland agricultural conversion was more intense in the middle and southern parts. While higher altitude areas exhibited forest loss, the lowland regions exhibited intense urbanization at the expense of rice-field and dryland farming. Urbanization of rice-field areas dominated in the northern lowlands, likely due to the industrialization of northern lowland cities, which has been evident over the last two decades due to government development policy. Urbanization of dryland farming areas was more evident in the middle to south-west BRB.

3.3. Potential Land-Use Drivers from Land Change Modeler

Table 4 lists LCM's performance in modeling the major transitions, and the importance ranks of the tested drivers. Overall, the model performances were good (higher than 0.8) for afforestation and deforestation processes. Urbanization from rice-fields was modeled with lower accuracy (0.64) compared to urbanization from dryland (0.8). This infers that this process of urbanization is relatively complex. This transition (RCF to BUA) might also be introduced by the lower accuracy land-use maps for rice-field class (average land-use class accuracies: 80.50–83.70, Appendix B).

Table 4. Relative importance of each driver for each land-use transition and model performance in explaining transitions.

Variable	Land-Use Transitions										Driver's Total Score * Rank	
	DRF	DRF	DRA	DRA	DRA	DRA	RCF	RCF	SHB	SHB		
	DRA	SHB	RCF	DRF	BUA	SHB	DRA	BUA	DRA	DRF		
Explanatory variable (driver)	DTR	4	2	5	4	1	4	2	2	2	2	28
	RFL	10	5	12	10	11	11	12	8	12	6	97
	DTC	9	11	6	6	6	7	11	3	5	4	68
	ELV	3	1	1	3	2	2	3	10	1	1	27
	SLP	11	9	11	11	3	8	8	9	11	11	92
	DTD	12	12	9	1	12	6	7	7	8	12	86
	DRD	5	3	3	5	5	1	1	5	3	3	34
	DEA	1	4	2	2	4	5	4	1	9	5	37
	DEB	2	8	8	7	9	3	10	4	7	10	68
	DAA	6	10	7	8	8	9	6	11	10	7	82
	DTC	7	7	4	9	7	10	9	12	4	9	78
	DTT	8	6	10	12	10	12	5	6	6	8	83
Accuracy rate	0.80	0.72	0.81	0.88	0.80	0.88	0.68	0.64	0.91	0.71		

* Drivers with lower scores signify more important drivers.

We acknowledge that errors could propagate from the land-use mapping to the land-use driver analysis. The lower performances of the land-use transition model were generally related to transitions involving rice and shrub classes. This may be affected by the accuracy of land-use map inputs. Appendix B shows that the mapping of rice-fields and shrubs has relatively low accuracy (producer and user accuracies of 82.6% and 83.7%), while Table 4 shows that the four land-use transitions with the lowest R^2 values (smaller than 0.75) are transitions that involve rice-field and shrubs. This implies that the accuracy of the land-use change modeling is controlling the accuracy of the transition model. Furthermore, there might be drivers affecting such transitions that cannot be spatially represented in the LCM platform. Socio-economic factors mostly operate at an individual scale and play a role in the family decision making process. Customs, family assets systems, living standards, capitals, poverty level, farming resilience, and personal perception, are types of factors influencing the decision-making process in land-use systems and often trigger the land-use change at individual level [14,103,104]. An example of how these factors work is exemplified by a household modeling of Deadman et al. [105] where a combination of

physical land characteristics and household behavior such as subsistence requirements, number of capitals, and labors determine the decision in land utilization.

The results show that the importance of the driver depends on the transition type. Overall, elevation, distance to roads and city, and future economy zonation plans were relatively the most influential variables as identified from their higher influence (low scores). Drivers affecting forest loss were generally associated with elevation and proximity to roads and economic centers. Terrain constraints such as extreme slopes, thin soil, and low fertility might impede forest encroachment and make forests unsuitable for farming, leaving it to develop shrubs or secondary growth forest. Reports indicate that the main cause of deforestation in the BRB is illegal logging [106–108].

3.4. Perceived Land-Use Change Drivers

The questionnaire responses suggest the drivers that operate at land-user level (Table 5). In the housing sector, the four biggest portions of variables perceived by respondents were water facilities, water availability, growing population, and access/location with a portion of responses of 97%, 95%, 60%, and 39% of total respondents, respectively. About 2% of farmer respondents converted farming land into housing also for the needs of growing families. The growing population in the BRB during 2005–2015 [82] appears to be closely linked to the built-up area expansion. More than 90% of responses included facility networks and water availability suggesting that these factors influence conversion of land to housing. The prevalence of road access and location in responses also signifies the economic factors behind housing development.

Table 5. Distribution of respondents' responses on factors affecting land-use change.

Source	Driver Group	Variables	Number	% *
Housing questionnaire respondents (N = 108)	Biophysical	Natural beauty (site quality)	21	19
		Natural water availability	105	97
		Slope	0	0
		Elevation	0	0
	Demography	Basic need/growing family members	65	60
	Economy	Investment (business)	17	16
		Big housing sales	10	9
		Price	23	21
	Infrastructure	Road access and location	42	39
		Distance to markets or school or workplace	5	5
		Facilities (communication and electricity)	103	95
	Policy and institutional	Safety/crime	18	17
		Understanding of spatial plan zonation	30	28
		Understanding of building and land tax responsibility	29	27
Agricultural questionnaire respondents (N = 193)	Biophysical	Drought or flood or diseases and disaster	61	32
		Infertile/unproductive/erosion	14	7
		Natural water availability	54	28
		Slope	0	0
		Elevation	0	0
	Culture	Social empowerment	75	39
	Land contract/customary land tenure system	14	7	

Table 5. Cont.

Source	Driver Group	Variables	Number	% *
Agricultural questionnaire respondents (N = 193)	Demography	Manpower availability and skills	12	6
		Converting farm for building a house (basic need)	3	2
	Economy	Funding for farming practices	7	4
		Needs of urgent huge cash	11	6
		Seeing neighbor success (business)	6	3
		High-cost land preparation and tillage	54	28
		Market price fluctuation/low price	157	81
		Access to buyers	4	2
		Loans and subsidies availability	101	52
	Infrastructure	Irrigation network	25	13
		Network availability for direct selling—ease of selling	52	27
	Policy and Institutional	Market guarantee	96	50
		Awareness of planning policy and land administration responsibility	54	28
	Technology	Production technology access and availability (i.e., seeds, fertilizers)	82	42
		Machinery application	105	54

* Relative to total respondent group (housing or agriculture).

Agriculture has long been a major livelihood for most people in the BRB. Farmers often change their plant types when facing less favorable conditions. Factors influencing farmers' decisions to change plant types (also decisions to leave land fallow) included market-related factors, farming expenses, individual economic ability, technology/infrastructure, and biophysical conditions. Manpower availability was also seen to contribute to farmland persistence. The net gain and loss analysis in Figure 4B showed the decline in agricultural land-uses, and East Java statistical data showed the decreasing manpower in this sector [83]. Among these perceived drivers, market factors were the most essential (81%), followed by technology—machinery applications (54%), loans and subsidies (52%), and market guarantee (50%). Biophysical factors such as disaster hazards, and water availability were perceived only by 32% and 28% of farmers as factors contributing to change. Interestingly, policy and institutional factors were regarded as the least important, featuring in only 28% of responses.

3.5. Agreement between LCM-Based Drivers and Questionnaire-Based Drivers

Table 6 lists the driver groups and corresponding variables that were identified as important by both the questionnaire and LCM-based analysis. Natural hazards, rainfall variability, and accessibility in terms of locations, road network, and distance to farm were variables with a high degree of agreement. Biophysical variables were more dominant in the results of geospatial modeling, while anthropogenic variables such as economy, culture, technology, policy, and demography were only evident as land-user perceptions. These results allow inference about the degree of human–nature interaction. For example, from the geospatial approach, slope, elevation, and rainfall were statistically significant. Yet, only rainfall was perceived as an important driver. This implies that agricultural changes in BRB were more influenced by internal anthropogenic factors such as technology and market forces, and less by biophysical conditions. Due to the restriction of the questionnaire method to agricultural and urban land-users who were willing to participate, this method provides limited insight into drivers of encroachment into legally protected areas and changes from one public land use to another. For these questions, different approaches such as the use of participatory mapping, needs of informant connectors, indirect interviews, and focus group discussions would be required [84–86]. The results in Tables 5 and 6

should be interpreted in context, predominant in the BRB, of legal transitions controlled by private landowners.

Table 6. Agreement of inferred drivers from questionnaires and geo-statistical model.

Driver Group	Variable	Perceived Drivers—Questionnaire	Ranked Driver—LCM	LCM Drivers	Agreement (Questionnaire—LCM)
Biophysical	Drought or flood or diseases or disaster	Yes	NA	DTD	Low
	Infertile/unproductive/erosion	No	No	DAA	High
	Natural water availability	Yes	No	RFL	Low
	Slope	No	No	SLP	High
	Elevation	No	Yes	ELV	Low
Culture	Social empowerment	No	NA	-	Low
	Land contract/customary land tenure system	No	NA	-	Low
Demography	Manpower availability and skills	No	NA	-	Low
	Converting farm for building a house (basic need)	No	NA	-	Low
Economy	Funding for farming practices	No	NA	-	Low
	Needs of urgent huge cash	No	NA	-	Low
	Seeing neighbor success (business)	No	NA	-	Low
	High-cost land preparation and tillage	Yes	NA	-	Low
	Market price fluctuation/low price	Yes	NA	-	Low
	Access to buyers	No	No	DEA, DEB, DTR, DTC	High
	Loans and subsidies availability	Yes	NA	-	Low
	Investment (business)	No	NA	-	Low
Infrastructure	Big housing sales	No	NA	-	Low
	Price	No	NA	-	Low
	Irrigation network	No	NA	-	Low
Policy and institutional	Network availability for direct selling—ease of selling	No	NA	-	Low
	Distance to markets or school or workplace (road access)	No	Yes	DTR	Low
	Market guarantee	No	NA	-	Low
Technology	Awareness of planning policy and land administration responsibility	No	No	DEA, DEB, DTF, DTT, DRD	High
	Safety/crime	No	NA	-	Low
	Production technology access and availability (i.e., seeds, fertilizers)	No	NA	-	Low
	Machinery application	Yes	NA	-	Low

Remarks: italic: drivers identified from the housing sector not available in the agricultural sector, NA: variable that cannot be represented in spatial data.

4. Discussion

4.1. Land-Use Changes in the Brantas River Basin

Our results demonstrate how satellite image-based land use mapping was useful for presenting the 20-year dynamics of land-use changes in BRB. Post-classification change detection results from two land-use maps showed the snapshots of land-use changes in

two periods, and thus identified the predominant land-use transitions in BRB. Massive urbanization has marked the changing landscape of the BRB from 1995 to 2015. Similar to other developing regions, the growing industrialization and economic zonation has led to urbanization [109] with, in this case, compensatory losses of rice-fields and dryland agriculture (Figure 6A,B). Post-classification change detection results show that urbanization appears to be the most stable process, meaning that once developed, there has been no or little chance to transform to other land-uses [90]. Dryland conversion to settlement occurred more intensely than rice-field conversion suggesting that rice-field conversion is less practicable. One plausible cause is that rice-fields in the BRB are mostly irrigated and the land price for irrigated areas is higher than for non-irrigated lands. In addition, current agricultural laws restrict conversion of irrigated lands (rice-fields) to other land-uses. This confirms the role of the socio-economic context in modifying the BRB landscape.

The spatial pattern of major land-use transitions in BRB highlights potential land use management problems. Both periods (1995–2005 and 2005–2015) were marked with forest conversion in mountain areas, massive rice conversion in the northern lowlands, and dryland farming loss mostly in the middle and southern lowlands. Considering that the forest concentration is at higher altitudes, the loss of forest would have hydrological consequences for lower regions with respect to intensified degradation. Increasing consequences in upper regions such as springs drying up, floods, and soil erosion have been increasingly reported [41]. Urban intensification in the lower BRB might exacerbate these consequences due to the increasing population exposed to floods, droughts, and poor-quality water supplies. Combating deforestation has been challenging and complex due to the socio-political context in Indonesia, such as enactment of local autonomy law [110].

4.2. Land-Use Transitions and Land-Use Patterns

At individual land-user level, the drivers are often related to external factors such as policy, socio-economic factors, and biophysical land conditions [27]. At this level, land-use change represents decision-making by land-users. Understanding these factors is essential in tropical developing regions as the transformation occurring in this level often leads to serious threats to sustainability. Therefore, besides quantitative modeling, a qualitative approach is commonly employed for investigating land-use change drivers [12,28].

Responses from local farmers in BRB inferred that agricultural land-use changes are not always related in simple ways to biophysical properties but also involve interactions of factors including cultural and socio-economic dimensions. For example, a study in upland Bromo (in south-eastern BRB) showed that improved roads led to better agricultural product delivery, which eventually triggered local people to cut down trees and convert to agriculture [111]. In this regard, roads appear to play a similar role in supporting continuing deforestation. It is important to note that agriculture remains a marginal sector for most farmers in BRB because most farmers have a small income (65% have an income < \$USD 200). Respondents show a high dependence on the compilers not only for easy selling but also for loans, leaving fewer options for managing their lands. Compilers here refers to people buying farmers' harvests on farm, often before harvest time at a lower than market price (this practice is termed "ijon"). Traditionally, compilers serve not only as buyers but also loan providers for farmers. In many cases, market prices can influence land-use conversions yet in the BRB this is not always the case. Around 25% of responses came from farmers stricken by minimum capital (low income, small land size, low education, lack of skills and experience) (Table 5), which to some degree explains why farmers may opt to keep growing the same crops. Efforts to convert land-use have implied that the processes are complex and involve several stages as outlined by [112]. Considering this, conversion of forest to new agricultural areas in the BRB might be associated with the easiest pathway to higher profits. The absence of alternatives to revenue generation has been acknowledged as a land degradation factor [113].

Information derived from the land-user questionnaires proved to be rich and detailed, qualitative, context-rich information able to be used to interpret land use management.

These data were difficult to convert to objective measurements. With regards to the factors affecting the land users' decisions, it is generally accepted that drivers at the individual level can vary and be unique [107,114,115]. This variability and uniqueness lead to challenges in designing questionnaires that comprehensively elucidate drivers—locally pertinent drivers may be missed.

4.3. Implication for Land-Use Change Modeling and Driver Assessment

LCM is a land-use model whose inputs are derived from varying geospatial datasets. For successful modeling, the accuracy of land-use map inputs is essential, and for this a high degree of land-use-map accuracy is preferable, with an 85% kappa accuracy sometimes used as a target [31]. Achieving high accuracy over areas with many land-use classes, such as the BRB, can be challenging. Generally, accuracy decreases with an increasing number of land-use classes [94]. This study utilized nine land-use classes with kappa accuracies of 87%, 83%, and 83% for the three studied years. Most previous LCM studies employed smaller numbers of land-use classes yet presented lower or similar LCM sub-model accuracies (39–91%) [24,116,117]. Despite the achievement of this study, there may be scope for better accuracy by optimizing the OBIA-mapping, which relied upon subjective selection of the ruleset.

Using both the questionnaires and geospatial modeling provided insight about the consistency and inconsistency between approaches in identifying drivers. Table 6, which only lists variables that were represented in both approaches, shows that biophysical variables were identified more commonly in the geospatial approach, while socio-economic and institutional variables were identified more commonly in the qualitative approach. One thing to note is that the PCA-based data reduction excluded some variables that were collinear with included variables from the geospatial analysis, so additional consistencies may be implicit. This might infer that variables which are significant at the regional level, might not be significant at the land-user level. Furthermore, as previously discussed, consistencies may be excluded due to the limitations of the geospatial data sets. We therefore acknowledge that the approach taken to understand the land-use change process is influenced by data and methodological limitations, in particular the challenge of integrating qualitative local-scale and geospatial regional-scale data sets requires further research. Decadal medium satellite image-based assessment cannot precisely outline the mechanism or process of each land-use trajectory, and further work is needed, that involves higher temporal resolution assessments and actual phenology characteristics.

4.4. Limitations of the Study

While the study has provided insight into the historic behavior of the landscape and drivers of changes, there are some limitations that are acknowledged and should be considered for future work. The first is that the study accommodated only the period 1995–2015 and excluded the more recent years, due to the lack of a complete decade. During these years, the BRB landscape is likely to have undergone and continue to undergo changes that may extend understanding of patterns and drivers of change and allow assessment of the medium-term impact of policies. Soon there will be opportunity to gain this further insight by updating the analysis to 2015–2025. There is also an opportunity to use our new understanding to project land-use change into the near future, 2025–2035, under policy scenarios, which we address in a separate work. From the geospatial modeling perspective, one limitation in this study's approach is the decision to use regional-level land-use analysis. While this approach is proven to be computationally efficient, specific local land-uses such as airports and local sand mining could not be accounted for despite their known influence on the landscape. A future study with a more detailed land-use class scheme would offer opportunity to examine this issue.

The scale of the geospatial data also presents limitations. For example, in this study, district level population data (the only population data available for this study) does not represent demographic variability at a lower (village) level. Another challenge is whether, and how meaningfully, cultural variables can be represented as geospatial data layers.

Factors such as social interaction and traditional customary land regulations cannot be easily represented in spatial data format. Land conflict, and the associated disagreements on zonation, lack of public access to data, and undocumented transitions from public to private land, create additional challenges in spatial data analysis. For example, there have been reports of land utilization for agriculture in national parks in Bromo Tengger Semeru (BTS) national park and Tahura Suryo (Suryo Grand Forest), which are supported by our visual assessment of high-resolution data from Google Earth. As a result, what was represented by legal spatial data (acknowledged park boundaries) might not always correspond with actual data (presence of farming gardens within park boundaries). The data availability limitations and complexity of specific factors affecting encroachment into protected areas are significant obstacles to a comprehensive understanding of land-use change drivers in the BRB and comparable regions and are perhaps the main limitation of this work. We recommend that, should the necessary data on land status become available, the research is extended to include this, and that complementary research attempts to understand the factors governing encroachment.

5. Conclusions

Over two decades (1995–2015), the BRB landscape has been marked by a reduction in vegetated areas. Forest area reduced from 1301 km² to 730 km² (11% to 6.2% of the total BRB area) and agricultural land-uses lessened from 9150 km² to 8048 km² (77% to 68%). A tripling in built-up areas signifies a rapidly urbanizing landscape. Major land-use transitions include forest conversion to dryland agriculture and agricultural area conversion to built-up area. The first phase of deforestation in the BRB is agricultural expansion, followed by conversion to built-up areas, which is nearly irreversible.

The biophysical and socio-economic drivers included in the geospatial modeling explain to a high degree the land-use transitions in the BRB over 1995–2015, which were mainly elevation, presence of roads, and access to urban centers and economic development centers. At land-user levels, the drivers are more complex and inter-related. The household and land-user questionnaires reveal (although incompletely) drivers that are localized and individualized. The questionnaire results were consistent with the geospatial modeling regarding the importance of rainfall, elevation, and access to economic centers, and thus provide high confidence about these results. The larger number of inconsistencies between the approaches set challenges for improved representation of cultural, demographic, and economic factors in geospatial modeling.

Author Contributions: Conceptualization, Bagus Setiabudi Wiwoho, Stuart Phinn, and Neil McIntyre; methodology, Bagus Setiabudi Wiwoho; software, Bagus Setiabudi Wiwoho; validation, Bagus Setiabudi Wiwoho; formal analysis, Bagus Setiabudi Wiwoho; writing—original draft preparation, Bagus Setiabudi Wiwoho; writing—review & editing, Stuart Phinn and Neil McIntyre; visualization, Bagus Setiabudi Wiwoho; supervision, Stuart Phinn and Neil McIntyre; funding acquisition, Bagus Setiabudi Wiwoho. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by LPDP PhD scholarship grant BUDI-LN, contract number 201701220110184.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found from the URL provided in the methods section.

Acknowledgments: In this section, you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. List of Drivers Implemented in Land-Users Questionnaire.

Sector	Driver Group	Variables	Reference
Agriculture	Biophysical	Drought or flood or diseases	[118]
		Infertile/unproductive/erosion	[26,119]
		Natural water availability	[26,120]
	Culture	Social empowerment	[15,121]
		Land contract/customary land tenure system	[17,32]
	Demography/ population	Manpower availability	[26]
		Growing family members	[26]
	Economy	Funding for farming practices	[15,32]
		Needs of urgent huge cash	[122]
		Seeing peer/neighbor success (business)	[121]
High-cost land preparation and tillage		[15]	
Market price fluctuation/low price		[23]	
Access to buyers		[123]	
Infrastructure	Loans and subsidies availability	[15]	
	Irrigation network	[7,124]	
Policy/ institutional	Network availability for direct selling—ease of selling	[32]	
	Market guarantee	[125]	
	Awareness to planning policy and land administration responsibility	[15]	
Technology	Agricultural technologies access and availability (i.e., seeds, fertilizers)	[17,126]	
	Applying machineries	[126]	
Housing	Biophysical	Natural beauty (site quality)	[124,127]
		Natural water availability	[120,127]
	Demography/ population	Basic need/growing family members	[128]
	Economy	Investment (business)	[129,130]
		Land/Housing Price	[15,128]
	Infrastructure	Road access and location	[26]
		Distance to markets or school or workplace	[26]
Facilities (communication and electricity)		[15,127]	
Policy/ institutional	Safety/crime	[127]	
	Understanding to spatial plan zonation	[131]	
	Understanding to tax and land regulation	[130]	

Appendix B

Table A2. Accuracy Assessment for Classified Images of BRB 1995, 2005, and 2015.

Land-Use	Code	1995			2005			2015		
		PA (%)	UA (%)	Average	PA (%)	UA (%)	Average	PA (%)	UA (%)	Average
Water	WTR	92.31	85.71	89.01	na*	na	na	96.36	98.15	97.26
Dryland forest	DRF	100.00	100.00	100.00	100.00	100.00	100.00	100.00	86.11	93.06
Mangrove forest	MGF	86.59	94.04	90.32	na	na	na	89.36	95.89	92.63
Dryland agriculture	DRA	93.26	93.99	93.63	90.68	88.43	89.56	91.89	86.11	89.00

Table A2. Cont.

Land-Use	Code	1995			2005			2015		
		PA (%)	UA (%)	Average	PA (%)	UA (%)	Average	PA (%)	UA (%)	Average
Built-up areas	BUA	86.84	91.67	89.26	89.13	93.18	91.16	81.89	87.83	84.86
Sand/soil (bareland)	PST	89.47	85.00	87.24	100.00	100.00	100.00	89.29	67.57	78.43
Shrubs and bushes	SMB	82.61	82.61	82.61	100.00	100.00	100.00	82.61	73.08	77.85
Rice	SWH	93.33	82.35	87.84	83.10	84.29	83.70	77.34	83.66	80.50
Ponds	TBK	96.15	96.15	96.15	100.00	100.00	100.00	92.68	97.44	95.06
Overall accuracy (%)			91.13			88.84			87.33	
Kappa accuracy (%)			87.06			83.01			83.1	
Sample size			823			251			1776	

* No aerial photos used that have water and mangrove forest in the scene.

Appendix C

Table A3. Land-Use Change Matrix of BRB for Period 1995–2004 and 2005–2015.

LULC 1995 (km ²)	LULC 2005 (km ²)								
	WTR	DRF	MGF	DRA	BUA	BRL	SHB	RCF	PND
Water (WTR)	49.38	0.02	0.49	11.76	5.46	0.65	0.00	12.35	3.79
Dryland forest (DRF)	0.26	781.95	0.00	413.20	0.78	0.44	103.38	1.85	0.00
Mangrove forest (MGF)	0.46	0.00	0.98	0.66	0.18	1.68	0.00	0.15	3.61
Dryland agriculture (DRA)	7.24	57.69	0.22	4889.48	448.67	5.51	14.48	459.63	3.44
Built-up areas (BUA)	0.00	0.00	0.00	0.00	841.64	0.00	0.00	0.00	0.00
Bareland (BRL)	1.02	1.05	0.42	10.17	5.18	9.42	5.16	4.35	6.44
Shrubs and bushes (SHB)	0.05	35.84	0.00	58.58	0.36	0.18	119.66	0.37	0.00
Rice-field (RCF)	3.48	0.27	0.00	380.85	207.77	2.55	0.17	2666.18	2.55
Ponds (PND)	2.12	0.02	0.94	1.69	3.13	7.40	0.00	1.69	171.82
LULC 2005 (km ²)	LULC 2015 (km ²)								
	WTR	DRF	MGF	DRA	BUA	BRL	SHB	RCF	PND
Water (WTR)	49.75	0.06	1.44	3.92	2.08	0.45	0.04	5.25	1.01
Dryland forest (DRF)	0.13	546.47	0.00	171.05	1.19	3.29	153.85	0.86	0.00
Mangrove forest (MGF)	0.17	0.00	2.11	0.00	0.00	0.42	0.00	0.02	0.32
Dryland agriculture (DRA)	12.57	151.53	1.18	4579.72	535.10	6.44	65.68	413.23	0.95
Built-up areas (BUA)	0.00	0.00	0.00	0.00	1513.16	0.00	0.00	0.00	0.00
Bareland (BRL)	0.27	0.22	2.41	3.03	4.10	8.43	0.63	2.77	5.97
Shrubs and bushes (SHB)	0.02	31.24	0.00	33.12	0.06	8.71	169.50	0.20	0.00
Rice-field (RCF)	11.73	1.17	0.15	482.29	294.31	5.60	0.27	2346.32	4.73
Ponds (PND)	1.13	0.00	5.55	0.37	3.70	18.70	0.00	6.17	156.05

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