Temporal Analysis of Land Cover Dynamics in Chhatrapati Sambhaji Nagar Using Sentinel-2 Imagery and Random Forest Classification

Yogesh R. Tayade[1] and Vijaya B. Musande[2]
[1]Department of Artificial Intelligence and Data Science, CSMSS CSCOE, Chhatrapati Sambhajinagar 431 002, Maharashtra, India
[2]Department of Computer Science and Engineering, Jawaharlal Nehru Engineering College, Chhatrapati Sambhajinagar 431003, Maharashtra, India

Keywords: RM - RandomForest, LULC - Landuse Landcover, GEE - Google Earth Engine.

Abstract: Urbanization presents a significant challenge for sustainable development, demanding a clear understanding of land-use and land-cover (LULC) changes. This study addresses this need by employing the Random Forest algorithm, a powerful tool for handling complex spatial and temporal data. We focus on Chhatrapati Sambhajinagar, a rapidly urbanizing city in India. A decade-long time series of Sentinel-2 satellite imagery (2014-2024) is utilized to overcome limitations in spatial resolution, spectral variability, and temporal dynamics, which often hinder accurate LULC classification. Through rigorous application of the Random Forest algorithm, the study meticulously identifies and analyzes LULC changes across the ten-year period. The key findings highlight a concerning trend: a decrease in vital land cover types, including water bodies and vegetation. Conversely, the study reveals a substantial increase in built-up areas and bare land, a clear indicator of urbanization's impact on Chhatrapati Sambhajinagar's landscape.

1 INTRODUCTION

Land Use and Land Cover (LULC) classification involves categorizing and mapping different land use and cover types using remote sensing data, but it encounters challenges such as spatial and temporal resolution limitations, mixed pixels, spectral variability, scale discrepancies, algorithm selection dilemmas, training data scarcity, and cloud/atmospheric interference. These obstacles demand a combination of advanced techniques, including machine learning algorithms, field validation, and expert knowledge, to accurately classify land cover types and understand their dynamics in a given area.

Considering the challenges, it's crucial to emphasize the scientific rigor and relevance of the Random Forest algorithm for Land Use and Land Cover (LULC) classification. Random Forest stands out as a robust and effective choice for this task due to its ensemble nature, which mitigates overfitting concerns often encountered in complex datasets like remote sensing imagery. Its capacity to handle high-dimensional data makes it particularly suitable for leveraging multispectral information inherent in remote sensing datasets for accurate classification of diverse land cover types. Furthermore, Random

Forest's ability to accommodate both categorical and continuous variables facilitates the integration of various spectral, spatial, and ancillary data layers, enhancing classification performance. Notably, its provision of variable importance measures aids in the interpretation of results, contributing to the scientific understanding of land cover dynamics. Thus, within the realm of scientific inquiry and analysis, Random Forest emerges as a compelling algorithmic choice for LULC classification tasks, underpinned by its robustness, versatility, and capacity for extracting meaningful insights from complex spatial datasets.

In this study, we employed spatiotemporal analysis using the Random Forest algorithm to analyze a decade-long time series of Sentinel-2 satellite imagery spanning from 2014 to 2024 over Chhatrapati Sambhaji Nagar. The selected Sentinel-2 bands utilized for this investigation include the visible and near-infrared bands: B2 (Blue), B3 (Green), B4

Tayade, Y. R. and Musande, V. B.
Temporal Analysis of Land Cover Dynamics in Chhatrapati Sambhaji Nagar Using Sentinel-2 Imagery and Random Forest Classification.
DOI: 10.5220/0013930900004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 5*, pages 427-434
ISBN: 978-989-758-777-1

(Red), B8 (Near-Infrared), along with additional spectral indices such as NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index). These bands and indices are particularly suitable for capturing temporal changes in land cover dynamics. Through rigorous classification, we categorized the temporal changes into four distinct classes: bare land, vegetation, built-up areas, and water bodies, enabling a comprehensive analysis of the spatiotemporal trends and dynamics in land cover within the study area over the specified timeframe.

2 RELATED WORKS

Land Use and Water Quality: Hua (2017) investigated the relationship between LULC changes and water quality, employing remote sensing and multivariate statistical techniques. The study highlighted that agricultural and urban expansion deteriorates water quality by increasing pollutant loads. Deforestation, industrial effluents, and excessive use of fertilizers contribute to the contamination of water bodies, affecting aquatic ecosystems and human health. Strategies such as buffer zones, sustainable agriculture, and improved wastewater treatment can help mitigate these negative impacts.

Spatio-Temporal Analysis of LULC Changes: Chamling and Bera (2020) examined the Bhutan-Bengal foothill region's LULC changes from 1987 to 2019, emphasizing the role of geospatial tools in policy-making. Their study showed how land transformation influenced ecological balance and socio-economic conditions. Similarly, Yesuph and Dagnew (2019) assessed LULC changes in Ethiopia's Beshillo Catchment, identifying deforestation and agricultural expansion as major driving forces. They highlighted the importance of integrating geospatial analysis with local governance to ensure sustainable land management.

Climate and Hydrological Impacts: Watson et al. (2000) and Romanowicz (2017) explored the links between LULC changes and climate, particularly the effects on hydrological cycles. They emphasized deforestation's role in altering precipitation and temperature patterns, leading to increased drought risks and reduced groundwater recharge. Changes in land cover also affect evapotranspiration and runoff, influencing flood and erosion patterns. These studies underline the need for adaptive water management strategies to counteract climate-induced hydrological disruptions.

LULC Change Models:Agarwal et al. (2002) provided a comprehensive review of LULC change models, highlighting spatial, temporal, and human decision-making factors. These models integrate socioeconomic variables, remote sensing data, and predictive analytics to simulate future land-use patterns. Similarly, Li et al. (2012) discussed urban sustainability and LULC in East Asia, linking land changes to public health outcomes. Their research indicated that unplanned urban expansion leads to increased pollution and habitat loss, necessitating the adoption of sustainable land-use policies.

Ecosystem Services and Land Use: Chen et al. (2014) analyzed LULC changes in China's Small Sanjiang Plain and their effects on ecosystem services. They found that agricultural expansion and urbanization reduced natural vegetation, leading to a decline in carbon sequestration and soil fertility. Pande et al. (2021) estimated crop and forest biomass using satellite data, contributing to resource management strategies. Their findings emphasize the importance of balancing economic growth with environmental conservation to maintain ecosystem integrity.

Urbanization and Microclimate Changes: Swain et al. (2016) and Chadchan & Shankar (2012) investigated the impact of rapid urbanization on urban microclimates, focusing on Indian cities. Their studies highlighted rising land surface temperatures due to urban expansion, causing heat stress and altering local weather patterns. The replacement of vegetated areas with impervious surfaces exacerbates the urban heat island effect, necessitating the integration of green infrastructure in urban planning.

Urbanization and Environmental Interactions: Bai et al. (2017) proposed a framework linking urbanization with environmental changes. Their study demonstrated how land-use changes affect air quality, biodiversity, and natural resource availability. Patra et al. (2018) emphasized groundwater depletion as a consequence of urban sprawl. They suggested that integrating groundwater recharge techniques and efficient water management policies can help sustain urban growth while minimizing environmental degradation.

Remote Sensing Applications in LULC Studies: Avtar et al. (2014) and Prasad & Ramesh (2019) used remote sensing to monitor traditional water bodies and ecologically fragile areas, respectively. These techniques enhance the ability to track land changes over time, supporting conservation efforts and sustainable planning. Hsieh (2021) integrated climate-sensitive urban planning in LULC assessments, demonstrating how satellite-based data can guide policy decisions for climate resilience.

Green Spaces and Sustainable Urban Planning: Ramaiah & Avtar (2019) reviewed urban green spaces' importance in rapidly urbanizing Indian cities. Their findings emphasized the role of green corridors, parks, and urban forests in mitigating air pollution, enhancing biodiversity, and improving residents' well-being. Ramaiah et al. (2020) analyzed how land cover influences land surface temperature in two proposed smart cities, suggesting that incorporating green spaces can significantly reduce urban heat stress.

GIS-Based LULC Analysis: GebreMedhin et al. (2019) utilized GIS and remote sensing to detect urban LULC dynamics in Axum Town, Ethiopia. Their study showed how GIS-based techniques help in visualizing and predicting urban expansion, aiding policymakers in sustainable city planning. Schellnhuber et al. (2012) warned about the implications of a 4-degree Celsius temperature rise due to LULC alterations, stressing the urgency of mitigating land degradation through proactive policies.

3 STUDY AREA

Chhatrapati Sambhajinagar, colloquially known as Aurangabad, lies in the heart of Maharashtra, India, positioned approximately 335 kilometers east of Mumbai. Nestled at coordinates around 19.8762° N latitude and 75.3433° E longitude, the city boasts a diverse topographical canvas, from sprawling plains to undulating landscapes interspersed with hills and valleys, reflecting a rich geological tapestry of basaltic lava flows and sedimentary formations. Leveraging remote sensing technologies, researchers can delve into a multitude of facets defining Aurangabad's geography. Through satellite imagery from platforms such as Landsat 8 and Sentinel-2, they can decipher intricate land use patterns, delineate urban expansion, and monitor the transformation of natural landscapes into built environments. These satellites, with their regular revisit times and multispectral capabilities, offer a comprehensive view of the region's evolving landscape over time. This granular insight extends to the assessment of vegetation cover, identifying areas of dense greenery alongside regions undergoing deforestation or degradation. Moreover, remote sensing facilitates the scrutiny of water resources, aiding in the management of rivers, lakes, and groundwater aquifers, while also unveiling pollution hotspots and monitoring water quality dynamics. In the context of Aurangabad's burgeoning urbanization, satellite data serves as a vital tool for urban planners, enabling them to chart sustainable development pathways and mitigate the environmental impact of rapid urban growth. Additionally, by capturing atmospheric parameters and land surface temperatures, remote sensing contributes indispensable inputs to climate studies, furnishing researchers with a comprehensive understanding of Aurangabad's environmental dynamics and resilience in the face of global climatic shifts. Figure 1 shows the Study Area - Chhatrapati Sambhajinagar (Aurangabad).

Figure 1: Study Area - Chhatrapati Sambhajinagar (Aurangabad).

4 METHODOLOGY

To study the geographical dynamics of Chhatrapati Sambhajinagar (Aurangabad), Maharashtra, from 2014 to 2024, Landsat 8 and Sentinel-2 satellite datasets were instrumental. Landsat 8, launched by NASA and the USGS in 2014, provides moderate-resolution imagery with a revisit time of approximately 16 days. Sentinel-2, part of the European Union's Copernicus program, offers high-resolution multispectral imagery with a revisit time of 5 days. Leveraging the capabilities of these satellites, researchers conducted a comprehensive analysis of Aurangabad's landscape. The area was classified into four major land cover classes: Vegetation, Bareland, Built-up Area, and Waterbodies. Through a meticulous examination of Landsat 8 and Sentinel-2 imagery, researchers discerned patterns of land use and land cover changes. The Vegetation class delineated areas of dense green cover, indicating ecological richness and potential habitat regions. Bareland regions, devoid of vegetation, were identified, suggesting natural degradation or anthropogenic activities such as mining. The Built-up Area class mapped urban sprawl and infrastructure development, offering insights into the city's expansion and population growth. Waterbodies classification provided information on the distribution and dynamics of rivers, lakes, and reservoirs, crucial for water resource management and environmental conservation efforts. By integrating Landsat 8 and Sentinel-2 datasets and employing these major classification classes, researchers gained a comprehensive understanding of Aurangabad's evolving landscape, facilitating informed decision-making for sustainable development and environmental management initiatives.

The Landsat 8 satellite, operated by NASA and the US Geological Survey, is renowned for its multispectral imagery with a spatial resolution of 30 meters and a revisit time of 16 days. The paper delves into the spectral characteristics of Landsat 8, highlighting its effectiveness in capturing detailed information about various land features.

Sentinel-2, another satellite system from the European Space Agency, stands out for its high-resolution multispectral imagery with spatial resolutions ranging from 10 to 60 meters. The research investigates the spectral bands of Sentinel-2 and assesses its potential for detailed land cover classification, including the discrimination of vegetation types, landforms, and water bodies.

Through a comparative analysis of these three satellites, the paper aims to elucidate the trade-offs between spatial resolution, temporal frequency, and spectral characteristics in the context of LULC mapping. Additionally, considerations such as cost, data accessibility, and processing requirements are discussed to provide a holistic framework for decision-making when selecting a satellite platform for LULC studies.

Therefore, the most efficient satellite often involves a combination: Landsat 8 + Sentinel-2: Offers detailed land cover maps with high spatial resolution and frequent updates for change detection.

4.1 Data Analysis

For the research paper focused on classifying the land cover of Chhatrapati Sambhajinagar (Aurangabad), Maharashtra, from 2014 to 2024, utilizing the RM algorithm offers a robust methodology. RM combines multiple decision trees to improve classification accurcy and robustness. The algorithm works by constucting a multitude ofdecision trees during training and outputs the mode of the classes predicted by individual trees as the final classification.

In the context of land cover classification, the RM algorithm excels in handling complex, high-dimensional datasets such as multispectral imagery from Landsat 8 and Sentinel-2 satellites. The algorithm's ability to handle large datasets and capture nonlinear relationships between spectral features and land cover classes makes it well-suited for this task.

The RM algorithm can be mathematically represented as follows:

4.2 Training Phase

- Given a training dataset $D=\{(x1,y1),(x2,y2),...,(xn,yn)\}D=\{(x1,y1),(x2,y2),...,(xn,yn)\}$, where $xixi$ represents the input features (spectral bands) and $yiyi$ represents the corresponding land cover class labels.
- RM builds multiple decision trees $T1$, 2, $TnT1$, $T2$,,Tn by randomly selecting subsets of features and data samples (bootstrap aggregating or bagging).
- At each node of the decision tree, a random subset of features is considered for splitting, and the best split is chosen based on criteria such as Gini impurity or information gain.
- The trees continue to grow until a stopping criterion is met, such as reaching a maximum depth or minimum number of samples per leaf node.

4.2.1 Prediction Phase

- During the prediction phase, each decision tree in the forest independently classifies the input data point.
- For a given input feature vector xx, each decision tree outputs a predicted class label.
- The final prediction is determined by aggregating the individual predictions through a majority voting scheme. The class with the most votes across all trees is assigned as the final prediction.

In the research paper, the RM algorithm would be applied to the Landsat 8 and Sentinel-2 datasets to classify the land cover of Aurangabad into the predefined classes (Vegetation, Bareland, Built-up Area, and Waterbodies). The performance of the classifier would be evaluated using metrics such as overall accuracy, precision, recall, and F1-score, and compared against other classification algorithms. Additionally, feature importance analysis could be conducted to identify the most influential spectral bands for land cover classification. Overall, leveraging RM for land cover classification provides a robust and efficient approach for analyzing the dynamics of Aurangabad's landscape over the specified period.

4.3 Feature Selection and Classification

In our research, feature selection for RM classification in Google Earth Engine (GEE) was conducted to accurately classify the land cover of Chhatrapati Sambhajinagar (Aurangabad), Maharashtra, from 2014 to 2024. Initially, relevant spectral bands from Landsat and Sentinel-2 satellite imagery were identified, including visible, near-infrared, and shortwave infrared bands, known to be informative for distinguishing between different land cover classes. Additionally, vegetation indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI) were derived from the available spectral bands to capture important vegetation-related information. Ancillary data layers such as elevation, slope, aspect, and land surface temperature were also incorporated as additional input features, utilizing the capabilities of GEE's ee.Terrain module and accessing other datasets through ee.ImageCollection. These selected features were combined into a single feature stack, ensuring they were on comparable scales. Subsequently, a RM classifier was instantiated using the ee.Classifier.randomForest() function, with parameters such as the number of trees in the forest and the number of input features to consider at each split specified. The dataset was divided into training and validation sets using random sampling, and the classifier was trained using the training dataset and evaluated using the validation dataset. Performance metrics including overall accuracy, kappa coefficient, precision, recall, and F1-score were computed to assess the classification accuracy of the trained model. By following this methodology, we aimed to achieve accurate and robust land cover mapping and analysis for Aurangabad, Maharashtra, facilitating informed decision-making for sustainable development and environmental management initiatives in the region.

In our research, the selection of sample points, training, and classification for RM in Google Earth Engine (GEE) was meticulously conducted to accurately assess the land cover dynamics of Chhatrapati Sambhajinagar (Aurangabad), Maharashtra, spanning from 2014 to 2024. Initially, sample points were strategically selected across the study area to ensure spatial representation and capture the variability of different land cover classes. This was achieved by employing random or systematic sampling techniques within each land cover class of interest. The sample points were then visually inspected and verified to ensure their accuracy and representativeness.

Subsequently, a RM classifier was trained using the selected sample points. The ee.Classifier.randomForest() function in GEE was employed to instantiate the classifier, with parameters such as the number of trees in the forest and the number of input features specified. The training dataset consisting of the sample points along with their corresponding land cover labels was used to train the classifier. During the training process, the classifier learned the relationship between the input features (e.g., spectral bands, vegetation indices, ancillary data) and the land cover classes.

Following the training phase, the trained RM classifier was applied to the entire study area for land cover classification. Satellite imagery, such as Landsat or Sentinel-2, covering the specified time period was utilized for classification. The classifier assigned a land cover class label to each pixel in the study area based on its spectral characteristics and the learned decision rules from the training phase.

To assess the accuracy of the classification, a validation dataset consisting of independently collected ground truth data or a subset of the original dataset was used. Performance metrics such as overall accuracy, kappa coefficient, precision, recall, and F1-score were computed by comparing the classified land cover map against the validation dataset.

By meticulously selecting sample points, training a RM classifier, and accurately classifying the land cover using GEE, our research aimed to provide valuable insights into the land cover dynamics of Aurangabad, Maharashtra, facilitating informed decision-making for land management and environmental conservation efforts in the region. Figure 2 shows the 2014. Figure 3 shows the 2024. Table 1 shows the Classification Details in Hectors.

Buitup Area:

Waterbodies:

Bareland:

Vegitation:

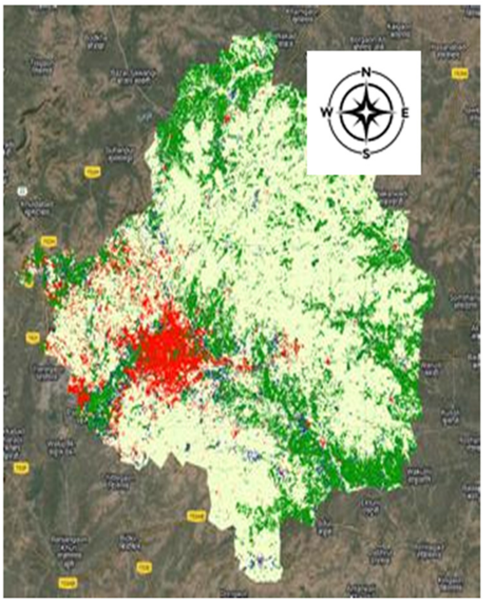


Figure 2 : 2014

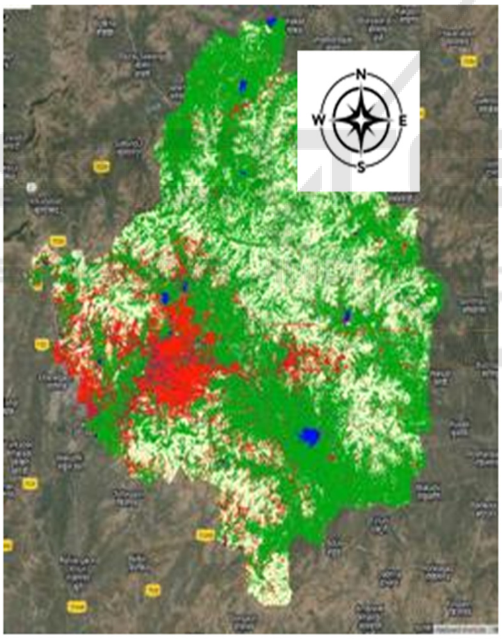
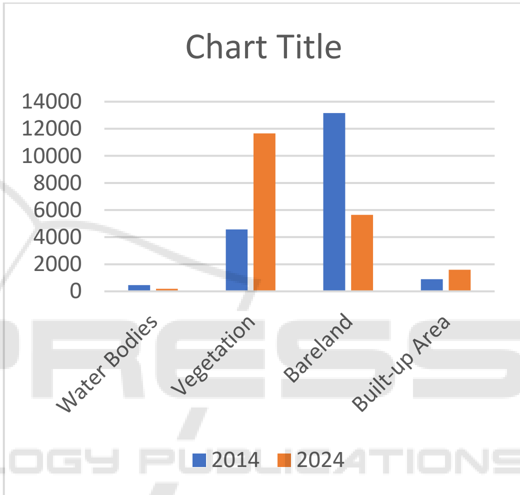


Figure 3: 2024.

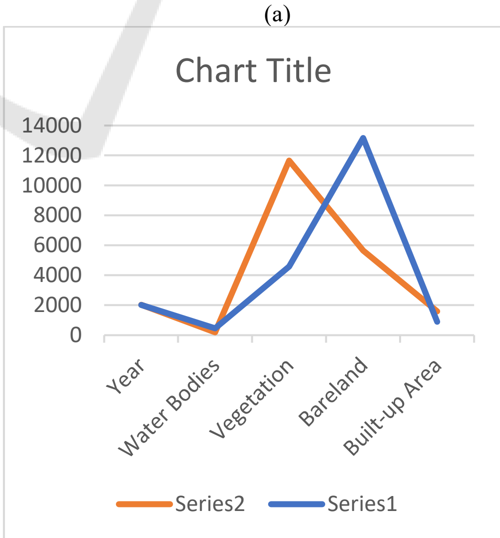
4.4 Statistics

Table 1: Classification Details in Hectors.

Year	Water Bodies (ha)	Vegetation (ha)	Bareland (ha)	Built-up Area (ha)
2014	457.54	4,573.53	13,160.36	893.85
2024	190.50	11,660.05	5,646.60	1,588.14



(a)



(b)

Figure 4(a),4(b): Classification Chart. (Values are in hectors)

5 CONCLUSIONS

The classification approach on the region of interest using RM is based on the training data and the accuracy based on the trained model using random forest algorithm. The observations from the results are over the timespan of study the water bodies and vegetation are gradually decreases whereas the builtup area and bareland increases gradually. It shows that the urbanization has major impact on the land cover parameter. The proposed method finding can be used for the further landuse landcover studies. This research not only demonstrates the effectiveness of the Random Forest algorithm in capturing intricate land cover dynamics but also provides valuable insights for policymakers and urban planners. Figure 4(a),4(b) shows the Classification Chart. (Values are in hectors) These insights can be leveraged to develop informed land management strategies that promote sustainable urban growth and environmental conservation in Chhatrapati Sambhajinagar and other rapidly developing cities

REFERENCES

Agarwal, C.; Green, G.M.; Grove, J.M.; Evans, T.P.; Schweik, C.M. A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice; Gen. Tech. Rep. NE-297; U.S. Department of Agriculture, Forest Service, Northeastern Research Station: Newton Square, PA, USA, 2002; Volume 297, 61p.

Avtar, R.; Herath, S.; Saito, O.; Gera, W.; Singh, G.; Mishra, B.; Takeuchi, K. Application of remote sensing techniques toward the role of traditional water bodies with respect to vegetation conditions. Environ. Dev. Sustain. 2014, 16, 995–1011.

Bai, X.; McPhearson, T.; Cleugh, H.; Nagendra, H.; Tong, X.; Zhu, T.; Zhu, Y.-G. Linking Urbanization and the Environment: Conceptual and Empirical Advances. Annu. Rev. Environ. Resour. 2017, 42, 215–240.

Chadchan, J.; Shankar, R. An Analysis of Urban Growth Trends in the Post-Economic Reforms Period in India. Int. J. Sustain. Built Environ. 2012, 1, 36–49.

Chamling, M.; Bera, B. Spatio-Temporal Patterns of Land Use/Land Cover Change in the Bhutan–Bengal Foothill Region Between 1987 and 2019: Study Towards Geospatial Applications and Policy Making. Earth Syst. Environ. 2020, 4, 1–14.

Chen, J.; Sun, B.-M.; Chen, D.; Wu, X.; Guo, L.-Z.; Wang, G. Land Use Changes and Their Effects on the Value of Ecosystem Services in the Small Sanjiang Plain in China. Sci. World J. 2014, 2014, e752846.

Ethiopia. Environ. Syst. Res. 2019, 8, 21.

GebreMedhin, A.; Biruh, W.; Govindu, V.; Demissie, B.; Mehari, A. Detection of Urban Land Use Land Cover Dynamics Using GIS and Remote Sensing: A Case Study of Axum Town, Northern Ethiopia. J. Indian Soc. Remote Sens. 2019, 47, 1209–1222.

Hong, H.T.C.; Avtar, R.; Fujii, M. Monitoring changes in land use and distribution of mangroves in the

Hsieh, C.-M. Sustainable Planning and Design: Urban Climate Solutions for Healthy, Livable Urban and Rural Areas. J. Urban Manag. 2021, 10, 1–2.

Hua, A.K. Land Use Land Cover Changes in Detection of Water Quality: A Study Based on Remote Sensing and Multivariate Statistics. J. Environ. Public Health 2017, 2017, 7515130.

Li, X.-H.; Liu, J.-L.; Gibson, V.; Zhu, Y.-G. Urban Sustainability and Human Health in China, East Asia and Southeast Asia. Curr. Opin. Environ. Sustain. 2012, 4, 436–442.

Mahmood, R.; Jia, S.; Zhu, W. Analysis of Climate Variability, Trends, and Prediction in the Most Active Parts of the Lake Chad Basin, Africa. Sci. Rep. 2019, 9, 6317.

Pande, C.B.; Moharir, K.N.; Kumar Singh, S.; Varade, A.M.; Elbeltagi, A.; Khadri, S.F.R.; Choudhari, P. Estimation of Crop and Forest Biomass Resources in a Semi-Arid Region Using Satellite Data and GIS. J. Saudi Soc. Agric. Sci. 2021, 20, 302–311.

Patra, S.; Sahoo, S.; Mishra, P.; Mahapatra, S.C. Impacts of Urbanization on Land Use/Cover Changes and Its Probable Implications on Local Climate and Groundwater Level. J. Urban Manag. 2018, 7, 70–84.

Prasad, G.; Ramesh, M.V. Spatio-Temporal Analysis of Land Use/Land Cover Changes in an Ecologically Fragile Area—Alappuzha District, Southern Kerala, India. Nat. Resour. Res. 2019, 28, 31–42.

Ramaiah, M.; Avtar, R. Urban Green Spaces and Their Need in Cities of Rapidly Urbanizing India: A Review. Urban Sci. 2019, 3, 94.

Ramaiah, M.; Avtar, R.; Rahman, M.M. Land Cover Influences on LST in Two Proposed Smart Cities of India: Comparative Analysis Using Spectral Indices. Land 2020, 9, 292.

Romanowicz, R.J. The Impacts of Changes in Climate and Land Use on Hydrological Processes. Acta Geophys. 2017, 65, 785–787.

Schellnhuber, H.J.; Hare, W.; Serdeczny, O.; Adams, S.; Coumou, D.; Frieler, K.; Martin, M.; Otto, I.M.; Perrette, M.; Robinson, A.; et al. Turn down the Heat: Why a 4 Deg C Warmer World Must Be Avoided; Sauvons le Climat-SLC: Paris, France, 2012; p. 110.

Swain, D.; Roberts, G.J.; Dash, J.; Vinoj, V.; Lekshmi, K.; Tripathy, S. Impact of Rapid Urbanization on the Microclimate of Indian Cities: A Case Study for the City of Bhubaneswar. In Land Surface and Cryosphere Remote Sensing III; International Society for Optics and Photonics: Bellingham, WA, USA, 2016; Volume 9877, p. 98772X.

Watson, R.T.; Noble, I.R.; Bolin, B.; Ravindranath, N.H.; Verardo, D.J.; Dokken, D.J. Land Use, Land-Use Change and Forestry: A Special Report of the

Intergovernmental Panel on Climate Change; Cambridge University Press: Cambridge, UK, 2000.
Yesuph, A.Y.; Dagnew, A.B. Land Use/Cover Spatiotemporal Dynamics, Driving Forces and Implications at the Beshillo Catchment of the Blue Nile Basin, North Eastern Highlands of