Assessing the Influence of Land Use/Land Cover Alteration on Climate Variability: An Analysis in the Aurangabad District of Maharashtra State, India

Md Masroor 1, Ram Avtar 2,*, Haroon Sajjad 1,*, Pandurang Choudhari 3, Luc Cimusa Kulimushi 4, Khaled Mohamed Khedher 5,6, Akinola Adesuji Komolafe 7, Ali P. Yunus 8,9 and Netrananda Sahu 10

Abstract: Examining the influence of land use/land cover transformation on meteorological variables has become imperative for maintaining long-term climate sustainability. Rapid growth and haphazard expansion have caused the conversion of prime agricultural land into a built-up area. This study used multitemporal Landsat data to analyze land use/land cover (LULC) changes, and Terra Climate monthly data to examine the impact of land transformation on precipitation, minimum and maximum temperature, wind speed, and soil moisture. The built-up area, water bodies, and barren lands have recorded a steep rise, while the agricultural area has decreased in the district. Drastic changes were observed in the climatic variables over the years. The precipitation and wind speed have shown decreasing trends during the study period. A positive relationship between soil moisture and agricultural land was found through a correlation analysis. Conspicuous findings about the positive relationship between the agricultural land and maximum temperature need further investigation. A multiple linear regression analysis demonstrated a negative relationship between the built-up area and precipitation. The intensity of the precipitation has reduced as a consequence of the developmental activities in the study area over the years. The built-up area, water bodies, and barren lands have recorded a steep rise, while the agricultural area has decreased in the district. Drastic changes were observed in the climatic variables over the years. The precipitation and wind speed have shown decreasing trends during the study period. A positive relationship between soil moisture and agricultural land was found through a correlation analysis. Conspicuous findings about the positive relationship between the agricultural land and maximum temperature need further investigation. A multiple linear regression analysis demonstrated a negative relationship between the built-up area and precipitation. The intensity of the precipitation has reduced as a consequence of the developmental activities in the study area. Moreover, a positive relationship was observed between the built-up area and maximum temperature. Thus, this study calls for policy implications to formulate a futuristic land-use plan considering climate change projection in the district.

Keywords: climate variability; google earth engine; machine learning algorithm; random forest; support vector machine; multiple linear regression
1. Introduction

Land use refers to human-induced land transformation for specified purposes such as agriculture, recreation and build-up, etc. In contrast, vegetation patterns, water bodies, soil, and natural land surface are included under land cover [1,2]. Both natural and anthropogenic activities may be attributed to the changing land use/land cover (LULC) pattern across geographical regions on the Earth [3–6]. The transformation of LULC into a built-up area increases the area under the impervious surface and affects the hydro-meteorological cycle on the planet. A microclimate is an ambient physical setting in atmospheric variables (precipitation, temperature, latent heat, etc.) in a given area over a period of time that is induced by natural and anthropogenic forcing. These atmospheric variables are generally affected by land use modifications and alter land–atmospheric interactions [7]. The exponential increase in population, expansion of areas under agricultural activities, rapid industrialization, and growth of urban sprawl have caused immense transformations to land use globally since the last century. These land use alterations are leading to the continuous destruction of natural ecosystems [8,9]. Recently, the increase in heat waves and temperature have been concerning issues arising out of the intensification of urbanization, as suggested by the policy makers and scientific community [10].

Unplanned urbanization has created significant negative consequences for the local environment [11]. Urbanization has also posed problems of air pollution, water degradation, and social transition [7,12]. These unfavorable implications have arisen mainly due to changes in LULC [13–16]. These changes have increased many environmental implications such as land degradation, loss of biodiversity, and forest fragmentation. LULC acts as a significant driver for bringing changes in the local climate. Removal of vegetation and faulty agricultural practices lead to an increase in the concentration of CO$_2$, and thus alter the climate pattern [17,18]. Therefore, the quantification and understanding of the land use dynamics at spatial and temporal scales are critical for the monitoring of urban dynamics and development of effective policies [19]. Climate variability is an intricate phenomenon considered as the changes in the mean state of the climate over a short time span (monthly and yearly), including extreme weather events (drought, flood, and cyclone). An increase in climate variability may also trigger hydrological events. It has been predicted that the global temperature may increase up to 1.5 $^\circ$C by 2050, while it may reach up to 40 $^\circ$C by the end of this century [17]. Schellnhuber et al. [20] reported that a rise of 2 $^\circ$C in the world’s average temperature will make the summer monsoon highly unpredictable, indicating that dry areas may become more dry and wet areas may become more wet. It is also anticipated that if the temperature increases to 4 $^\circ$C, the area will be transformed from semi-arid climate (BSh) to hot desert climate (BWh). Aurangabad district, having a semi-arid climate, will be likely to experience such changes. Assessing trends of climate variability is important for monitoring and forecasting the climate variables in order to mitigate and adapt these changes to lessen the impacts of disasters and improve the resilience of society [21].

A large amount of research has demonstrated the usefulness of geospatial technology and computational algorithms to monitor LULC change [13,22,23]. Many techniques have been utilized to classify LULC [24–29] and the maximum likelihood classification technique has been widely utilized by scholars [2,30,31]. Recently, researchers have emphasized the use of machine learning algorithms to analyze LULC change [32–36]. A support vector machine (SVM) [37–42], artificial neural network [43], random forest [44,45], and decision tree [46] are common machine learning algorithms that have been used recently. Moreover, Google Earth Engine (GEE) is an effective platform for monitoring changes in LULC at a spatiotemporal scale. It is widely adopted for its effectiveness and accurate detection of local and global anomalies in land use/land cover phenomena [47,48].

Numerous studies were carried out to assess the impact of LULC on climate variability [49–51]. Most of these studies were conducted using one climatic variable, rainfall or temperature. None of these studies used other essential climatic variables (minimum and maximum temperature, precipitation, soil moisture, and wind speed) to be impacted by land use/land cover dynamics. The present study makes a concerted attempt to investi-
gate the implications of land use/land cover change on climate variability in Aurangabad district, Maharashtra. The study also intends to find the best-fit machine learning classifier for LULC classification.

2. Study Area

Aurangabad district is one of the highly drought-affected districts located in the central part of the Maharashtra state in India (Figure 1). A major part of the district coincides with the Godavari River basin, while a smaller part of the district is situated in the northwest of the Tapi River basin within the state. The district has an area of 10,755.5 km² and is located at 19°15′ and 20°40′ N latitudes and 74°37′ and 75°52′ E longitudes. The district is bordered on the north by Jalgaon district, on the west by Nashik district, on the south by Ahmednagar and Beed districts, and on the east by Parbhani and Buldhana districts. A population of nearly 3.7 million resides in the district. It is drained by the tributaries of the Godavari and Tapi rivers. It has a semi-arid climate based on Köppen’s climate classification. The onset of the rainy season in the district begins in June and lasts until September, which is followed by the winter season from October to February, and the summer season is restricted to March, April, and May. The average rainfall in the district is estimated to be 734 mm, with a minimum temperature of 5.6 °C and a maximum temperature of 45.9 °C. Cold waves occur in the district during the winter season due to the eastward passage of western disturbances. The historical climate records showed that the highest maximum temperature (46 °C) was recorded on 25 May 1905, while the minimum temperature (2 °C) was recorded on 2 February 1911. The district receives maximum rainfall during the monsoon season between June and September. The cloud cover during the monsoon season makes weather more comfortable and the daily range of the maximum temperature decreases [52]. Thunderstorms and high-speed winds are common from November to April.

![Figure 1](image-url)

**Figure 1.** The study area: (a) Its location in India (b) Aurangabad district.

The district has a diverse topography and landscape, with hills and plains. Satmala hills cover most of the northern part of the district. The district is set on the Deccan Trap, which has very thin alluvial deposits along the major rivers. The basaltic lava layers of the Deccan Trap are the most significant geological structure in the district. There are two different lava flow layers. The top layer is made up of vesicular basalt and the bottom layer is made up of massive basalt [53]. Deep and medium black soil is generally found...
in the district. The texture and depth of the soil varies from north to south. Shallow and poor soils are mostly found in the northern part of the district, while it becomes fairly rich in nutrients and deep in the south. It is rich in natural nutrients like magnesia, iron, lime, and alkalis, which is suitable for growing dry crops such as cotton, jowar (Sorghum), bajra (*Pennisetum glaucum*), etc. Agriculture is the main occupation of the people, and farmers are mostly dependent on rainfall for growing crops. Most parts of the district are vulnerable to drought due to less availability of water [54]. Expansion of the Aurangabad city and haphazard industrial development has created more stress on the water resources in the district.

3. Database and Methodology

3.1. Satellite Datasets

Cloud-based data from Landsat has been utilized for this study in the Google Earth Engine platform. For the Landsat OLI/TRS sensors, atmospherically corrected surface reflectance datasets were used. Four visible, one near-infrared (NIR) band, and two short-wave infrared (SWIR) bands were processed to generate the surface reflectance, and two thermal infrared (TIR) bands were processed to generate the brightness temperature. We have used the images from 1999, 2004, 2009, 2014, and 2019 to assess land use/land cover in the study area at an interval of five years. An interval for each year for land use/land cover was not possible due to inconsistencies (high cloud cover) in the satellite data. Therefore, five-year intervals were utilized. The study area is covered by three tiles of satellite images. Thus, we required at least three tiles for a particular year to assess land use/land cover. In the month of October, November, and December, the study area gets a clear sky. This is why the satellite images for these months were taken. However, some satellite images still got cloud cover. In that case, we used a less than 10% cloud cover filter. We were able to get at least three images of the study area for each particular year. A total number of 75 satellite images were utilized in the framework of the time period. The interval of five years was used for the land use/land cover analysis.

Machine learning algorithms, namely the classification and regression tree (CART), random forest (RF), support vector machine (SVM), continuous naïve (CN), and minimum distance (MD) techniques, were utilized to find the best fit classification technique. These classifiers were utilized to classify the study area into four land use/land cover classes, namely waterbodies, built-up, agricultural land, and barren land. GEE was used to carry out the whole classification process. In the first step, code was run to load the Landsat cloud-free satellite images. Sample training data were extracted in GEE using mean pixel values of the spectral signatures. These datasets were used as a training test for classifying the land use/land cover using machine learning algorithms. Initially, we added eighty samples. This procedure was followed by adding more sample data until high accuracy classification results were obtained. The data were split randomly into the training (70%) and testing (30%) datasets. Detailed methodology is illustrated in Figure 2.

3.1.1. Random Forest Algorithm

The pixel value-based random forest machine learning algorithm was used for land use/land cover classification. In contrast to other algorithms, the accuracy of random forest classifiers in GEE is very high for Landsat imagery [55]. It has the advantage of being a highly efficient and nonlinear supervised classifier. It is capable of yielding effective results [56–59]. It involves the classification of the data into multiple decision trees to produce an accurate class. This RF was applied, and ten decision trees were incorporated (as per the requirement of the RF algorithm) to classify the satellite images into different classes using the square root of variables. In this algorithm, we first used the spectral signature samples to assign LULC classes. Then these spectral values were split into training and testing datasets. The training datasets provided trees. Classes of trees yielded a forest. Finally, the required classes of LULC on the basis of maximum voting were
obtained. The data were split randomly into the training (70%) and testing (30%) datasets. The random forest model is constructed as:

$$m(x) = t_0(x) + t_1(x) + t_2(x) + t_3(x) + t_4(x).$$

(1)

where, $m(x)$ is the final model and $t_1, t_2, t_3,$ and $t_4$ are the base models.

Figure 2. Details of the methodological framework.

3.1.2. Support Vector Machine

The SVM is one of the most widely used non-parametric, supervised classification algorithms [40,42]. Vapnik and Chervonenkis [60] proposed this classification based on statistical learning theory. Later, it was widely used by Osuna et. al. [61] and Pal [62]. This algorithm has an advantage over traditional LULC classifiers in terms of training datasets and accuracy [41,42]. LULC classes in this algorithm are distinguished by using hyperplanes. The hyperplane (optimum minimization) distinguishes the classification problem into predefined sets of classes that are consistent with the training (70%) data. The algorithm identified the pattern in the training data and applied the same configuration to a separate evaluation dataset. After that, it validated it with the testing data (30%). Here, we used a linear kernel with gamma values that were null at cost one of SVM for defining
the hyperplane boundary to classify the satellite images into different LULC classes. This hyperplane separation boundary can be mathematically expressed as:

\[ w \cdot x_i + b \geq +1 \quad \text{for all } y = +1 \]  
\[ w \cdot x_i + b \leq -1 \quad \text{for all } y = -1 \]  

The combination of Equations (2) and (3) is expressed as:

\[ y_i(w \cdot x_i + b) - 1 \geq 0 \]  

The set of functions (space) is explained by:

\[ f_{w,b} = \text{sign}(w \cdot x_i + b) \]  

The constraint employed on the unique pair \((w, b)\) for each space hypothesis is given as:

\[ \min_{i=1,...,k} |w \cdot x_i + b| = 1 \]  

The hyperplanes in the above equation are called canonical hyperplanes, which represent linear decision surfaces [62]. The distance associated with pair \((w, b)\) from a point \(x\) to the hyperplane is explained by:

\[ d(x; w, b) = \frac{|x \cdot w + b|}{||w||} + \ldots \]  

### 3.1.3. Classification and Regression Tree

The CART develops a binary decision tree using the samples of training data (70%). A single input variable and a split point on that variable are represented by each root node. The tree’s leaf nodes have an output variable that is used to make a prediction [46]. This classifier was used to logically classify the image in different classes based on the decision trees. In this algorithm, we used maximum nodes with no limits because of the large dataset, and a minimum of one leaf to create at least one node for each decision tree. Based on the required information, this method divides the input data into groups and generates trees, leaving one group. Finally, The trees are validated with the left-out group (30%) [47]. The following equation was used to classify the satellite data:

\[ i(t) = -\sum_{j=1}^{k} p(w_j/t) \log p(w_j/t) \]  

where, \(t\) denotes root node, \(i(t)\) is the impurity measures of \(t\), \(p(w_j/t)\) is the proportion of pattern \(x_i\) allocated to class \(w_j\) at node \(t\). Each non-terminal node is then divided into two further nodes, as given in the Equation (2):

\[ \Delta i(s, t) = i(t) - p_L i(t_L) - p_R i(t_R) \]  

where, \(t_L\) and \(t_R\), such that \(p_L, p_R\) are the proportions of entities passed to the new nodes, are \(t_L, t_R\), respectively.

### 3.1.4. Naïve Bayes (NB)

This algorithm utilizes a probabilistic approach contained in the Bayes theorem [63,64]. It is based on the Gaussian probability distribution, where interdependence between every pair of features is assumed [65]. However, this condition is hardly met in more complex data. In this algorithm, we used lambda (0.000001 value) to avoid assigning zero probability to classes not seen during the training dataset. The same lambda values were utilized to validate the training data (70%) with the testing data (30%). This posterior probability, \(P(c \mid x)\), was calculated using the Bayes theorem. The effect of the predictor \(x\)
on class (c) is assumed to be independent of other predictors. This interdependence can be enumerated as:

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$  \hspace{1cm} (10)

$P(c | x)$ is the posterior probability.
$P(c)$ is the prior probability of class.
$P(x | c)$ is the probability of predictor of a given class.
$P(x)$ is the prior probability of predictor.

Based on the above equations, the GEE script was performed to classify the satellite images into different classes.

3.1.5. Minimum Distance

This algorithm calculates the distance from an unknown pixel $(BV_{ijk})$ for each mean vector. In this classification algorithm, we used the cosine distance (spectral angle from the unnormalized class mean). It determined the average values of pixel allocation for each training dataset and where each class was compared to the distance from the pixel values that were not classified to an average pixel value for each class. The pixel was allocated to a class with the lowest average distance [66]. This is essentially based on the K Nearest neighbors, if K Nearest is greater than the total number of classes, which will be set equal to the number of classes. We have used the K Nearest value of 1 to determine classes. The data was split into the training (70%) and testing (30%) datasets. This can be mathematically expressed as:

$$\text{Dist} = \sqrt{\left( BV_{ijk} - \mu_{ck} \right) + \left( BV_{ijl} - \mu_{cl} \right)}$$  \hspace{1cm} (11)

where $\mu_{ck}$ and $\mu_{cl}$ represent the mean vectors for class c, measured in bands k and l.

Based on the above equations, the GEE script was performed to classify the satellite images into different classes.

A simplified scheme of all the machine learning classifiers is presented in Figure 3. Sample signatures were taken from throughout the study area for each layer (Figure 4). The sampled data were divided into training (70%) and testing (30%) datasets [47]. Classified maps were visually checked using satellite-based images and were validated through field data [45]. GEE codes for all of the machine learning classifiers are provided in the Appendix A.

Figure 3. Schematic representation of various classifiers. (a) Random Forest, (b) Support Vector Machine, (c) Classification and Regression Tree, (d) Naïve Bayes (e) Minimum Distance.
3.2. Meteorological Parameters and Soil Moisture

To assess climate variability, Terra Climate monthly data, which was maintained by Idaho University, have been utilized from 1999 to 2019. This dataset combines three global gridded climate data, namely the WorldClim version 1.4 and 2, CRU Ts4.0, and JRA-55 [67]. Terra Climate datasets were validated using meteorological station data obtained from the Global Historical Climatology Network (GHCN). We have also validated the precipitation data of the Terra Climate dataset with IMD station data to find out the reliability of these datasets locally, for the period of 1999 to 2016. The trend of the IMD station data and Terra Climate data have shown similar patterns in the datasets (Figure 5). Correlations between the Terra Climate data and in-situ IMD observation stations data were found to be positive and significant. The correlation between both datasets was found to be 0.859 for the Aurangabad district. The average monthly minimum temperature, average monthly maximum temperature, average monthly soil moisture, average monthly precipitation, and average monthly wind speed were used for the analysis of climate variability.

Figure 4. Location of the samples taken for LULC classification.
Figure 5. Trend in IMD station and Terra Climate average monthly precipitation (1999–2016).

3.2.1. Trend Analysis Using Mann–Kendall’s Test

The Mann–Kendall test was used to assess the precipitation trend:

\[
S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} \text{Sign}(y_i - y_j)
\] (12)

Here, \(y_j\) = precipitation, \(n\) = time series of the data, \(\text{Sign}(y_i - y_j) = -1\) for \((y_i - y_j) < 0\), \(\text{Sign}(y_i - y_j) = 0\) for \((y_i - y_j) = 0\), \(\text{Sign}(y_i - y_j) = 1\) for \((y_i - y_j) > 0\).

Mean and variance for statistic \((S)\) were derived as:

\[
E(S) = 0
\] (13)

\[
\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} - \sum_{h=1}^{g} l_h(l_h - 1)(2l_h + 5)
\] (14)

where, \(l_h\) is the number of ties for the hth value and \(g\) is the number of tied values. The adjustment for the tied data are represented in the second term. The test was computed as:

\[
Z_{MK} = \begin{cases} 
\frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0, S = 0, \text{ or } S < 0 \\
0 & S > 0, S = 0, \text{ or } S < 0 \\
\frac{S+1}{\sqrt{\text{Var}(S)}} & S > 0, S = 0, \text{ or } S < 0
\end{cases}
\] (15)

If \(S > 0, S = 0, \text{ or } S < 0\). Positive and negative \(Z_{MK}\) values show an increasing and decreasing trend, respectively. For examining the monotonic trend at a \(p\) significance level, the absolute value of \(Z\), greater than \(Z_1 = h/2\), is obtained from the table of the standard normal cumulative distribution for the null hypothesis [56].

3.2.2. Sen’s Slope Estimator for Magnitude of the Trend

The magnitude of the trend was predicted using the Sen’s estimator statistics, where the slope \((T_i)\) of all the data pairs is computed as

\[
T_i = \frac{y_j - y_k}{j - k}
\] (16)
For $i = 1, 2, 3, 4, 5 \ldots n$. Where, $y_j$ and $y_k$ are considered as data values at time $j$ and $k$ ($j > k$) correspondingly. The median of these $N$ values of $T_i$ is represented as Sen’s estimator of the slope, which is given as:

$$Q_i = \begin{cases} 
\frac{T}{N+1} & \text{if } N \text{ is odd} \\
\frac{1}{2} \left( \frac{T}{N} + \frac{T}{N+2} \right) & \text{if } N \text{ is even}
\end{cases}$$

(17)

where positive and negative values of $Q_i$ indicate the increasing and decreasing trend of the time series.

3.3. Correlation and Multiple Linear Regression

The Pearson correlation method was utilized to find out the relationship between four distinct LULC classes and hydro-meteorological parameters. The Pearson correlation coefficient was performed using the following equation [68]:

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}}$$

(18)

$r$ = correlation coefficient
$x_i$ = values of the $x$-variable in a sample
$\bar{x}$ = mean of the values of the $x$-variable
$y_i$ = values of the $y$-variable in a sample
$\bar{y}$ = mean of the values of the $y$-variable

A multiple linear regression was performed to examine the influence of the land use/land cover change on meteorological variables. It was executed as:

$$r_i = \beta_0 + \beta_1 q_i 1 + \beta_2 q_i 2 + \ldots + \beta p q_i p + \epsilon_i \text{ for } i = 1, 2, \ldots n2$$

(19)

where $q$ = land use/land cover class and $r$ = climate variable.

The regression line for the explanatory variables ($q_1, q_2, \ldots, q_p$) can be expressed as [69]:

$$\mu r = \beta_0 + \beta_1 q_1 + \beta_2 q_2 + \ldots + \beta p q_p$$

(20)

3.4. Limitations of the Study

We were first confronted with the problem of the availability of continuous satellite data. Thus, we utilized the data with five-year intervals. Secondly, the available satellite images were being disrupted by clouds. The images were rectified by applying a cloud-free filter in GEE. The availability of cloud-free and consistent remote sensing data can yield results with better accuracy.

4. Results

The Classification and regression tree (CART), random forest (RF), support vector machine (SVM), continuous naïve, and minimum distance machine learning algorithms were utilized to find the best fit classification technique. Based on the results and overall accuracy, the random forest technique was found to be the most suitable technique for further land use/land cover classification (Table 1). Comparative images of CART, RF, SVM, continuous naïve, and minimum distance revealed that the CART classifier has classified the satellite images very poorly (Figure 6). This is because the classifier was not able to differentiate between the built-up and barren land.
Table 1. Accuracy of LULC classifiers.

| Classifier         | Model Accuracy | Field Data Accuracy | Overall Accuracy |
|--------------------|----------------|---------------------|------------------|
| CART               | 0.74           | 0.78                | 0.76             |
| Random Forest      | 0.84           | 0.89                | 0.86             |
| SVM                | 0.84           | 0.86                | 0.85             |
| Continuous Naive   | 0.85           | 0.81                | 0.83             |
| Minimum Distance   | 0.81           | 0.84                | 0.83             |

Figure 6. Comparison of CART, RF, SVM, continuous naïve, and minimum distance classifiers.
4.1. Temporal Analysis of Land Use/Land Cover

Multispectral images from Landsat for the years 1999, 2004, 2009, 2014, and 2019 were examined in order to analyze the land use transformation in the study area. LULC of Aurangabad district is largely determined by physio-climatic conditions of the area. No forest area is found in the district. As well, based on the local land utilization, there are only four major classes considered in the district, namely built-up, agriculture, barren land, and water bodies (Figure 7). Table 2 illustrates the details of the different land use classes. The LULC analysis revealed an increase in the built-up area in the last two decades, as illustrated in Figure 7. Most of the area of the district is covered with agriculture and barren land. Table 2 revealed significant temporal changes in LULC in terms of the different areas. The results show that the area under built-up, water bodies, and barren lands have increased, while agricultural land exhibited a decrease in its area. The built-up and water bodies have shown an increase in area between 1999 and 2019. The built-up area has increased eight times, mainly due to the growth of the settlement since 1999. The built-up area has increased from 0.61% in 1999 to 4.89% in 2019. Most of the peripheral agricultural land was converted into built-up area. The area under water bodies has increased due to the construction of new dams and ponds.

![Spatial distributions of LULC in the study area during 1999–2019.](image)

**Figure 7.** Spatial distributions of LULC in the study area during 1999–2019.

**Table 2.** Different LULC categories for 1999, 2004, 2009, 2014 and 2019 using Landsat data.

| Class          | 1999 Area (km²) | 1999 Area (%) | 2004 Area (km²) | 2004 Area (%) | 2009 Area (km²) | 2009 Area (%) | 2014 Area (km²) | 2014 Area (%) | 2019 Area (km²) | 2019 Area (%) |
|----------------|-----------------|---------------|-----------------|---------------|-----------------|---------------|-----------------|---------------|-----------------|---------------|
| Water bodies   | 180.8           | 1.68          | 243.5           | 2.26          | 232.6           | 2.16          | 236.7           | 2.20          | 350.9           | 3.26          |
| Built-up       | 65.4            | 0.61          | 79.2            | 0.74          | 225.8           | 2.10          | 470.4           | 4.37          | 525.4           | 4.89          |
| Agricultural land | 6430.0        | 59.78         | 6123.4          | 56.93         | 8745.5          | 81.31         | 7807.4          | 72.59         | 5697.1          | 52.97         |
| Barren Land    | 4079.3          | 37.93         | 4309.5          | 40.07         | 1551.5          | 14.43         | 2241            | 20.84         | 4182.1          | 38.88         |
| Total          | 10,755.5        | 100           | 10,755.5        | 100           | 10,755.5        | 100           | 10,755.5        | 100           | 10,755.5        | 100           |
4.2. Temporal Analysis of Meteorological Parameters (1999–2019)

The monthly and annual mean of the climate variables, particularly precipitation, minimum temperature, maximum temperature, soil moisture, and wind speed, were assessed using an MK test for Aurangabad district. Various statistics like minimum, maximum, mean, Standard Deviation (SD), Z-Value Mann–Kendall (ZMK), Pre-whitened Sen’s slope, Sen’s slope, and p-values are shown in Tables 3–7. These tables also indicate the MK statistics and p-values derived at 10%, 5%, and 1% levels of significance. The Z-values of the MK test were ascertained to determine the increasing or decreasing trend in the climate variables. The MK test findings are explained in separate detail for each climate variable.

Table 3. Monthly and annual MK result for maximum temperature.

| Months   | Minimum | Maximum | Mean | SD | ZMK       | Prewhitened Sen’s Slope | Sen’s Slope | p-Value |
|----------|---------|---------|------|----|-----------|--------------------------|-------------|---------|
| January  | 27.8    | 34.0    | 29.1 | 1.3| −1.655 *  | −0.059                  | −0.036      | 0.0980  |
| February | 30.8    | 34.0    | 32.5 | 0.9| −0.746    | −0.028                  | −0.020      | 0.4555  |
| March    | 34.3    | 38.0    | 36.1 | 0.9| −0.162    | −0.011                  | −0.032      | 0.8711  |
| April    | 37.2    | 40.4    | 38.9 | 0.7| −0.552    | −0.012                  | −0.010      | 0.5813  |
| May      | 38.3    | 41.6    | 40.1 | 0.8| 3.926 *** | 0.107                   | 0.105       | 0.0001  |
| June     | 33.1    | 37.1    | 34.8 | 1.1| 2.174 **  | 0.129                   | 0.110       | 0.0297  |
| July     | 27.6    | 31.7    | 30.0 | 0.8| 0.811     | 0.019                   | 0.028       | 0.4173  |
| August   | 28.2    | 31.1    | 29.6 | 0.7| 1.784 *   | 0.042                   | 0.052       | 0.0744  |
| September| 28.7    | 31.2    | 30.0 | 0.6| 0.032     | 0.005                   | 0.015       | 0.9741  |
| October  | 30.3    | 32.9    | 31.6 | 0.7| 0.811     | 0.024                   | 0.024       | 0.4173  |
| November | 28.9    | 32.1    | 30.6 | 0.8| −0.487    | −0.018                  | −0.006      | 0.6265  |
| December | 27.4    | 30.5    | 29.3 | 0.8| −0.292    | −0.017                  | −0.009      | 0.7703  |

*** 1% significance, ** 5% significance, and * 10% significance, respectively.

Table 4. Monthly and annual MK results of minimum temperature.

| Months   | Minimum | Maximum | Mean | SD | ZMK       | Prewhitened Sen’s Slope | Sen’s Slope | p-Value |
|----------|---------|---------|------|----|-----------|--------------------------|-------------|---------|
| January  | 12.2    | 18.3    | 13.5 | 1.3| −0.811    | −0.0211                  | −0.0106     | 0.4173  |
| February | 14.7    | 17.8    | 16.5 | 0.9| −0.0973   | −0.0048                  | −0.0042     | 0.9225  |
| March    | 17.9    | 21.6    | 19.7 | 1.0| 0.5516    | 0.0308                   | 0.0215      | 0.5813  |
| April    | 22.4    | 25.5    | 24.1 | 0.7| −0.6164   | −0.0154                  | −0.0157     | 0.5376  |
| May      | 23.9    | 27.0    | 25.5 | 0.7| 4.0555 ***| 0.1106                   | 0.0994      | 0.0001  |
| June     | 22.3    | 25.9    | 23.6 | 1.1| 2.5631 ** | 0.1282                   | 0.1021      | 0.0104  |
| July     | 21.5    | 24.0    | 22.5 | 0.6| 0.6164    | 0.0185                   | 0.0226      | 0.5376  |
| August   | 20.9    | 23.2    | 21.8 | 0.6| 1.9142 *  | 0.0403                   | 0.0545      | 0.0556  |
| September| 20.1    | 22.4    | 21.1 | 0.5| 0.8760    | 0.0214                   | 0.0255      | 0.3810  |
| October  | 18.4    | 21.0    | 19.6 | 0.7| 0.5516    | 0.0212                   | 0.0314      | 0.5813  |
| November | 14.5    | 17.7    | 16.1 | 0.8| 1.0707    | 0.0301                   | 0.0413      | 0.2843  |
| December | 11.7    | 14.6    | 13.3 | 0.9| 0.0324    | 0.0006                   | 0.0369      | 0.9741  |

*** 1% significance, ** 5% significance, and * 10% significance, respectively.
Table 5. Monthly and annual MK results of precipitation.

| Months     | Minimum | Maximum | Mean | SD  | ZMK       | Prewhitened Sen's Slope | Sen's Slope | p-Value |
|------------|---------|---------|------|-----|-----------|--------------------------|-------------|---------|
| January    | 0.0     | 12.1    | 1.7  | 2.9 | −2.6005   | −1.2801                  | 0           | 7.9482  |
| February   | 0.0     | 3.6     | 0.8  | 1.1 | 6.5014    | 1.1968                   | 0           | 9.4816  |
| March      | 0.0     | 26.7    | 5.8  | 7.7 | −2.9199   | −4.4345                  | 3.5388      | 7.7028  |
| April      | 0.0     | 16.9    | 4.5  | 4.7 | 1.2004    | 2.0696                   | 1.2283      | 2.2996  |
| May        | 0.0     | 71.4    | 18.8 | 19.0| −1.1355   | −7.4434                  | −5.3695     | 2.5614  |
| June       | 18.7    | 250.1   | 142.3| 53.4| −1.8493   | −4.0923                  | −1.4622     | 6.4411  |
| July       | 31.2    | 263.5   | 165.3| 64.1| 8.7599    | 2.177                    | 3.1491      | 3.8103  |
| August     | 54.3    | 313.6   | 152.0| 56.5| −8.7599   | −1.2975                  | −1.1899     | 3.8103  |
| September  | 46.8    | 262.4   | 153.4| 58.7| 1.6546    | 5.8286                   | 4.4866      | 9.7993  |
| October    | 1.2     | 242.1   | 56.7 | 50.7| 1.1355    | 1.6098                   | 8.9211      | 2.5614  |
| November   | 0.0     | 185.8   | 21.8 | 41.4| 8.111     | 3.4544                   | 3.0979      | 4.173   |
| December   | 0.0     | 21.2    | 3.4  | 5.7 | 8.8378    | 6.9348                   | 0           | 3.7681  |

Table 6. Monthly and annual MK results of soil moisture.

| Months     | Minimum | Maximum | Mean | SD  | ZMK       | Prewhitened Sen's Slope | Sen's Slope | p-Value |
|------------|---------|---------|------|-----|-----------|--------------------------|-------------|---------|
| January    | 6.3     | 36.4    | 20.2 | 6.5 | 0.1622    | 0.0762                   | 0.0350      | 0.8711  |
| February   | 6.0     | 26.9    | 16.8 | 4.6 | 0.0324    | 0.0169                   | 0.0224      | 0.9741  |
| March      | 5.7     | 21.6    | 14.4 | 3.6 | 0.0324    | 0.0298                   | 0.0141      | 0.9741  |
| April      | 5.4     | 18.0    | 12.7 | 2.9 | 0.1622    | 0.0311                   | 0.0093      | 0.8711  |
| May        | 5.2     | 15.5    | 11.3 | 2.4 | 0.1622    | 0.0253                   | 0.0063      | 0.8711  |
| June       | 8.2     | 91.9    | 19.8 | 19.8| 0.2271    | 0.0337                   | 0.0430      | 0.8203  |
| July       | 8.9     | 115.7   | 58.8 | 39.5| 0.4867    | 1.0539                   | 1.3363      | 0.6265  |
| August     | 9.0     | 121.3   | 70.6 | 37.8| 0.2271    | 0.0501                   | 0.9217      | 0.8203  |
| September  | 8.3     | 121.4   | 83.8 | 34.8| 0.4867    | 0.9886                   | 1.1060      | 0.6265  |
| October    | 7.7     | 121.4   | 55.3 | 28.0| 1.2004    | 1.8144                   | 1.4012      | 0.2300  |
| November   | 7.2     | 115.3   | 39.2 | 25.0| 0.9409    | 0.5473                   | 0.5752      | 0.3468  |
| December   | 6.7     | 60.3    | 26.4 | 11.5| 0.8111    | 0.3567                   | 0.3414      | 0.4173  |

Table 7. Monthly and annual MK results of wind speed.

| Months     | Minimum | Maximum | Mean | SD  | ZMK       | Prewhitened Sen's Slope | Sen's Slope | p-Value |
|------------|---------|---------|------|-----|-----------|--------------------------|-------------|---------|
| January    | 8.9     | 18.3    | 16.1 | 1.9 | −2.5631 **| −0.1699                  | −0.1330     | 0.0104  |
| February   | 6.3     | 18.2    | 15.5 | 2.5 | −0.6813   | −0.0433                  | −0.0424     | 0.4957  |
| March      | 6.9     | 20.2    | 16.1 | 2.8 | −3.1471 ***| −0.3690                  | −0.1830     | 0.0016  |
| April      | 14.4    | 25.8    | 19.6 | 3.1 | −2.0440 **| −0.2143                  | −0.2609     | 0.0410  |
| May        | 25.2    | 38.4    | 32.2 | 3.5 | −2.3684 **| −0.2823                  | −0.2841     | 0.0179  |
| June       | 22.0    | 39.8    | 32.5 | 4.8 | −2.5631 **| −0.5167                  | −0.4070     | 0.0104  |
Table 7. Cont.

| Months  | Minimum | Maximum | Mean | SD   | ZMK    | Prewhitened Sen’s Slope | Sen’s Slope | p-Value |
|---------|---------|---------|------|------|--------|-------------------------|-------------|---------|
| July    | 26.4    | 46.5    | 35.8 | 6.0  | 0.3569 | 0.1187                  | 0.0732      | 0.7212  |
| August  | 18.3    | 41.2    | 28.4 | 5.8  | −1.1355| −0.2193                 | −0.2193     | 0.2561  |
| September| 13.0   | 28.6    | 20.7 | 4.2  | 0.0973 | 0.0579                  | −0.0714     | 0.9225  |
| October | 5.9     | 13.3    | 10.1 | 1.9  | −3.0173*** | −0.2464                 | −0.1341     | 0.0026  |
| November| 6.6     | 15.1    | 11.9 | 2.2  | −0.4218| −0.0607                 | −0.0838     | 0.6732  |
| December| 10.0    | 15.7    | 13.3 | 1.4  | −1.2004| −0.0903                 | −0.0919     | 0.2300  |

*** 1% significance and ** 5% significance, respectively.

4.2.1. Maximum Temperature

An increase in temperature is one of the indications of global climate change. Table 3 illustrates the various statistics and trends for the maximum temperature in the Aurangabad district. It ranges from 27.4 °C to 41.6 °C. The results of the MK test for the monthly maximum temperature data revealed an increasing trend for the months of May (at a 1% level of significance), June (at a 5% level of significance), and August (at a 10% level of significance), while January had a decreasing trend (at a 10% level of significance). Long-term anomalies in the average annual maximum temperature revealed inter-annual variability in the Aurangabad district. The pattern of monthly maximum temperature depicts that Aurangabad district receives a high maximum temperature during the summer session in February, March, April, and June, while it experiences a low maximum temperature in the winter season in November, December, and January. The spatial trend for the maximum temperature revealed that Aurangabad district has been observing an increasing trend (Figure 8a). Figure 9 demonstrates the notable changes that occurred over a given time period (1999–2019). The southern part of the district showed a considerable change in the maximum temperature, from 32 °C in 1999 to 34 °C in 2017—and again 32 °C in 2018. Similarly, the central part of the study area experienced a maximum temperature of 32 °C, or even lesser, throughout the study period. The maximum temperature in the northern part of the district was found to be constant from 1999–2017, i.e., >34 °C, whereas in 2018 it decreased to 33 °C. The findings for the maximum temperature also revealed that the maximum temperature reached up to 32 °C in 2018, while it was more than 34 °C in the northern parts of the district. A maximum temperature of more than 34 °C was also identified in the northern and southern parts of the district in 2003, 2009, and 2014. These temperature changes may be attributed to the transformation of agricultural land to barren land.

4.2.2. Minimum Temperature

The minimum temperature ranges from 11.7 °C to 27 °C in the Aurangabad district (Table 4). The results of the MK test for the monthly minimum temperature data depict an increasing trend for the months of May (at a 1% level of significance), June (at a 5% level of significance), and August (at a 10% level of significance). The pattern of the monthly minimum temperature shows that the district experiences high minimum temperatures in the months of April, May, June, July, and August, while it receives low minimum temperatures in the months of November, December, January, and February. The spatial trend for the minimum temperature also revealed that Aurangabad district has been observing an increasing trend (Figure 8b). The minimum temperature follows the pattern of the maximum temperature. Figure 10 shows an annual minimum temperature that ranged between <18 °C and >21 °C. The persistent minimum temperature has been observed in the central part of the district (19–20 °C). The southern part of the district experienced temperatures ranging between 20 °C and 21 °C from 2009 to 2018. More than a 21 °C minimum temperature has been observed in the northern part of the district. A decreasing
pattern in the minimum temperature (18 °C–19 °C) has been observed clearly in grey patches in the central part of the district. Overall, there has been a rise in the minimum temperature for the whole district over the analyzed time period. This finding is in confirmation with the previous studies using monthly global data, e.g., Alexander et al. [49].

**Figure 8.** Spatial climate variability: (a) maximum temperature, (b) minimum temperature, (c) precipitation, (d) soil moisture, and (e) wind speed.

### 4.2.3. Precipitation

The short rainy season, which starts from May and lasts into October, contributes a substantial amount of precipitation. The results of the MK test for the monthly precipitation data revealed a decreasing trend for the months of January, March, May, June, and August (Table 5). The remaining months have an increasing trend. However, these results were not statistically significant. The pattern of monthly precipitation depicts that Aurangabad district receives maximum precipitation during the monsoon period in June, July, August, and September, while it receives substantially less precipitation in the winter season in December, January, and February. The spatial trend for precipitation revealed that Aurangabad district has been experiencing a decreasing trend (Figure 8c). As Figure 11 depicts, the precipitation maps revealed the fluctuating pattern in the study area. The precipitation values varied from <500 mm to >800 mm. An increasing pattern in precipitation from 1999 to 2011 was observed. Moreover, it starts declining from 2012 to 2018 (Figure 11). A regional variation of the precipitation pattern could be observed in the study area, and the northern part of the Aurangabad district receives precipitation varying from 600 mm to 800 mm, while the southern and western part of the district received less than 500 mm of precipitation. The years of 2001, 2002, and 2003 were identified as dry years, as these years received less precipitation—i.e., <600 mm. Similarly, the years of 2005, 2006, 2009, 2010, 2011, and 2013 were observed as wet years that experienced maximum precipitation (>700 mm). However, the district received lesser annual precipitation (600 mm) recently (Figure 11).
4.2.2. Minimum Temperature

The minimum temperature ranges from 11.7 °C to 27 °C in the Aurangabad district (Table 4). The results of the MK test for the monthly minimum temperature data depict an increasing trend for the months of May (at a 1% level of significance), June (at a 5% level of significance), and August (at a 10% level of significance). The pattern of the monthly minimum temperature shows that the district experiences high minimum temperatures in the months of April, May, June, July, and August, while it receives low minimum temperatures in the months of November, December, January, and February. The spatial trend for the minimum temperature also revealed that Aurangabad district has been observing an increasing trend (Figure 8b). The minimum temperature follows the pattern of the maximum temperature. Figure 10 shows an annual minimum temperature that ranged between <18 °C and >21 °C. The persistent minimum temperature has been observed in the central part of the district (19 °C–20 °C). The southern part of the district experienced temperatures ranging between 20o and 21 °C from 2009 to 2018. More than a 21 °C minimum temperature has been observed in the northern part of the district. A decreasing pattern in the minimum temperature (18 °C–19 °C) has been observed clearly in grey patches in the central part of the district. Overall, there has been a rise in the minimum temperature for the whole district over the analyzed time period. This finding is in confirmation with the previous studies using monthly global data, e.g., Alexander et al. [49].

Figure 9. Temporal variations in maximum temperature.

Figure 10. Temporal change in minimum temperature.
4.2.4. Soil Moisture

Soil moisture is the water content present on the soil surface. Large variations in soil moisture were observed in the district (Figure 12). Seasonal change, as well as precipitation variation, played an important role in determining soil moisture. Soil moisture varied from 5.2 to 121.4 in the Aurangabad district (Table 6). The results of the MK test for the monthly soil moisture showed an increasing trend for all the months. However, these results were not statistically significant. The pattern of monthly soil moisture revealed that it observed high soil moisture during the monsoon season in the months of July, August, September, and October, while it experienced low soil moisture in the months of February, March, April, and May. The spatial trend of soil moisture revealed that most parts of the district experienced an increasing trend (Figure 8d). The spatial annual average values of soil moisture varied between <20% and >50%. The lowest soil moisture (<20%) was observed in the year 2001. A high content of soil moisture was found in 2005, 2006, 2010, and 2011. The recent five-year analysis showed a decreasing trend in soil moisture content in the study area (Figure 12).
### Table 6. Monthly and annual MK results of soil moisture.

| Months | Minimum | Maximum | Mean | SD    | ZMK | Prewhitened Sen’s Slope | Sen’s Slope | p-Value |
|--------|---------|---------|------|-------|-----|--------------------------|-------------|---------|
| January | 6.3     | 36.4    | 20.2 | 6.5   | 0.1622 | 0.0762                  | 0.0350     | 0.8711  |
| February| 6.0     | 26.9    | 16.8 | 4.6   | 0.0324 | 0.0169                  | 0.0224     | 0.9741  |
| March  | 5.7      | 21.6    | 14.4 | 3.6   | 0.0324 | 0.0298                  | 0.0141     | 0.9741  |
| April  | 5.4      | 18.0    | 12.7 | 2.9   | 0.1622 | 0.0311                  | 0.0093     | 0.8711  |
| May    | 5.2      | 15.5    | 11.3 | 2.4   | 0.1622 | 0.0253                  | 0.0063     | 0.8711  |
| June   | 8.2      | 91.9    | 19.8 | 19.8  | 0.2271 | 0.0337                  | 0.0430     | 0.8203  |
| July   | 8.9      | 115.7   | 58.8 | 39.5  | 0.4867 | 1.0539                  | 1.3363     | 0.6265  |
| August | 9.0      | 121.3   | 70.6 | 37.8  | 0.2271 | 0.0501                  | 0.9217     | 0.8203  |
| September | 8.3    | 121.4   | 83.8 | 34.8  | 0.4867 | 0.9886                  | 1.1060     | 0.6265  |
| October | 7.7      | 121.4   | 55.3 | 28.0  | 1.2004 | 1.8144                  | 1.4012     | 0.2300  |
| November| 7.2      | 115.3   | 39.2 | 25.0  | 0.9409 | 0.5473                  | 0.5752     | 0.3468  |
| December| 6.7      | 60.3    | 26.4 | 11.5  | 0.8111 | 0.3567                  | 0.3414     | 0.4173  |

### Figure 12. Temporal change in soil moisture.

#### 4.2.5. Wind Speed

Significant variations were found in the wind speed. Wind speed varied from 5.9 to 46.5 m/s in the Aurangabad district (Table 7). The results of the MK test for the monthly wind speed revealed a decreasing trend for the months of March and October (at a 1% level of significance), and a decreasing trend for the months of January, April, May, and June (at a 5% level of significance). The pattern of monthly wind speed showed that it experienced high wind speeds in the months of May, June, July, and August, while it observed low wind speeds in the months of October, November, and December. The spatial trend for the wind speed depicted a decreasing trend in the district (Figure 8e). The annual average wind speed varied from <19 m/s to >22 m/s (Figure 13). A stable wind speed has been observed during 1999–2006, i.e., 21 m/s–22 m/s. Drastic changes in the wind speed were observed during 2007–2018. The low wind speed was observed for the years 2010 and 2018, where it varied from 19 m/s to 20 m/s.

#### 4.3. Correlation between LULC Change and Meteorological Parameters

A correlation analysis was carried out to ascertain the relationship between LULC change and the meteorological parameters. The results revealed that a significant correlation was found between agricultural land and soil moisture (1% level of significance). As well, the maximum temperature was positively related with agricultural land (5% level of significance). There was a negative correlation that existed between barren land and soil moisture (1% level of significance). Furthermore, water bodies were negatively correlated with wind speed (1% level of significance). This finding is in line with Nagne et al. [70]. Waterbodies also have a weak correlation with other variables. It was also revealed that waterbodies and built-up area have a strong positive correlation. An increase in the area under built-up and water bodies was observed. In addition, agricultural land has a strong
negative correlation with barren land, while it has a strong positive correlation to soil moisture, minimum and maximum temperature, and precipitation. Last, barren land has a strong negative correlation with soil moisture, and minimum temperature and maximum temperature (Table 8).

Figure 13. Temporal change in wind speed.

Table 8. Relationship between LULC classes and Climate variables.

| Variables          | Waterbodies | Built-Up | Agricultural Land | Barren Land | Soil Moisture | Minimum Temperature | Maximum Temperature | Precipitation | Wind Speed |
|--------------------|-------------|----------|-------------------|-------------|---------------|---------------------|--------------------|--------------|------------|
| Waterbodies        | 1           |          |                   |             |               |                     |                    |              |            |
| Built-up           | 0.732       | 1        |                   |             |               |                     |                    |              |            |
| Agricultural Land  | −0.402      | 0.034    | 1                 |             |               |                     |                    |              |            |
| Barren Land        | 0.228       | −0.237   | −0.979 **         | 1           |               |                     |                    |              |            |
| Soil Moisture      | −0.187      | 0.221    | 0.972 **          | −0.993 **   | 1             |                     |                    |              |            |
| Minimum temperature| 0.142       | 0.417    | 0.806             | −0.877      | 0.877         | 1                   |                    |              |            |
| Maximum temperature| −0.549      | −0.173   | 0.881 *           | −0.819      | 0.781         | 0.73                | 1                  |              |            |
| Precipitation      | −0.468      | −0.502   | 0.735             | −0.622      | 0.672         | 0.501               | 0.687              | 1            |            |
| Wind Speed         | −0.947 *    | −0.765   | 0.192             | −0.016      | −0.042        | −0.257              | 0.473              | 0.296        | 1          |

** Significant at 1% level. * Significant at 5% level.
4.4. Influence of Land Use/Land Cover Change on Meteorological Variables

A multiple linear regression analysis revealed a significant impact of change in agricultural land on the maximum temperature and soil moisture. There was a conspicuous finding of the positive relationship between agricultural land and maximum temperature, which needs further investigation. It also revealed that agricultural land has affected all climatic variables. However, it was not ascertained significantly. The barren land has a negative impact on precipitation and soil moisture. An increase in the built-up area has negatively influenced precipitation, minimum temperature, and soil moisture, while it has positively influenced the maximum temperature. As well, no effect of water bodies was observed on any climatic variable in the study area (Table 9).

Table 9. Impact of LULC change on climate variables.

| Climatic Factors/LULC          | Agricultural Land | t  | Barren Land | t  | Built-Up | t  | Water Bodies | t  |
|-------------------------------|-------------------|----|-------------|----|----------|----|--------------|----|
| Precipitation                 | 0.735             | 1.878 | -1.1 *      | -10.461 | -1.303 * | -8.668 | 0.737 | 4.916 |
| Maximum Temperature           | 0.881 **          | 3.23 | -0.829      | -1.527 | 0.228    | 0.294 | -0.193 | -0.249 |
| Minimum Temperature           | 0.806             | 2.358 | -1.068      | -2.758 | -0.256  | -0.462 | 0.573 | 1.037 |
| Soil Moisture                 | 0.972 ***         | 7.208 | -1.073 *     | -12.314 | -0.165 | -1.324 | 0.179 | 1.438 |
| Wind Speed                    | 0.192             | 0.338 | 0.232        | 0.733 | 0.050    | 0.110 | -1.037 | -2.296 |

* 10% level of significance, ** 5% level of significance and *** 1% level of significance.

5. Discussion

The changes in LULC have considerably affected the spatiotemporal pattern of the climate of the Aurangabad district during 1999–2019. The development of the Aurangabad city center experienced exponential growth from 1999 to 2019. Kannad, located in the northwestern part, and Sillod, in the northeastern part of Aurangabad city, have emerged as satellite towns in the district. The city is rapidly expanding towards Waluj, in the southwestern side of the district. The month of January and February experience slightly higher temperatures in the winter season. Extreme summer occurs in April and May. The advancement of the southwest monsoon drops the temperature in the summer and weather becomes more comfortable in the district. The retreating monsoon again increases the daily temperature in the first week of October. After that, it drops constantly and soil moisture decreases in the winter season. During the southwest monsoon season, and in the latter half of the summer, winds are generally moderate in speed. The months of June and July have slightly higher wind speeds than other months (Table 7). The climate of the district is normally dry, which makes for low soil moisture and leads to severe drought conditions. From 1999 to 2003, very low soil moisture was observed in the study area (Figure 12). The lowest soil moisture and precipitation were recorded in 2001, and it was considered the driest year during the period from 1999–2019. The spatial and temporal climate of Aurangabad district has been facing a decrease in precipitation and an increase in temperature. Large variations were observed in the spatiotemporal distribution of precipitation (Figure 11). These variations were high during the monsoon season (Table 5). However, no consistent trend was noticed in the pattern of precipitation. High precipitation leads to an increase in the area under agriculture, while low precipitation may sometimes render the land uncultivated. As the area under agriculture and water bodies increased, this process has influenced the microclimate of the study area. Large areas under agriculture and water bodies helped in evapotranspiration, which helped in the occurrence of precipitation. However, there were marked variations in precipitation and increasing trends in the maximum temperature were noticed, mainly because of rapid urbanization and industrial development. An increasing trend in the maximum and minimum temperature was recorded during 1999–2019. City and Industrial Development Corporation (CIDCO) has developed commercial and industrial centers around Aurangabad city, which have resulted in the
conversion of periphery and rural areas into urban areas. Similar results were also observed by Nagne et al. [71], wherein the surrounding area of barren land and agricultural land was converted to a built-up area in Aurangabad city. Industrial development in the study area has also triggered rural to urban migration, leading to rapid urbanization surrounding the city. As a result, the temperature has increased [72]. Industrial development, which took place earlier, has increased the emission of carbon dioxide and carbon monoxide into the environment [73]. The development of agricultural land is also responsible for the emission of nitrous oxide and methane due to the excessive use of fertilizers. December 1999 was recorded as the coldest month (11.6 °C) in Aurangabad district because of the cold wave generated from the western disturbance in northern India. Built-up areas have negatively influenced precipitation. Built-up areas have continuously increased, though they covered a lower proportion of other land use classes. Agricultural land influenced the maximum temperature positively. Variations in the area under this land use category during the study period may be attributed to this influence. The barren land affected precipitation negatively. The large area under barren land acts as barrier to the local hydrological cycle, leading to a lowering of precipitation. The visual interpretation of the maximum and minimum temperature revealed that barren land located in the northern part of the district has a major influence on the temperature distribution in the study area (Figures 7, 9 and 10). This part has a higher temperature in comparison to other parts of the district. Massive plantations should be carried out in this region for temperature reduction, as the impervious barren lands are highly prone to heat absorption.

Remarkably few scenarios for future research in this research domain have been developed. Research with consistent and regular data on climate variables and LULC dynamics can effectively be carried out to understand the effect of landscape alteration on the behaviour of meteorological parameters and the micro-climate. This is a major research priority. A large amount of research was carried out in GEE on a macro scale that has shown major dynamics of the changes in climate and LULC. However, the magnitude and intensity of such changes are not the same everywhere. Micro-level case studies can help to investigate and document these changes in different geographical regions. Cloud-based computation, accessibility to various datasets, and effective analysis in GEE may provide an excellent platform for exploring various dimensions of the LULC intersection with climate variability.

6. Conclusions

This study examined the influence of LULC change on climate variability in the Aurangabad district of Maharashtra state in India. We analyzed land use/land cover dynamics using machine learning algorithms during 1999–2019. The climate variability was examined using a Mann–Kendall’s and Sen’s slope. The relationship between LULC classes and climate variables was established using a Pearson correlation. A multiple linear regression was performed to examine the influence of land use/land cover change on climate variables. Land use/land cover analysis revealed that Aurangabad city is expanding rapidly. The enormous pressure of the developmental activities in the surrounding areas has resulted in the conversion of prime agricultural land into built-up areas. The results also revealed that built-up, water bodies, and barren lands have shown a steep rise over the years. An increase in areas under the impervious surface has caused an increase in the maximum and minimum temperature. Wide variations occurred in precipitation at the spatial and temporal scales. The decreasing trend in wind speed and soil moisture in recent years was observed in the study area. Built-up area was found to be negatively associated with the precipitation, minimum temperature, and soil moisture, while it was positively associated with the maximum temperature. Though large variations in climate variables were observed, an increase in area under built-up and barren land have influenced the minimum and maximum temperature, precipitation, and soil moisture in the study area. Further experiment-based analysis is required to ascertain a clearer impact of land use/land cover dynamics on climate variability. The study calls for climate change-based futuristic
land use planning for the district, considering the development of small satellite towns. The methodology adopted in this study can be effectively utilized for analyzing the impact of land use/land cover change on climate variability, particularly at a micro-scale.

Author Contributions: Author Contributions: Conceptualization, M.M., R.A. and H.S.; methodology, M.M.; validation, M.M., P.C. and L.C.K.; formal analysis, K.M.K., A.A.K. and H.S.; writing-original draft preparation, M.M.; writing-review, H.S., R.A., N.S., A.P.Y. and K.M.K.; project administration, H.S.; funding acquisition, K.M.K., R.A., N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Deanship of Scientific Research at King Khalid University through the large research groups under grant number RGP.1/372/42.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study is publicly available on google earth engine platform. Anyone can access data using their log in ID and passwords.

Acknowledgments: We would like to thank USGS for Landsat satellite data and University of Idaho and Indian Meteorological Department for meteorological data. We acknowledge the support by the Deanship of Scientific Research at King Khalid University, Saudi Arabia for providing research grant number RGP.1/372/42. The authors are thankful to all the anonymous reviewers for the constructive comments and valuable suggestions which helped us to improve the overall quality of our manuscript.

Conflicts of Interest: There is no conflict of interest among authors.

Appendix A

GEE code for classification:
Importing and loading of dataset.
Map.addLayer(COI)
Map.centerObject(COI);
var l8 = l8.filterBounds(COI).filterDate('2019-10-01','2019-11-28').filterMetadata
('CLOUD_COVER','less_than',10);
var l8 = ee.Image(l8.mean().clip(COI));
print(l8)
Map.addLayer(l8)
//merge all
var trainingPoints = water2019.merge(Built2019).merge(Agri2019).merge(Barren2019);
var trainingRegions = l8.sampleRegions({
collection:trainingPoints,
properties:['class'],
properties:[
scale:90
]);
print(trainingPoints)
print(trainingRegions)
//randomise the collection
trainingRegions = trainingRegions.randomColumn({seed:0});
print(trainingRegions)
//split training and test set
var training = trainingRegions.filter(ee.Filter.lt('random',0.7));
var validation = trainingRegions.filter(ee.Filter.gte('random',0.7));
print(training)
print(validation)
//define classifier
var classifier = ee.Classifier.CART().train({

features:training,
classProperty:‘class’,
inputProperties:l8.bandNames()
})
var classified = l8.classify(classifier);
Map.addLayer(classified, {min: 0, max: 3, palette: ['#161dff', '#e73a12', '#2cff46', '#e7df81']}, 'classified image19')
//calculate test accuracy on test data
var testAccuracy = validation
.classify(classifier)
.errorMatrix(‘class’, ‘classification’)
.accuracy();
print(‘CART testAccuracy’, ee.Number(testAccuracy));
//confusion matrix accuracy
var con = classifier.confusionMatrix().accuracy();
print(con)
//RandomForest
var classifier1 = ee.Classifier.randomForest(10).train(
features:training,
classProperty:‘class’,
inputProperties:l8.bandNames()
})
var classified1 = l8.classify(classifier1);
Map.addLayer(classified1,[min: 0, max: 3, palette: ['#161dff', '#e73a12', '#2cff46', '#e7df81']],'classified image19RF')
//validation RF
var testAccuracy = validation
.classify(classifier1)
.errorMatrix(‘class’, ‘classification’)
.accuracy();
print(‘randomForest testAccuracy’, ee.Number(testAccuracy));
//confusion matrix accuracy
var con = classifier1.confusionMatrix().accuracy();
print(con)
//exporting image
Export.image.toDrive(
image: classified1,
description: ‘classified_image19RF’,
scale: 30,
region: COI
});
//svm
var classifier = ee.Classifier.svm(
kernelType: ‘LINEAR’,
gamma: null,
cost: 10
});
//Train the classifier.
var trained = classifier.train(training, ‘class’, l8.bandNames());
//Classify the image.
var classifiedSVM = l8.classify(trained);
Map.addLayer(classifiedSVM, {min: 0, max: 3, palette: ['#161dff', '#e73a12', '#2cff46', '#e7df81']}, ‘SVM19’);
//validation svm
var testAccuracy = validation.
classify(trained).
errorMatrix('class', 'classification')
.accuracy();
print('SVM testAccuracy', ee.Number(testAccuracy));
// confusion matrix accuracy
var con = trained.confusionMatrix().accuracy();
print(trainAccuracy1);
// exporting svm image
Export.image.toDrive({
image: classifiedSVM,
description: 'SVM19',
scale: 30,
region: COI
});
// continuousNaive
var classifier2 = ee.Classifier.continuousNaiveBayes().train(
features: training,
classProperty: 'class',
inputProperties: l8.bandNames()}
);
var classified2 = l8.classify(classifier2);
Map.addLayer(classified2, [min: 0, max: 3, palette: ['#161dff', '#e73a12', '#2cff46', '#e7df81']], 'classified image19Naive')
// validation Naive
var testAccuracy = validation.
classify(classifier2).
errorMatrix('class', 'classification')
.accuracy();
print('Naive testAccuracy', ee.Number(testAccuracy));
// confusion matrix accuracy
var con = trained.confusionMatrix().accuracy();
print(con);
// exporting naive image
Export.image.toDrive({
image: classified2,
description: 'classified image19Naive',
scale: 30,
region: COI
});
// minimumdistance
var classifier3 = ee.Classifier.minimumDistance('cosine').train(
features: training,
classProperty: 'class',
inputProperties: l8.bandNames()}
)
var classified3 = l8.classify(classifier3);
Map.addLayer(classified3, [min: 0, max: 3, palette: ['#161dff', '#e73a12', '#2cff46', '#e7df81']], 'classified image19minimumdistance')
// validation minimum distance
var testAccuracy = validation.
classify(classifier3).
errorMatrix('class', 'classification')
.accuracy();
print('minimum distance testAccuracy', ee.Number(testAccuracy));
// confusion matrix accuracy
var con = trained.confusionMatrix().accuracy();
print(con);
// exporting minimumdistance image
Export.image.toDrive({
  image: classified3,
  description: 'minimumdistance',
  scale: 30,
  region: COI
});

References
1. 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. [CrossRef]
2. 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. [CrossRef]
3. 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 Ethiopia. *Environ. Syst. Res.* **2019**, *8*, 21. [CrossRef]
4. 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.
5. Romanowicz, R.J. The Impacts of Changes in Climate and Land Use on Hydrological Processes. *Acta Geophys.* **2017**, *65*, 785–787. [CrossRef]
6. 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. [CrossRef]
7. 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. [CrossRef]
8. 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. [CrossRef]
9. 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. [CrossRef]
10. 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. [CrossRef]
11. 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. [CrossRef]
12. 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. [CrossRef]
13. 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. [CrossRef]
14. 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. [CrossRef]
15. 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. [CrossRef]
16. Hsieh, C.-M. Sustainable Planning and Design: Urban Climate Solutions for Healthy, Livable Urban and Rural Areas. *J. Urban Manag.* **2021**, *10*, 1–2. [CrossRef]
17. Ramaiah, M.; Avtar, R. Urban Green Spaces and Their Need in Cities of Rapidly Urbanizing India: A Review. *Urban Sci.* **2019**, *3*, 94. [CrossRef]
18. 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. [CrossRef]
19. 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. [CrossRef]
20. Schellnhuber, H.J.; Hare, W.; Serdeczny, O.; Adams, S.; Cournou, D.; Friel, 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.
21. 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. [CrossRef]
22. Hong, H.T.C.; Avtar, R.; Fujii, M. Monitoring changes in land use and distribution of mangroves in the southeastern part of the Mekong River Delta, Vietnam. *Trop Ecol.* 2019, 60, 552–565. [CrossRef]

23. Gibril, M.B.A.; Bakar, S.A.; Yao, K.; Idrees, M.O.; Fradhan, B. Fusion of RADARSAT-2 and Multispectral Optical Remote Sensing Data for LULC Extraction in a Tropical Agricultural Area. *Geocarto Int.* 2017, 32, 735–748. [CrossRef]

24. Wentz, E.A.; Nelson, D.; Rahman, A.; Stefanov, W.L.; Roy, S.S. Expert System Classification of Urban Land Use/Cover for Delhi, India. *Int. J. Remote Sens.* 2008, 29, 4405–4427. [CrossRef]

25. As-syakur, A.R.; Adnyana, I.W.S.; Arthana, I.W.; Nuarsa, I.W. Enhanced Built-Up and Bareness Index (EBBI) for Mapping Built-Up and Bare Land in an Urban Area. *Remote Sens.* 2012, 4, 2957–2970. [CrossRef]

26. Rwanga, S.S.; Ndambuki, J.M. Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *Int. J. Geosci.* 2017, 8, 611. [CrossRef]

27. Sihana, M.; Dutta, S.; Sajjad, H. Assessing Land Transformation and Its Relation with Land Surface Temperature in Mumbai City, India Using Geospatial Techniques. *Int. J. Urban Sci.* 2019, 23, 205–225. [CrossRef]

28. Shaharum, N.S.N.; Shafri, H.Z.M.; Gambo, J.; Abidin, F.A.Z. Mapping of Krau Wildlife Reserve (KWR) Protected Area Using Landsat 8 and Supervised Classification Algorithms. *Remote Sens. Appl. Soc. Environ.* 2018, 10, 24–35. [CrossRef]

29. Bazan, G.; Castrorao Barba, A.; Rotolo, A.; Marino, P. Geobotanical Approach to Detect Land-Use Change of a Mediterranean Landscape: A Case Study in Central-Western Sicily. *Geojournal* 2019, 84, 795–811. [CrossRef]

30. Sekertekin, A.; Marangoz, A.M.; Akcin, H. Pixel-based classification analysis of land use land cover using sentinel-2 and landsat-8 data. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* 2017, XLII-4/W6, 91–93. [CrossRef]

31. Allam, M.; Bakr, N.; Elbably, W. Multi-Temporal Assessment of Land Use/Land Cover Change in Arid Region Based on Landsat Satellite Imagery: Case Study in Fayoum Region, Egypt. *Remote Sens. Appl. Soc. Environ.* 2019, 14, 8–19. [CrossRef]

32. Jamali, A. Land Use Land Cover Mapping Using Advanced Machine Learning Classifiers: A Case Study of Shiraz City, Iran. *Earth Sci. Inform.* 2020, 13, 1015–1030. [CrossRef]

33. Chang, Y.; Hou, K.; Li, X.; Zhang, Y.; Chen, P. Review of Land Use and Land Cover Change Research Progress. *IOP Conf. Ser. Earth Environ. Sci.* 2018, 113, 012087. [CrossRef]

34. Surabuddin Mondal, M.; Sharma, N.; Kappas, M.; Garg, P.K. Modeling of Spatio-Temporal Dynamics of Land Use and Land Cover in a Part of Brahmaputra River Basin Using Geoinformatic Techniques. *Geocarto Int.* 2013, 28, 632–656. [CrossRef]

35. Veldkamp, A.; Lambin, E.F. Predicting Land-Use Change. *Agric. Ecosyst. Environ.* 2001, 85, 1–6. [CrossRef]

36. Regasa, M.S.; Nones, M.; Adebá, D. A Review on Land Use and Land Cover Change in Ethiopia. *Land* 2021, 10, 585. [CrossRef]

37. Singh, S.K.; Srivastava, P.K.; Gupta, M.; Thakur, J.K.; Mukherjee, S. Appraisal of Land Use/Land Cover of Mangrove Forest Ecosystem Using Support Vector Machine. *Environ. Earth Sci.* 2014, 71, 2245–2255. [CrossRef]

38. Traoré, F.; Bonkoungou, J.; Compaoré, J.; Kouadio, L.; Wellens, J.; Hallot, E.; Tychon, B. Using Multi-Temporal Landsat Images and Support Vector Machine to Assess the Changes in Agricultural Irrigated Areas in the Mogotdgo Region, Burkina Faso. *Remote Sens.* 2019, 11, 1442. [CrossRef]

39. Wang, L.; Jia, Y.; Yao, Y.; Xu, D. Accuracy Assessment of Land Use Classification Using Support Vector Machine and Neural Network for Coal Mining Area of Hegang City, China. *Nat. Environ. Pollut. Technol.* 2019, 18, 335–341. [CrossRef]

40. Noonı, İ.K.; Duker, A.A.; Van Duren, I.; Addae-Wireko, L.; Osı Jnr, E.M. Support Vector Machine to Map Oil Palm in a Heterogeneous Environment. *Int. J. Remote Sens.* 2014, 35, 4778–4794. [CrossRef]

41. Hearst, M.A.; Dumas, S.T.; Osuna, E.; Platt, J.; Scholkopf, B. Support Vector Machines. *IEEE Intell. Syst. Appl.* 1998, 13, 18–28. [CrossRef]

42. Evgeniou, T.; Pontil, M. Support Vector Machines: Theory and Applications. In *Machine Learning and Its Applications: Advanced Lectures*; Paliouras, G., Karkaletsis, V., Spyropoulos, C.D., Eds.; Springer: Berlin/Heidelberg, Germany, 2001; pp. 249–257. [CrossRef]

43. Mo, Y.; Zhong, R.; Sun, H.; Wu, Q.; Du, L.; Geng, Y.; Cao, S. Integrated Airborne LiDAR Data and Imagery for Suburban Land Cover Classification Using Machine Learning Methods. *Sensors* 2019, 19, 1996. [CrossRef]

44. Adam, E.; Mutanga, O.; Odindi, J.; Abdel-Rahman, E.M. Land-Use/Cover Classification in a Heterogeneous Coastal Landscape Using RapidEye Imagery: Evaluating the Performance of Random Forest and Support Vector Machines Classifiers. *Int. J. Remote Sens.* 2014, 35, 3440–3458. [CrossRef]

45. Oliphant, A.J.; Thenkabail, P.S.; Teluguntla, P.; Xiong, J.; Guima, M.K.; Congalton, R.G.; Yadav, K. Mapping Cropland Extent of Southeast and Northeast Asia Using Multi-Year Time-Series Landsat 30-m Data Using a Random Forest Classifier on the Google Earth Engine Cloud. *Int. J. Appl. Earth Obs. Geoinf.* 2019, 81, 110–124. [CrossRef]

46. Yang, C.; Wu, G.; Ding, K.; Shi, T.; Li, Q.; Wang, J. Improving Land Use/Land Cover Classification by Integrating Pixel Unmixing and Decision Tree Methods. *Remote Sens.* 2017, 9, 1222. [CrossRef]

47. Hu, Y.; Hu, Y. Land Cover Changes and Their Driving Mechanisms in Central Asia from 2001 to 2017 Supported by Google Earth Engine. *Remote Sens.* 2019, 11, 554. [CrossRef]

48. Midekisa, A.; Holl, F.; Savory, D.J.; Andrade-Pacheco, R.; Gething, P.W.; Bennett, A.; Sturrock, H.J.W. Mapping Land Cover Change over Continental Africa Using Landsat and Google Earth Engine Cloud Computing. *PLoS ONE* 2017, 12, e0184926. [CrossRef]
49. Alexander, L.V.; Zhang, X.; Peterson, T.C.; Caesar, J.; Gleason, B.; Tank, A.M.G.K.; Haylock, M.; Collins, D.; Trewin, B.; Rahimzadeh, F.; et al. Global Observed Changes in Daily Climate Extremes of Temperature and Precipitation. *J. Geophys. Res. Atmos.* **2006,** *111*, D05109. [CrossRef]

50. Pieke, R.A.; Adegbeke, J.; Beelaert-N-Przekurat, A.; Hiemstra, C.A.; Lin, J.; Nair, U.S.; Niyogi, D.; Nobis, T.E. An Overview of Regional Land-Use and Land-Cover Impacts on Rainfall. *Tellus B Chem. Phys. Meteorol.* **2007,** 59, 587–601. [CrossRef]

51. Gogoi, P.P.; Vinoj, V.; Swain, D.; Roberts, G.; Dash, J.; Tripathy, S. Land Use and Land Cover Change Effect on Surface Temperature over Eastern India. *Sci. Rep.* **2019,** 9, 8859. [CrossRef]

52. Masroor, M.; Rehman, S.; Sajjad, H.; Rahaman, M.H.; Sahana, M.; Ahmed, R.; Singh, R. Assessing the Impact of Drought Conditions on Groundwater Potential in Godavari Middle Sub-Basin, India Using Analytical Hierarchy Process and Random Forest Machine Learning Algorithm. *Groundw. Sustain. Dev.* **2021,** 13, 100554. [CrossRef]

53. Ahir, K.R.; Deshpande, S.M. Assessment of Water Quality of the Maniyad Reservoir of Parla Village, District Aurangabad: Suitability for Multipurpose Usage. *Int. J. Recent Trends Sci. Technol.* **2011,** 1, 91–95.

54. Vidyasagar, G.S.; Dhumal, R.; Gawali, B.W. Analysis and Modelling of Drinking Water Utilities by Using GIS: In Aurangabad City, Maharashtra, India. *CSIT* **2018,** 6, 77–81. [CrossRef]

55. Teluguntla, P.; Thenkabail, P.S.; Oliphant, A.; Xiong, J.; Gunma, M.K.; Congalton, R.G.; Yadav, K.; Huete, A. A 30-m Landsat-Derived Cropland Extent Product of Australia and China Using Random Forest Machine Learning Algorithm on Google Earth Engine Cloud Computing Platform. *ISPRS J. Photogramm. Remote Sens.* **2018,** 144, 325–340. [CrossRef]

56. Masroor, M.; Rehman, S.; Avtar, R.; Sahana, M.; Ahmed, R.; Sajjad, H. Exploring Climate Variability and Its Impact on Drought Occurrence: Evidence from Godavari Middle Sub-Basin, India. *Weather Clim. Extrem.* **2020,** 30, 100277. [CrossRef]

57. Rodriguez-Galiano, V.F.; Ghimire, B.; Rogan, J.; Chica-Olmo, M.; Rigol-Sanchez, J.P. An Assessment of the Effectiveness of a Random Forest Classifier for Land-Cover Classification. *ISPRS J. Photogramm. Remote Sens.* **2012,** 67, 93–104. [CrossRef]

58. Oliphant, A.J.; Thenkabail, P.S.; Teluguntla, P.; Xiong, J.; Congalton, R.G.; Yadav, K.; Massey, R.; Gunma, M.K.; Smith, C. NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-Support Analysis Data (GFSAD) Cropland Extent 2015 Southeast Asia 30 m V001. Available online: https://lpdaac.usgs.gov/dataset_discovery/measures/measures_products_table/gfsad30seace_v001 (accessed on 5 August 2021).

59. Rahmati, O.; Choubin, B.; Fatamabadi, A.; Coulon, F.; Soltani, E.; Shahabi, H.; Mollaefar, E.; Tiefenbacher, J.; Cipullo, S.; Ahmad, B.B.; et al. Predicting Uncertainty of Machine Learning Models for Modelling Nitrate Pollution of Groundwater Using Quantile Regression and UNEEC Methods. *Sci. Total Environ.* **2019,** 688, 855–866. [CrossRef] [PubMed]

60. Vapnik, V.N.; Chervonenkis, A.Y. On the Uniform Convergence of Relative Frequencies of Events to Their Probabilities. *Theory Probab. Appl.* **1971,** 16, 264–280. [CrossRef]

61. Osuna, E.; Freund, R.; Gisior, F. Support Vector Machines: Training and Applications. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 1997.

62. Pal, M. Factors Influencing the Accuracy of Remote Sensing Classifications: A Comparative Study. Available online: http://eprints.nottingham.ac.uk/10314/ (accessed on 12 November 2021).

63. Shetty, S. Analysis of Machine Learning Classifiers for LULC Classification on Google Earth Engine. Available online: http://essay.utwente.nl/83543/ (accessed on 12 November 2021).

64. John, G.H.; Langley, P. Estimating Continuous Distributions in Bayesian Classifiers. In Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence (UAI’95), Montreal, QC, Canada, 18–20 August 1995; Morgan Kaufmann Publishers Inc.: San Francisco, CA, USA, 1995; pp. 338–345.

65. Zhang, H. Exploring Conditions for the Optimality of Naïve Bayes. *Int. J. Pattern Recognit. Artif. Intell.* **2005,** 19, 183–198. [CrossRef]

66. Devi, M.R. Land Use and Land Cover Classification Using RGB&L Based Supervised Classification Algorithm. *Eng. Technol.* **2011,** 2, 14.

67. Abatzoglou, J.T.; Dobrowski, S.Z.; Parks, S.A.; Hegewisch, K.C. TerraClimate, a High-Resolution Global Dataset of Monthly Climate and Climatic Water Balance from 1958–2015. *Sci. Data* **2018,** 5, 1–12. [CrossRef]

68. Pearson, K.; Galton, F. VII. Note on Regression and Inheritance in the Case of Two Parents. *Proc. R. Soc. Lond.* **1895,** 58, 240–242. [CrossRef]

69. Mubende, M. (Ed.) Introduction. In *Climate Time Series Analysis: Classical Statistical and Bootstrap Methods*; Atmospheric and Oceanographic Sciences Library; Springer International Publishing: Cham, Switzerland, 2014; pp. 3–30. [CrossRef]

70. Tundisi, J.G.; Matsumura-Tundisi, T.; Arantes Junior, J.D.; Tundisi, J.E.M.; Manzini, N.F.; Ducrot, R. The Response of Carlos Botelho (Lobo, Broa) Reservoir to the Passage of Cold Fronts as Reflected by Physical, Chemical, and Biological Variables. *Braz. J. Biol.* **2004,** 64, 177–186. [CrossRef]

71. Nagne, A.D.; Vibhute, A.D.; Dhumal, R.K.; Kale, K.V.; Mehrotra, S.C. Urban LULC Change Detection and Mapping Spatial Variations of Aurangabad City Using IRS LISS-III Temporal Datasets and Supervised Classification Approach. In *Data Analytics and Learning*; Nagabhushan, P., Guru, D.S., Shekar, B.H., Kumar, Y.H.S., Eds.; Lecture Notes in Networks and Systems; Springer: Singapore, 2019; pp. 369–386. [CrossRef]

72. Ghosh, S.; Deshmukh, M. Naïve Geolocation of Urban Heat Islands in Aurangabad City (Maharashtra State) Using Remote Sensing and Ancillary Data. In Proceedings of the 2020 International Conference on Smart Innovations in Design, Environment, Management, Planning and Computing (ICSIDEMPC), Aurangabad, India, 30–31 October 2020; pp. 341–346. [CrossRef]

73. Bataille, C.G.F. Physical and Policy Pathways to Net-Zero Emissions Industry. *WIREs Clim. Chang.* **2020,** 11, e633. [CrossRef]