

Article

Deploying the Total Operating Characteristic to Assess the Relationship between Land Cover Change and Land Surface Temperature in Abeokuta South, Nigeria

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Abstract: Urbanization affects land cover and a region's prevailing land surface temperature (LST). As a result, understanding the effects of urbanization on LST and land cover change is critical for effectively planning, managing, and monitoring urban development and undesired LST change. This paper, therefore, examines the relationship between the change in four land cover categories and LST during 1987–2004 and 2004–2021. Our approach uses the Total Operating Characteristic (TOC) to study the relationship between LST change and the losses and gains in four land cover categories: infrastructure, vegetation, water, and bare land in Abeokuta South, Nigeria. We derived the land cover and LST dataset from satellite imagery at time points 1987, 2004, and 2021. Our results show that most of the vegetation in the study area transitions to bare land and infrastructure during both time intervals, while most of the bare areas transition to infrastructure and vegetation. Furthermore, the TOC analysis shows vegetation loss, gain in infrastructure, and bare land occurs more intensively at segments between increased thresholds of LST values during both time intervals. Conversely, vegetation gain, infrastructure, and bare land loss occur more intensively at segments between decreased LST values. The methods discussed herein can reveal important insights and stimulate the needed conversation concerning the effective planning, managing, and monitoring of urban development and undesired LST change.

Keywords: land change; land cover; urban; TOC; vegetation; temperature



Citation: Bilintoh, T.M.; Ishola, J.I.; Akansobe, A. Deploying the Total Operating Characteristic to Assess the Relationship between Land Cover Change and Land Surface Temperature in Abeokuta South, Nigeria. *Land* **2022**, *11*, 1830. <https://doi.org/10.3390/land11101830>

Academic Editors: Zobaidul Kabir, Salim Momtaz, Mahfuz Kabir and Mashura Shammi

Received: 2 September 2022

Accepted: 16 October 2022

Published: 18 October 2022

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1. Introduction

Land cover change stemming from urbanization often results in a change in land surface temperature (LST)—a phenomenon many scientists have attributed to increased population and migration [1,2]. The United Nations estimates that the global population will reach 8.5 billion, 9.7 billion, and 11.2 billion by 2030, 2050, and 2100 respectively [3]. Feeley and Silman [4] and Tian et al. [5] have argued that population increase occurs largely in tandem with land cover change. Many studies concerning the relationship between population change and urbanization reveal that anthropogenic activities often convert vegetation and open spaces into infrastructure developments, such as housing units [5–7]. With such impervious surfaces, urban areas often experience increased solar radiation absorption and higher thermal conductivity with the tendency to release stored heat during the day or night [8]. These solar radiations may impact global climate change and cause heat-related diseases such as heat exhaustion, heat stroke, and skin cancer [9].

An unprecedented proliferation of remotely sensed data has led to an increase in literature on the relationship between LST and land cover categories such as vegetation. For instance, [10] used remotely sensed data to examine the relationship between LST, NDVI, and six land cover categories in Medan City, North Sumatera Province. Their study revealed a negative correlation between LST and NDVI with higher temperatures occurring in urban

areas. Similarly, [11] examined the relationship between LST, Normalized Difference Moisture Index, and land cover categories during varying times of the day in the Henan province of China. They concluded that an increase in LST is often associated with urban areas. Although different, these approaches all have some aspects in common, including land cover maps and LST maps derived from satellite imagery. A perusal of their approach reveals that they examined the relationship between LST and the land cover categories at each time point instead of during a time interval (a time interval is a duration between two time points). It is important to examine the relationship between LST land cover change during a time interval or multiple time intervals because transitions among land cover categories result in land change, such as urbanization, which might impact LST change. Thus, knowing which category's change affects another category reveals the processes that influence land cover change and, by extension, change in LST.

Other studies have examined the relationship between land cover change derived from the transitional matrix during two time points and LST [5,6,10–14]. The general approach in these studies is to compute losses and gains from the land cover maps and interpret the losses and gains in isolation from the changes in LST, thus treating the land cover change as an isolated analysis. These studies then create scatter plots and compute matrices such as the coefficient of determination (R^2) to examine the relationship between LST and land cover categories at each time point, thus missing important information concerning the direct relationship between changes among land cover categories and LST. A key problem associated with using the scatter plots and R^2 to examine the relationship between land cover and LST change is the failure to reveal or communicate certain salient details. For example, the size of the spatial extent under consideration, the intensities at which a category's losses and gains occur in relation to LST, and the size of the category's losses and gains—are important details that cannot be gleaned from the sole reliance on the usage of scatter plots and R^2 .

The Total Operating Characteristic (TOC) developed by [15] and subsequently modified by [16] has desirable features that can address the main problem described in the previous paragraph. The TOC is a statistical method that measures the relationship between the thresholds of a ranked index variable and a binary variable. Four entries from a contingency table create the TOC: hits, misses, false alarms, and correct rejections. These four entries communicate critical information, such as the size of the spatial extent and the size of the presence of the binary variable in the spatial extent. The TOC also computes a metric called the area under the curve (AUC), analogous to the R^2 . Several studies have employed the use of the TOC [14–19]. However, despite the popularity of TOC in land change studies, no study has employed the TOC to examine the relationship between land change and LST.

Thus, this paper uses the TOC to examine the relationship between LST and the losses and gains in four land cover categories during two time intervals. Our approach is unique because we examine (1) the direct relationship between losses and gains of each category and change in LST, (2) the threshold of LST change associated with each category's losses and gains, and (3) the intensity at which a category's losses and gains occur with relation to change in LST.

2. Materials and Methods

2.1. Study Region

Abeokuta is the state capital of Ogun State, located in southwest Nigeria (at 7.1608 N and 3.3483 E latitude and longitude). Abeokuta is estimated to be approximately 70 km north of Lagos, and its environs encompass approximately 212 square kilometers. It had a population of 250,295 between 2006 and 2021 [20]. The average annual rainfall is 963 mm, and the temperature is normally between 26 and 28 degrees Celsius [21]. Basement rock in the north and sedimentary strata from the eastern Dahomey basin in the south form the geology of the area.

Abeokuta became the administrative capital of Ogun state in 1976. Subsequently, Abeokuta has experienced rapid urban growth and a surge in socio-economic, political, and cultural activities revealed in industrial development, growing land use, and physical development [1]. It is located in Lagos-Ibadan metropolitan area and is part of the broader metropolitan economic hub (see Figure 1). The advantageous location, coupled with a wide set of local resources, rapid population expansion, and improved political standing, has resulted in a flurry of economic activity.

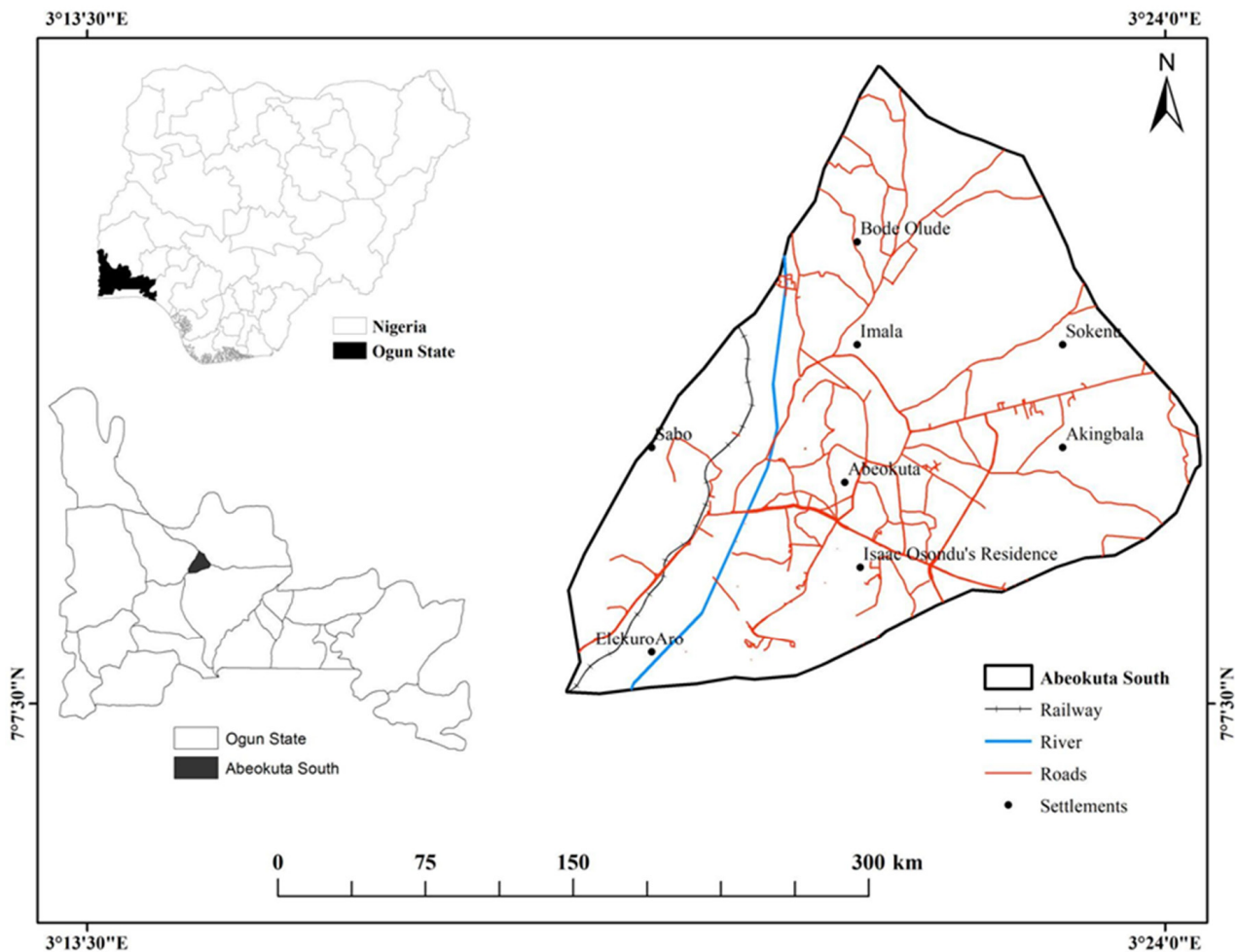


Figure 1. Map of the study area.

2.2. Data Sources and Processing Level 1

We sourced Landsat data spanning 1998, 2004, and 2021 from Earth Explorer (<https://earthexplorer.usgs.gov>) on 21 January 2021. We achieved this by using the boundary of the study area as a guide to specifying the region needed for the analysis. Table 1 provides detailed information concerning the specific Landsat sensors we employed as data sources: The Thematic Mapper TM, Enhanced Thematic Mapper Plus (ETM+), and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) onboard Landsat 5, Landsat 7, and Landsat 8, respectively, were used for creating Land cover maps and LST raster files.

Table 1. Data description.

S/n	Sensor	Resolution	Year
1	Landsat 5	30 m	1987
2	Landsat 7	30 m	2004
3	Landsat 8	30 m	2021

Next, we preprocessed all the raster files using the Semi-Automatic Classification Plugin (SCP) within the QGIS 3.26.3 environment. The SCP allows users to derive LST and conduct preprocessing of satellite images. We took advantage of this capability to obtain preprocessed and LST raster files from the Landsat data. Equations (1) and (2) show how the SCP computes LST from Landsat sensors. Readers can obtain detailed information concerning the SCP and Equations (1) and (2) from [22]. After obtaining the preprocessed raster files for each time point, we used the SCP Plugin to derive land cover maps. Table 2 provides the names of the land cover categories along with the definition of each category. Finally, we conducted error assessments for each land cover map. We obtained overall accuracies (kappa coefficients), which we report as follows: 86.5%, 0.81%, and 0.81%, corresponding to 1987, 2004, and 2021. Despite creating the land cover maps in QGIS, we reformatted the maps in TerrSet.

$$T_B = K_2 / \ln[(K_1 / L_\lambda) + 1] \quad (1)$$

where:

K_1 = Band-specific thermal conversion constant of 671.62, 607.76, and 666.09 for Landsat 4, 5 and 7 (in watts/meter squared μm)

K_2 = Band-specific thermal conversion constant of 1284.30, 1260.56, and 1282.71 for Landsat 4, Landsat 5, and Landsat 7 (in kelvin). For Landsat 8, the K_1 and K_2 values are provided in the image metadata file

L_λ is the Spectral Radiance at the sensor's aperture, measured in watts/(meter squared μm).

$$T = T_B / [1 + (\lambda * T_B / c_2) * \ln(e)] \quad (2)$$

where:

λ = wavelength of emitted radiance

$c_2 = h * c / s = 1.4388 \times 10^{-2} \text{ m K}$

h = Planck's constant = $6.626 \times 10^{-34} \text{ J s}$

s = Boltzmann constant = $1.38 \times 10^{-23} \text{ J/K}$

c = velocity of light = $2.998 \times 10^8 \text{ m/s}$

Table 2. Description of land cover classes.

Land Cover	Description
Vegetation	Areas predominantly covered by different tree species with high-density continuous canopy, areas that were disturbed by fires and/or logging, and forest resulting from natural regrowth.
Water	Artificial lakes, where aquaculture and/or salt production activities dominate.
Bare land	Any open space without dominant vegetation and infrastructural development.
Infrastructure	An area that is non-vegetated which includes roads, highways and constructions.

2.3. Data Sources and Processing Level 2

The purpose of the second level of data processing is to create input data for the TOC software. First, we converted the maps in Figure 2a,b into binary raster files. The binary raster files for Figure 2a use 1 to denote the presence of the loss of a category and 0 to denote the absence of loss. Similarly, Figure 2b uses 1 to denote the presence of the gain of a category and 0 to denote the absence of gains of the category. Creating the binary maps required that we split Figure 2a,b into each category's losses and gains and, subsequently, classify the losses and gains. Next, we computed the change in LST during each time interval. There can be only two time intervals since we have three time points. We computed LST for the two time intervals by subtracting (1) the LST map at 1987 from

the LST map at 2004 and (2) the LST map at 2004 from the LST map at 2021. The results from computing LST change showed three categories of change negative (decrease in LST), positive (increase in LST), and 0 (no change in LST). Figure 3 shows the results for the changes in LST during both time intervals.

Finally, we use the TOC curve generator to generate curves showing the relationship between each binary map and the changes in LST. The software requires three inputs: binary data, continuous data, and a mask. In this study, the binary data is the raster files of the binary losses and gains in the land cover categories, while the raster files of LST change are the continuous variable. A raster file with all the pixels within the study area set to a value of 1 served as the mask.

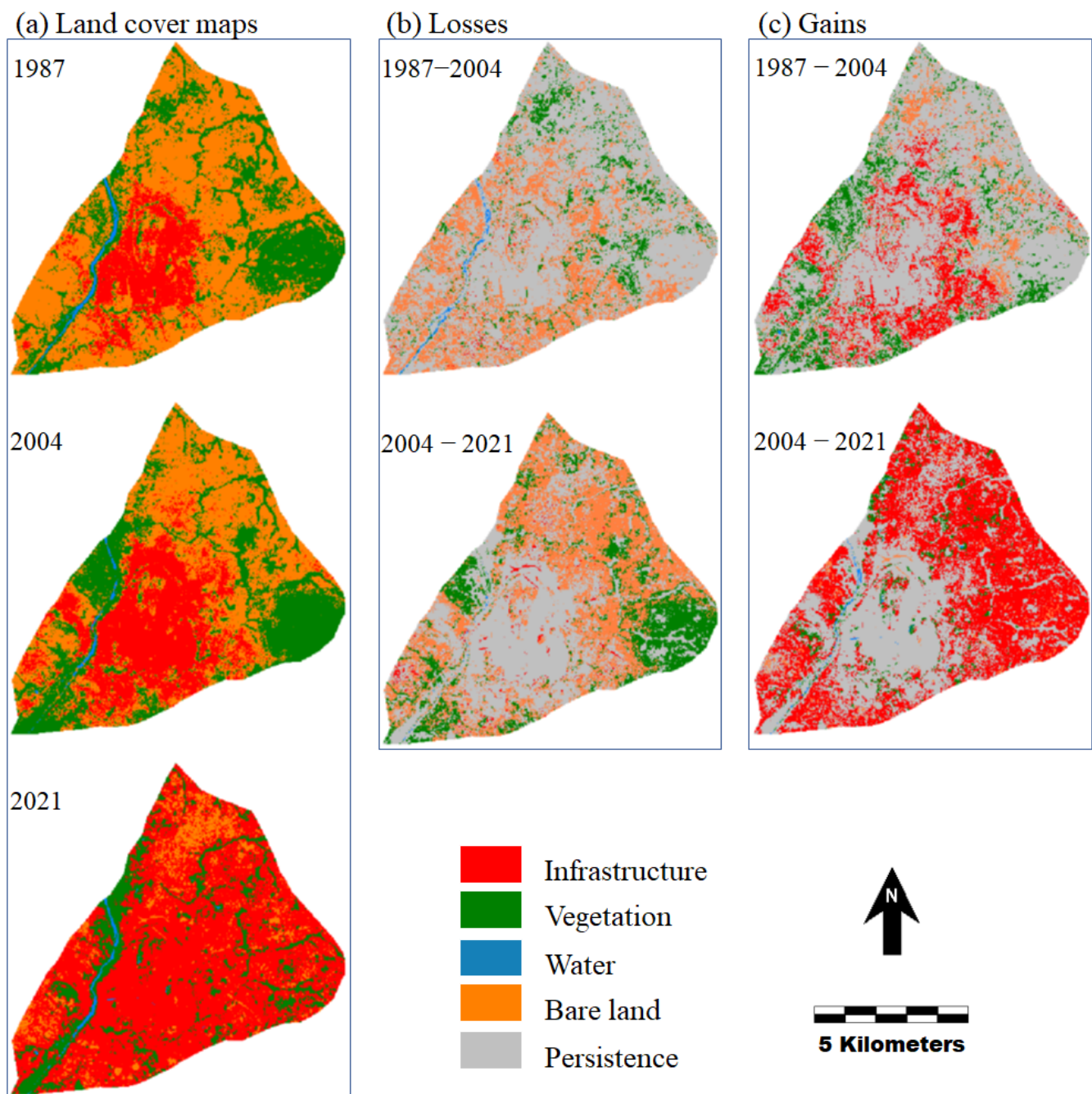


Figure 2. Land cover maps at time points and during time intervals.

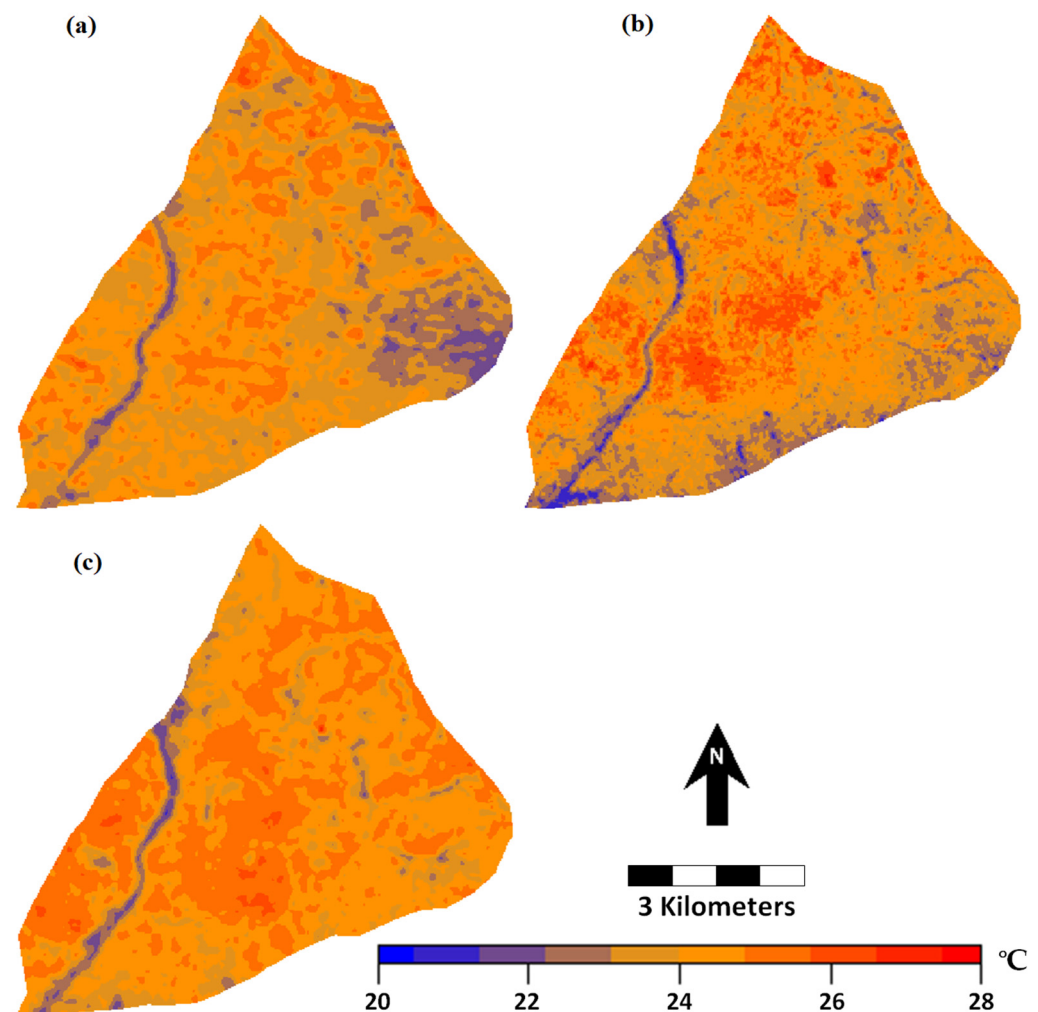


Figure 3. (a) 1987 LST map, (b) 2004 LST map, and (c) 2021 LST map.

3. Results

LST differences between 1987–2004 and 2004–2021 range between about -4 and 4 °C (see Figure 4). The maps of LST differences reveal that the high values in LST increase occur in the central part of the study area and areas with previous vegetation cover during the first time interval. During the second time interval, increased LST occurs mostly in areas with previous vegetation cover compared to areas with infrastructure. Decreased LST occurs in areas with gains and persistence in vegetation and water during the first time interval. We observe a similar pattern for vegetation and the persistence of infrastructure during the first time interval.

Figure 5 is analogous to the transition matrix. Moving from left to right (rows) reveals the sizes of land cover categories at the beginning time point while moving from top to bottom (columns) reveals the sizes of land cover categories at the second time point. In addition, the last row and last columns show each category's gross losses and gains during a time interval. Figure 4 shows that infrastructure and vegetation lose the most to bare land during the first time interval. Water loses the most to vegetation while bare land loses the most to infrastructure. The last column shows that infrastructure gained the most during the first time interval due to bare land transitioning to infrastructure. The transition pattern of losses in infrastructure, water, and bare land during the second time interval is similar to what we observed during the first time interval. Conversely, most of vegetation's losses during the second time interval are attributable to a transition from vegetation to infrastructure. Infrastructure gained the most from bare land and vegetation during the second time interval, while vegetation gained the most from bare land during the second

time interval. Water and bare land gained the most from vegetation during the second time interval. Overall, bare land lost the most during both time intervals, followed by vegetation; while infrastructure gained the most. It is worth noting that the sizes of the gross loss of vegetation and bare land increased from the first time interval to the second time interval. Similarly, the gross gain of infrastructure increased from the first time interval to the second time interval.

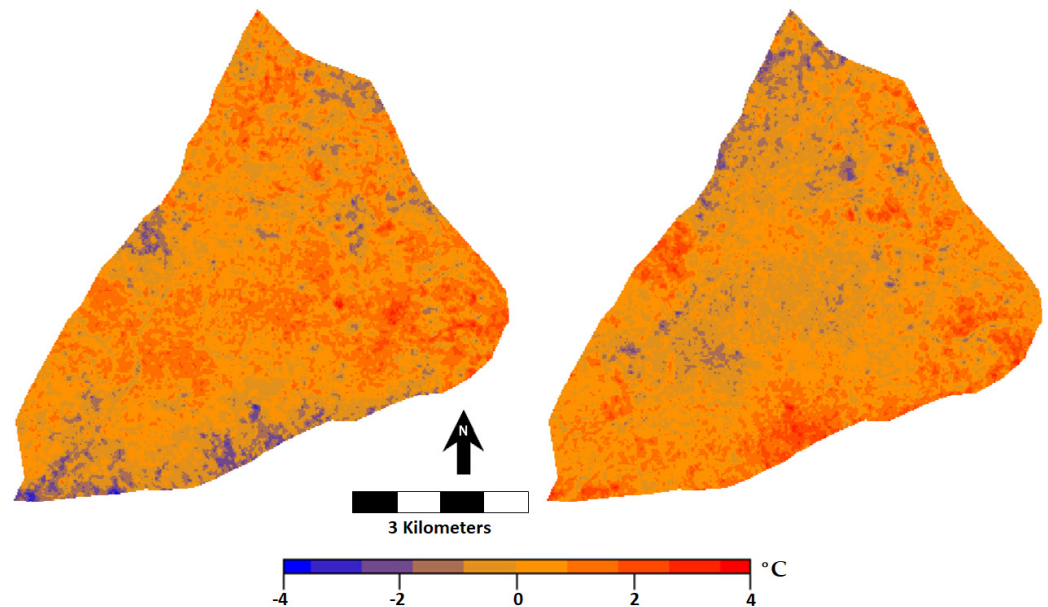


Figure 4. LST maps of change during 1987–2004 and 2004–2021 from left to right.

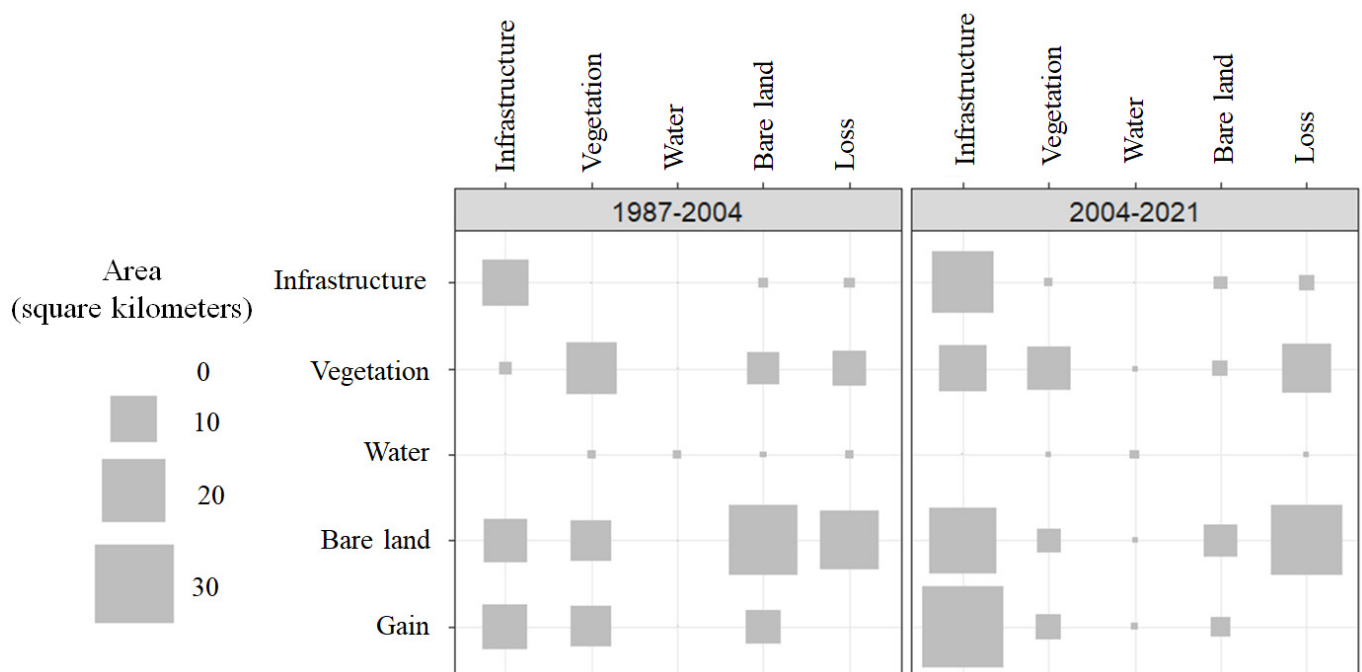


Figure 5. Transitional matrix during 1987–2004 and 2004–2021.

The TOC curves show the relationship between the gains, losses, and LST change during each time interval. Figure 6a,b shows that infrastructure losses intensify at intermediate and increased LST change (segments between -0.3 and 0.7 °C and 0.7 and 1.7 °C). We obtain this information by comparing the steepest segment of a category's curve (blue curve) to the uniform line (pink line). The uniform line indicates a random relationship

between the binary variable and the continuous variable; thus, the uniform line has an AUC value of 0.5. An AUC value lesser than 0.5 signifies a less than random relationship, while an AUC value greater than 0.5 signifies a greater than random relationship. An AUC value of 1 signifies a perfect relationship between the binary and continuous variables. Figure 6c,d shows that vegetation loss occurs most intensively at increased LST (segment between 1.7 and 3.7). We refer to positive LST changes as an increase because the LST change maps derive from the difference between the preceding and former LST maps, e.g., the 2004 LST map minus the 1987 LST map. As a result, a positive change means the temperature in 2004 was higher than in 1987. Conversely, we refer to an LST change as a decrease if the difference between the two LST maps results in negative LST values. Predictably, no change in LST refers to 0 difference in LST. Figure 6a–d shows a decrease in AUC values during the second time interval.

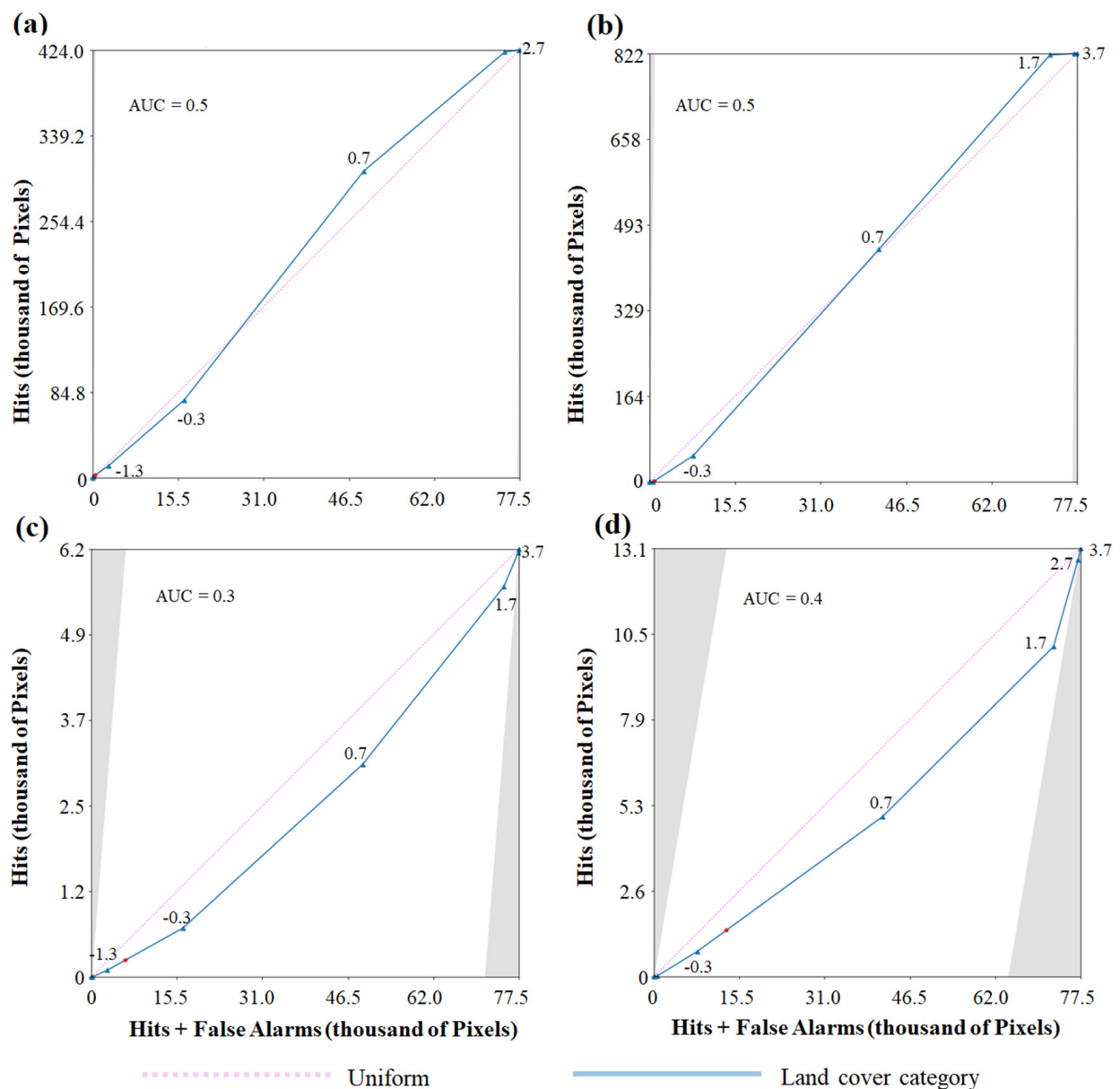


Figure 6. TOC curves for the losses of (a,b) infrastructure during the first and second time intervals, and (c,d) vegetation during the first and second time intervals. The red mark on the curves shows the threshold at which misses = false alarms.

Figure 7a,b shows that water losses occur intensively at decreased LST changes during the first time interval, but losses occur intensively at intermediate LST changes during the second time interval. Similarly, Figure 7c,d shows that bare land losses occur intensively at decreased LST during the first time interval, but losses occur intensively at intermediate LST changes during the second time interval. The TOC curve for the loss of Water during the first time interval has an AUC value of 0.9, signifying an almost perfect relationship between Water loss and LST change. However, the AUC value decreased by 0.2 during the second time interval. On the other hand, Bare land's AUC values increased from 0.3 to 0.4 during the temporal ext.

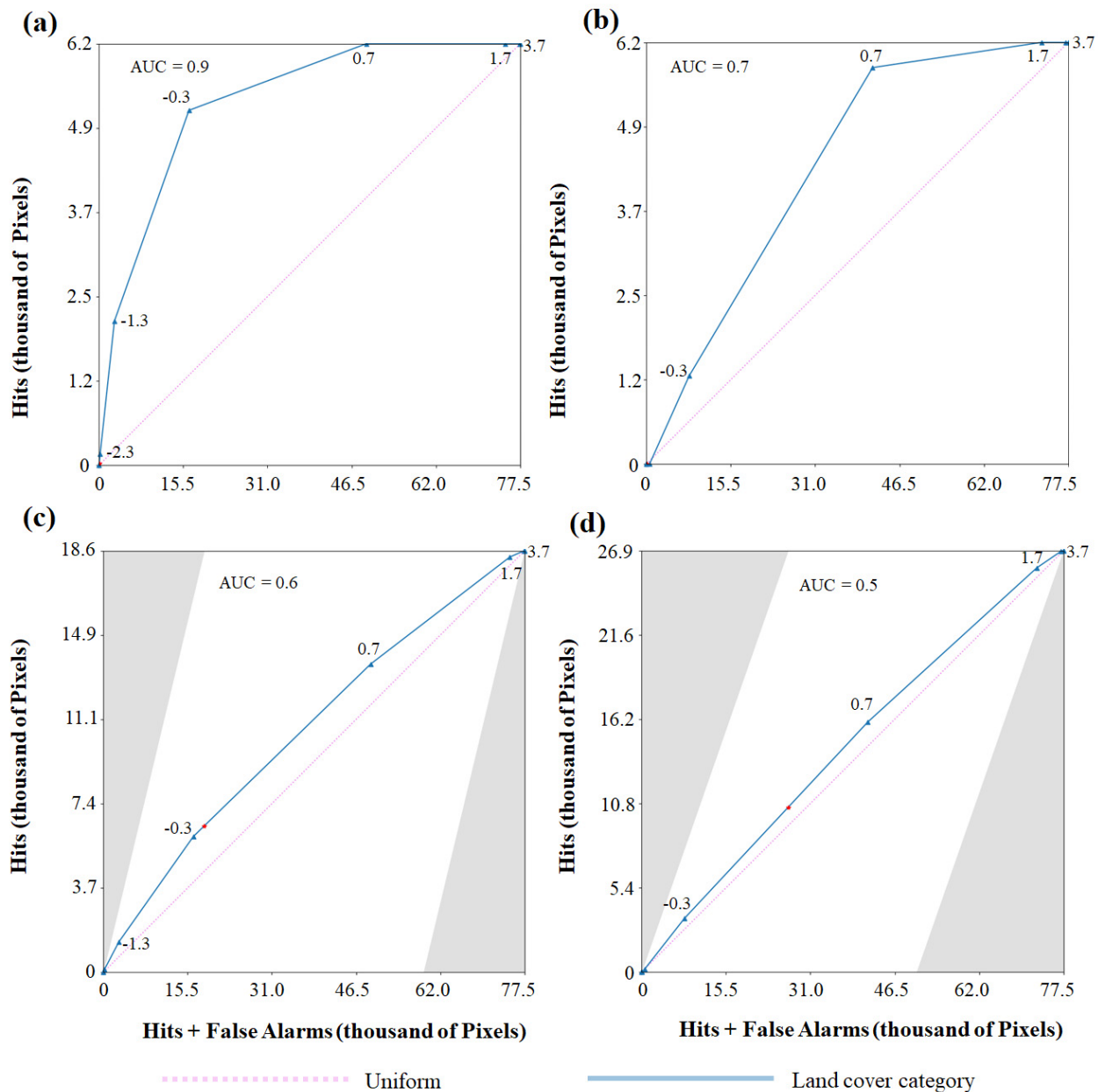


Figure 7. TOC curves for the losses of (a,b) Water during the first and second time intervals and (c,d) Bare land during the first and second time intervals.

Infrastructure gains occur intensively at intermediate and increased LST during both time intervals (see Figure 8, specifically a and b). The AUC values for infrastructure loss are less than 0.5 during both intervals, depicting a less than a random relationship between infrastructure gains and LST change. Figure 8c,d shows that vegetation gains occur intensively between 0 °C and decreased (−0.3 °C) LST while maintaining AUC

values (approximately 0.7) higher than random. Figure 9a,b shows that water gains occur intensively at lower LST change during the first time interval but gains occur intensively at decreased (cooler) LST change during both time intervals. Both curves are below the area under the uniform curve; thus, water's gains have AUC values less than 0.5 indicating a less-than-random relationship with LST change. Figure 9c,d shows that bare land gains occur intensively at increased (segment between 1.7 and 3.7 °C) LST during both time intervals. Figures 6–9 show the size of the presence or gains on the vertical axis as hits. Furthermore, all the TOC curves show the size of the spatial extent as the sum of hits and false alarms on the horizontal axis, which in this study is 77.5 thousand pixels $\approx 70 \text{ km}^2$. The red marks on all the TOC curves reveal the thresholds at which misses equal false alarms.

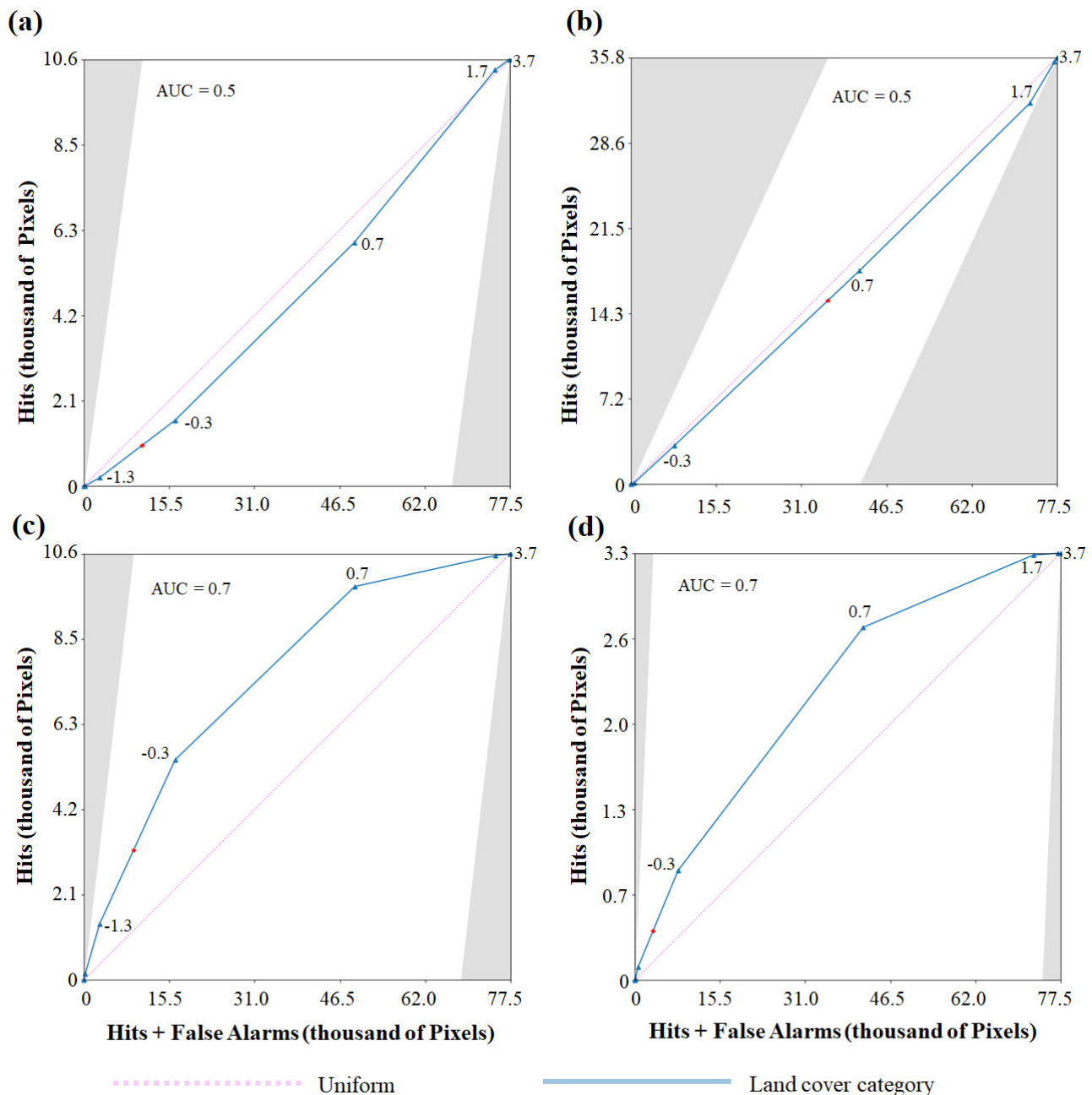


Figure 8. TOC curves for the gains of (a,b) infrastructure during the first and second time intervals and (c,d) vegetation during the first and second time intervals.

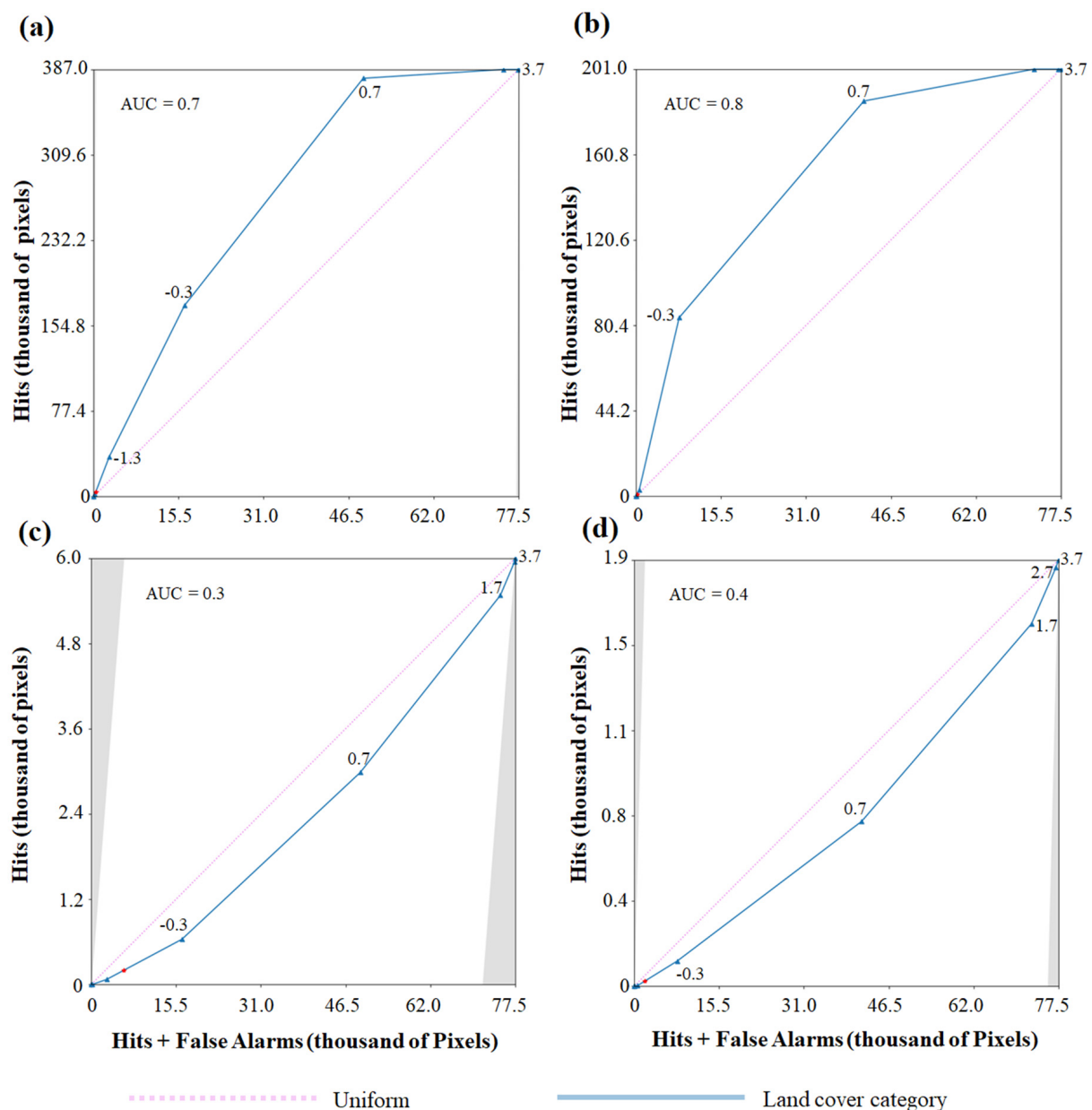


Figure 9. TOC curves for the gains of (a,b) water during the first and second time intervals and (c,d) bare land during the first and second time intervals.

4. Discussion

Change is a process that occurs over time and not at a time point [23,24]. As a result, studying the relationship between land cover change and LST change requires that scientists compare time intervals and not time points. Some existing literature [25,26] promises to discuss change, but a perusal of these papers shows no graphic comparison between land cover and LST change. Indeed, most of these studies only use the word change in the title but analyze the land cover and LST datasets at each time point. A transition matrix is a common approach to computing change among categorical datasets, e.g., land cover maps, especially if the goal is to compare two time points. The traditional transition matrix uses numbers to show the transition sizes from one time point to another.

Figure 2b,c derive from the transitional matrix. However, Figure 5 uses squares instead of numbers to depict the transitions among categories. Therefore, Figure 2b,c serves as a window through which scientists can concisely and efficiently study the quantitative distribution of the transitions of the land cover categories. For instance, Figure 2b shows

that during 1987–2004, bare land lost the most around infrastructure, while Figure 2c shows that infrastructure gained the most from the loss of Bare land. This echoes [27], who assessed land cover change between 1991 and 1999 in Central Puget Sound, Washington. Therefore, these observations can serve as the fulcrum for scientists to investigate the reason for the transition. In our case, we argue that developers and the planning agencies found it convenient to target bare areas for infrastructural development for the following reasons: (1) the large size of bare land at the start of each time point and (2) the conversion of bare land to infrastructure require less land preparation and financial commitment. The maps for the losses and gains during 2004–2021 show that bare land and the large patch of vegetation continued to lose to infrastructure. However, the losses occurred in the northeastern, southeastern, and southwestern parts of the study area. Again, we attribute this to the convenience and cost of building Infrastructure on bare land instead of vegetated areas.

The previous paragraph described the spatial distribution of the land cover transitions within the study area. Figure 4 takes the description further by providing quantitative information concerning the land cover transitions. Let us revisit Figure 5 by examining the transition matrix for 1987–2004. The last column's transition matrix uses varying squares to show each category's gross loss. It is clear that bare land has the largest square in that column, thus experiencing the largest size of loss during the second time interval. The size of the square is approximately 20 Km². If we carry out the same exercise for the last row, we can retrieve information concerning the gross gains of the categories. The largest square in that column is attributable to infrastructure, and its size is approximately 10 km². Thus, Figure 4 provides quantitative support concerning what we observed in Figure 2b,c. In effect, Figure 4 quantitatively confirms the observations drawn from Figure 2b,c. Therefore, it is critical for the Town and Country Planning agencies and all stakeholders to combine Figures 2 and 5 for a holistic assessment of the land change process.

Vegetation losses occurring intensively at increased LST reflect vegetation's critical role in decreasing temperature. Vegetation serves as a thermal insulator between the ground and the atmosphere. As a result, a decrease in vegetation cover may decrease the insulating properties vegetation offers. Despite this revelation, anthropogenic activities continue to decrease vegetation cover [28]. Figure 2b demonstrates this by showing that almost all the vegetation in the study area transitions to infrastructure during the second time interval. It is, therefore, logical to conclude that a gain or increase in vegetation cover will result in a decrease in LST. This is evident in Figure 8c,d. Therefore, we recommend that agencies responsible for planning and controlling developmental rates ensure developers conserve vegetation cover while encouraging the planting of trees or ornamental vegetation around infrastructures such as office and residential settlements. Water losses occurred intensively at decreased and intermediate LST change. We suspect this is because of the relatively small size of the water transitions.

Conventionally, scientists describe dry, bare land (composed mostly of dry soil) as a good conductor of heat. Therefore, inferably, the losses in bare land in the study area should be associated with a decreased LST, while gains in bare land should be associated with an increase in LST change. Indeed, that is the case in the study area. Figure 7c,d shows that infrastructure losses result in decreased LST, while Figure 9c,d shows that bare land gains occur intensively at increased LST. A similar situation exists for [29], who examined the relationship between land cover change and LST in the Dongting lake area, China.

We suspect data quality may account for some of the relationships between the land cover changes and LST. As an example, let us turn our attention to Table 2, which provides the definitions for the four land cover categories. Table 2 defines bare land as any open space without dominant vegetation and infrastructural development. Despite the clear definition of bare land, the spatial resolution of the land cover map will play a critical role in our ability to depict bare land. The land cover maps are at a spatial resolution of 30 * 30 m—indicating that we can only classify objects $\geq 30 * 30$ m. Some bare areas may consist of larger proportions of soil and smaller proportions of vegetation, e.g., shrubs or grass seedlings. In such instances, [30] shows that the satellite sensor may assign the

dominant category to that pixel location, which will invariably affect any pixel analysis. Conducting similar studies at a finer spatial resolution could be a way to mitigate the problems associated with data quality.

While we obtained all the satellite imagery during January 1987, 2004, and 2021, perusing each image's metadata reveals a variation in the days of acquisition. The metadata reveals that 1987, 2004, and 2021 correspond to acquisition days: 09, 16, and 22. The variations in the days of image acquisition could be a potential source of temperature variation. For instance, it is possible that it rained during any of the days of image acquisition. Indeed, Ref. [31] reports 1% increase in precipitation between January 1 and 22, 2021. It is, therefore, possible that the variations in rainfall influence the variations in LST at each time point in rainfall patterns. We suggest that future studies account for the change in LST attributable to rainfall.

5. Conclusions

Our study shows that infrastructure, vegetation, infrastructure, and bare land are the main land cover categories impacting LST change in the study area. We arrive at this conclusion by examining the relationship between the changes in four land cover categories and LST change. The relationships described in this paper emanate from processes occurring on the landscape. Thus, understanding the changes' processes is crucial to providing interventions to mitigate undesirable relationships and land change processes such as increased LST. However, processes occur during time intervals and not at time points. Scientists, therefore, need to match changes in land cover during time intervals to corresponding changes in LST during the same time interval. Unfortunately, while data for these processes abound, there is a lack of methods to facilitate such comparisons. Therefore, this study illustrates how the TOC can facilitate such comparison by comparing changes in two variables. The TOC achieves this by comparing the losses and gains (binary variables) during multiple time intervals to the threshold of LST changes (continuous variable) during the same time intervals. In addition, the TOC makes our approach unique because we examine (1) the direct relationship between losses and gains of each category and change in LST, (2) the threshold of LST change associated with each category's losses and gains, and (3) the intensity at which a category's losses and gains occur with relation to change in LST. Finally, this paper focuses on methods applicable to studying the relationship between land change and LST. As a result, while we do not focus on the details of the land cover categories, such as sub-categories of vegetation and bare land, the method described in this paper applies to studies involving land cover change at sub-categorical levels. The TOC, therefore, provides tremendous opportunities to explore land change at the sub-categorical level.

Author Contributions: Conceptualization, T.M.B. and J.I.I.; methodology, T.M.B.; validation, A.A.; formal analysis, T.M.B.; T.M.B., J.I.I. and A.A.; data curation, T.M.B.; writing—original draft preparation, T.M.B., J.I.I. and A.A.; writing—review and editing, T.M.B.; visualization, A.A.; supervision, T.M.B. and J.I.I.; project administration, T.M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data presented in this study are available on request from the corresponding author. The data are not publicly available because they are part of ongoing research.

Acknowledgments: The authors would like to thank the anonymous reviewers for their comments and suggestions which contributed to the further improvement of this paper.

Conflicts of Interest: The authors have declared no conflict of interest.

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