AIMS Geosciences

AIMS Geosciences, 11(1): 228–253.
DOI: 10.3934/geosci.2025010
Received: 10 December 2024
Revised: 09 February 2025
Accepted: 05 March 2025
Published: 20 March 2025

https://www.aimspress.com/journal/geosciences

Research article

Impacts of urbanization on land use change and its incidences on the climate: Case of Bingerville City (Ivory Coast, West Africa)

Kinanlie Sandrine Traore[1,*], Salomon Obahoundje[2], Asseypo Célestin Hauhouot[1], and Arona Diedhiou[3,4,*]

1. Institut de Géographie Tropicale (IGT), Université Félix Houphouët Boigny, Abidjan, Côte d'Ivoire
2. International Water Management Institute (IWMI), Accra, Ghana
3. Laboratoire des Sciences de la Matière, de l'Environnement et de l'Energie Solaire (LASMES)—African Centre of Excellence on Climate Change, Biodiversity and Sustainable Development/Université Félix Houphouët Boigny, 22 BP 582 Abidjan 22, Abidjan, Ivory Coast
4. University Grenoble Alpes, IRD, CNRS, Grenoble INP, IGE, F-38000 Grenoble, France

* **Correspondence:** Email: traore.kinanlie@ufhb.edu.ci; arona.diedhiou@ird.fr; Tel: 2250709710787.

Abstract: This study aimed to assess the impact of urbanization on land use dynamics and its consequences on the local climate of the town of Bingerville for the period from 1990 to 2020. Land cover classification was based on Landsat data for the years 1990, 2000, 2015, and 2020 in order to perform a diachronic analysis of surface conditions. Precipitation and temperature data were used to assess local climate trends. A number of extreme precipitation indices (PRCPTOT, RR1, SDII, CWD, CDD, R95p, and R99p) and temperature indices (TN10p, TN90p, TX10p, TX90p, and WSDI) were calculated. The results show a sharp increase in the built-up area from 1990 to 2020, with 32.11 km² (29.68% per year), compared with forest or crops, i.e., 19.09 km² (0.62% per year), and scrubland or fallow land, i.e., 13.21 km² (1.39% per year). However, extreme precipitation indices such as annual precipitation (PRCPTOT), rainy days (RR1), consecutive rainy days (CWD), and extremely rainy days (R99p) have increased from 2011 to 2020. In addition, buildings are correlated with RR1 and CWD. This could be one of the key factors contributing to the occurrence of flooding in the town of Bingerville, which is probably linked to urbanization. As for extreme temperature indices, most show a statistically insignificant trend, except for cold days (TX10p) and hot days (TX90p), which have a statistically significant trend of 0.004 and 0.018, respectively. This means that there have been changes in these two indices. Consecutive hot days (WSDI) and TX90p increased from 2010 to 2016, and buildings also correlated with these two indices. Consequently, changes in land use could have an influence on local temperature through the urban heat island (UHI) phenomenon. However, uncontrolled urbanization has an impact on the local climate. The town authorities need to be aware of this, and be rigorous in this area, to avoid future disasters in Bingerville.

Keywords: Land use dynamics; urbanization; local climate; climate extremes; emerging city; Bingerville

1. Introduction

Urbanization is a global phenomenon. Only 30% of the world's population lived in cities in 1950, 55% in 2018, and there will be 68% by 2050 [1]. Between 1990 and 2015, 12.8 million hectares were urbanized in Asia, Africa, and Latin America, compared with 4.6 million in North America, Europe, and Oceania [2]. Urbanization also takes the form of the construction of housing and commercial areas, leading to both urban sprawl and urban densification [2]. This phenomenon is often unplanned and destroys open and green spaces, creating a major problem [3].

Historically, the African continent underwent slow urbanization during the first decade of colonization, but it really took off after the Second World War. The continent is experiencing rapid population growth and urbanization, which presents both economic opportunities and challenges in terms of urban infrastructure and services, especially for sustainable development [4].

According to [5], urbanization promotes good economic results and improves the standard of living of many people. It helps hundreds of millions of people move from rural areas with fewer opportunities to urban centers to take advantage of better opportunities. But this urbanization brings with it many challenges, such as a reduction in vegetation cover and an expansion of impermeable surfaces such as buildings, car parks, pavements, and other types of construction [3]. According to [6], changes in land use have considerable effects on ecosystems. This change in land use also favors a change in the energy balance [7]. Changes in humidity and wind speed are due to changes from rural to urban land [8]. Rapid urbanization affects the urban rainfall-runoff process and increases the risk of urban flooding [9]. In addition, Ivory Coast experienced 20 deaths and 18 billion XAF (~USD 29,971,950) in losses and damage in 2018 due to heavy rainfall [10]. In the district of Abidjan, since 2009, an average of 13 people have lost their lives each year as a result of flooding [11].

In [12], an article focusing on climate change in Africa, it is stated that rising temperatures will increase the number and severity of heatwaves, particularly in urban areas [13]. The rapid growth of urbanization is creating the urban heat island (UHI), which can form at any time of the year, during all weather conditions and in all seasons [3]. The urban heat island develops an energy demand and contributes to the transmission of secondary pollutants such as ozone [14]. A study [15] investigated the importance of evaluating urban spatial form (USF) indicators on land surface temperature (LST) to reduce UHI-related problems.

However, urbanization has an impact on climate change, which in turn poses enormous risks of urban warming [16]. This warming has intensified the urban heat island effect in cities and has had a huge impact on the urban ecosystem, the water cycle, the atmospheric environment, human health, and urban infrastructure [17]. The rapid expansion of Abidjan's urban areas has heightened the formation of urban heat islands, particularly in densely built-up regions lacking vegetation, making them more susceptible compared to peripheral zones [13].

In addition, the rapid urbanization of Abidjan, with its attendant housing problems and noise pollution, is motivating people to move to the new upmarket towns on the outskirts [18]. This has also prompted developers to move toward other nearby towns [19], such as Bingerville, which is becoming a land reserve. Interest in the town of Bingerville was justified by the growing need for housing in Côte d'Ivoire's economic capital as a result of the population explosion.

At the end of the 1970s, the Ivory Coast government introduced stabilization programs and the Structural Adjustment Programme (SAP). These various programs weakened urban development programs and led the authorities to rethink the planning system in order to adapt it better to the context of the time [20]. In addition, preserving the agricultural areas to the north and east of Bingerville increased productivity, slowed urbanization, and provided a green belt. Despite all the efforts made by the Ivorian government, we note that urbanization is persisting, which may have an effect on the local climate and environment of the town [21].

Today, several methods are in vogue to study land change and climate change, such as urban sprawl, thermal environment, the urban heat island, and machine learning algorithms. [22] used the cellular automata (CA) model, which is based on geographical partitioning. They demonstrated the credibility of the SOM-HC-PLUS model for handling spatio-temporal heterogeneity studies on the partitioning of land use changes. [23] examined the microclimatic characteristics of the city of Burdur (Turkey) using ENVI-Met models of climate data at different times of the day. To mitigate vulnerability to heat, the Urban Heat Vulnerability Index (HVI) was developed to better understand the most exposed areas [16]. Markov-FLUS, which has the strong ability to predict the spatial pattern of land use with a high kappa coefficient, was used by [6]. In addition, the XGBoost model was used by [15] to evaluate urban spatial form (USF) indicators from three perspectives, namely landscape configuration, building morphology, and social development, and their influence on surface temperature at several grid scales. Despite the effectiveness and adaptation of these models in other contexts, they will not be used in this study because of our objectives. However, our approach is based first on the mapping of urban space [24], and then on the calculation of extreme climate indices [25,26]. Finally, we will correlate the two using Pearson's correlation [14].

However, studies on the impact of urbanization at the local climate scale are rare in West Africa and almost non-existent in Ivory Coast. [25] calculated six rainfall indices in five West African countries (Ivory Coast, Senegal, Niger, Burkina Faso, and Benin) using Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) data. Several studies have been carried out in Côte d'Ivoire to assess the impact of climate change on catchment areas or regions using extreme temperature and rainfall indices [26,27].

Climate studies generally focus on large cities or regions in West Africa in general, and in Ivory Coast in particular. Small towns are little studied, even though they are experiencing strong urban growth, which can have effects on the local climate. Most of the studies focus on the district of Abidjan and the sub-prefecture of Bingerville. In local analyses, the effect of urbanization on climate indices is almost non-existent. In addition, the climate studies carried out in Greater Abidjan do not focus on the extreme temperature indices (TN10p, TX10p, TN90p, TX90p, and WSDI), which are important for assessing energy consumption and the impact on the population's health. For all these reasons, we decided to carry out further studies on this subject in the town of Bingerville.

The importance of this study is that CHIRPS and Climate Hazards Group Infrared Temperature with Station (CHIRTS) data at 5 km was used to understand the evolution of the local climate in the town of Bingerville, due to the lack of ground observation data [25]. The effects of urbanization on climate indices were studied. Extreme temperature indices (TN10p, TX10p, TN90p, TX90p, and WSDI) were used to understand energy consumption and the impact on the health of the population.

The aim of this work is to understand the impact of urbanization on land use dynamics and their consequences on extreme indices of local climate in Bingerville. This study is structured as follows: Section 1 presents the study area, the data used, and the methodology applied. Section 2 presents the results of the study in terms of changes in surface conditions, trend changes in rainfall and temperature, and the relationship between changes in urbanization and rainfall, temperature, and extreme indices. Section 3 discusses the results and conclusions.

2. Data and method

2.1. Presentation of the study area

The town of Bingerville (Figure 1) is located at latitude 5°21'20 North and longitude −3°53'7 West in the district of Abidjan. It is a town in the eastern suburbs of Abidjan (the economic capital of Ivory Coast). However, the town of Bingerville is undergoing rapid urbanization, which has accelerated in recent years. This is due to strong demographic growth, from 12,527 inhabitants in 1975 to 204,656 in 2021 according to the Recensement Général de la Population et de l'Habitat (RGPH). The town is bordered to the north by the villages of Akandjé, Aguein, and Akoyaté, to the south by the Ebrié lagoon, to the west by the commune of Cocody, and to the east by the villages of Mbato-Bouaké and Akoué Agban. It is dominated by an undulating topography with a succession of hills [20]. It has a low slope of 0° in the northeast and a high slope of 30° in most of the north and west of the town of Bingerville (Figure 2). This town has many slopes. It also benefits from a sub-equatorial climate with a bimodal regime, like that of Abidjan, characterized by four seasons: two dry seasons and two rainy seasons. The dry seasons, according to our umbrothermal diagram, are from January to February for the first dry season and in August for the second dry season. The rainy seasons run from March to July for the first dry season, and from September to December for the second. There are watercourses running throughout the city, taking their source in either the Ebrié or Adjin lagoons. The city's soil is ferralitic, deep, and highly desaturated. It consists mainly of sand on the coastal plain and on the plateau, with sand on the surface and clay at depth. This soil is strongly affected by climate [20].

2.2. Date

A number of data were used for this study, including Landsat satellite images to assess land use dynamics, demographic data to determine population growth rates, Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) and Climate Hazards Group InfraRed Temperature with Station

(CHIRTS) data to detect trend changes in rainfall and temperature. Population data were obtained from the Institut National de la Statistique (INS) of Côte d'Ivoire.

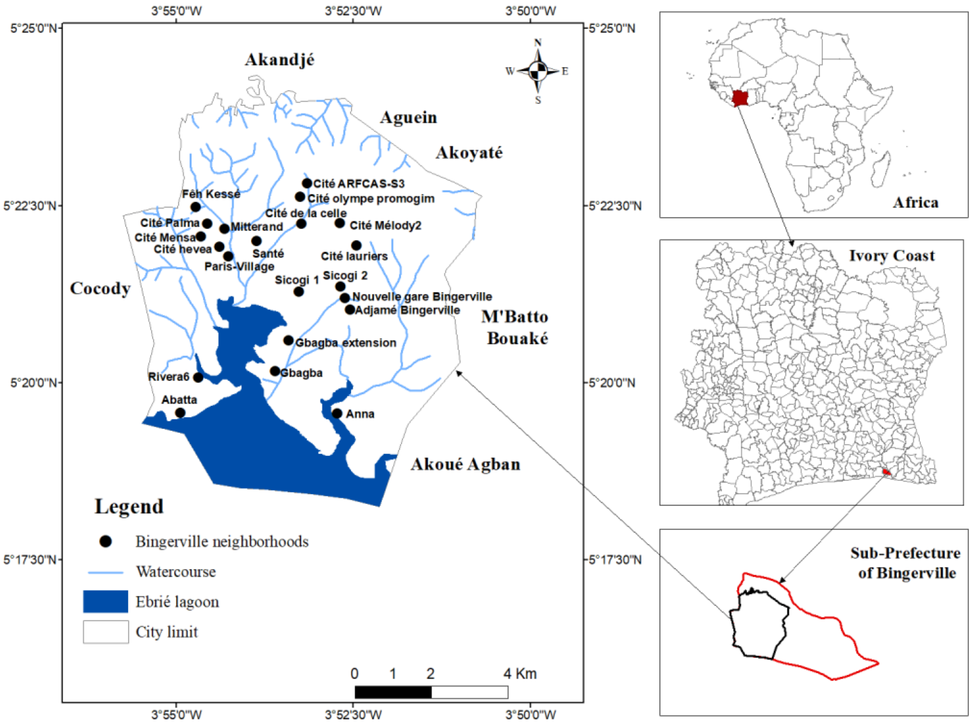


Figure 1. Location of the town of Bingerville.

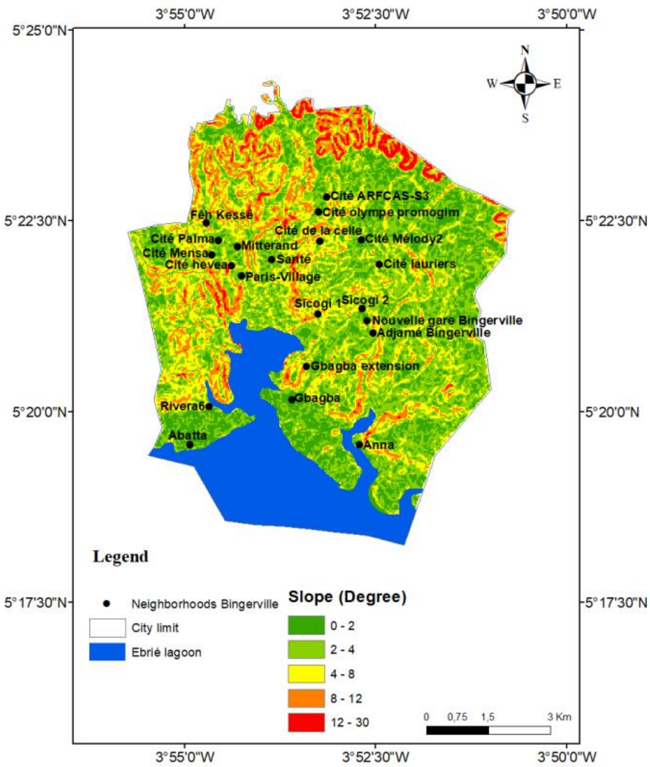


Figure 2. Slope map.

2.2.1 Landsat data

The Landsat images obtained are from three sensors: Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), and Operational Land Imager (OLI) for the years 1990, 2000, 2015, and 2020. These images were downloaded from the United State Geological Surveys (USGS) website (http://earthexplorer.usgs.gov). The data extracted are for the months of January to April, and are cloud-free. One scene covers our study area, which is 195056. These three satellites have 30 m resolution scenes.

2.2.2. CHIRPS and CHIRTS data

CHIRPS (Climate Hazards Group Infrared Precipitation with Stations) is a set of near-global precipitation data. It covers the 50°S–50°N zone from 1981 to the present day. CHIRPS combines satellite images at a spatial resolution of 0.05 degrees with data from in situ stations to create gridded precipitation time series for trend analysis and seasonal drought monitoring [28]. It is calculated over a five-day period and can be downloaded from https://www.chc.ucsb.edu/data/chirps [25]. They are supplied by the USGS (United States Geological Survey) to FEWSNET (Famine Early Warning Systems Network) at the AGRHYMET (Agronomy, Hydrology, Meteorology) regional center [29]. The CHIRPS data used in our study are from 1990 to 2020.

CHIRTS (Climate Hazards Group Infrared Temperature with Station) data was developed by the Climate Hazards Center (CHC), using near-global data (60°S–70°S). Resolution is 0.05° × 0.05°, or 5 km for daily maximum and minimum temperature s. The CHIRTS database extends from 1981 to 2016. The CHIRTS data used for our study are from 1990 to 2016.

The CHIRPS data were validated in West Africa by [25]. This validation consisted in comparing average monthly rainfall over the period from 1998 to 2010 between the CHIRPS dataset and rainfall data extracted from the updated BADOPLUS database. They concluded that CHIRPS-based rainfall data are good enough to be used for flood monitoring in West Africa. As Ivory Coast is part of West Africa, we can also conclude the same for our CHIRPS data. CHIRPS data have also been validated with SODEXAM data by [30] in his article Exploitation de données CHIRPS et TERRACLIMATE pour l'étude des pluies urbaines sur le district autonome d'Abidjan (Côte d'Ivoire) and concluded the same as [25].

2.3. Methods

2.3.1. Land use analysis

The spatial dynamics of the town of Bingerville were studied using a multiscalar analysis of remote sensing images. This involved a diachronic study of changes due to urbanization, using Landsat satellite images. The Landsat images used for the analysis are from 1990, 2000, 2015, and 2020.

Land cover classification can be performed using three main approaches, namely pixel-based, sub-pixel-based, and object-based approaches. Each approach has its advantages and limitations, and their literature review is well detailed [31]. In our study, the maximum likelihood pixel-based supervised classification method was used. Maximum likelihood remains the most widely used method for Landsat images [31,32].

However, pre-processing was carried out after downloading the Landsat images, namely radiometric and atmospheric correction. The land cover of the town of Bingerville was classified into four classes: water, forest or crops, scrub or fallow land, and built-up areas. The water here is the Ebrié lagoon, and the built-up areas are the urbanized areas, roads and land covered by buildings and other artificial structures, residential areas, and commercial services. “Forest or crop” refers to the growth of trees, evergreens and other plants that cover a large area or agricultural land, land covered by crops, and plantations. “Scrub or fallow land” refers to grass, meadows, and green or cultivated areas that are now at rest.

Furthermore, land classification can be a source of errors caused by geometric errors, classification errors, and undefined classes [33]. To calibrate and validate the land cover of the town of Bingerville, accuracy was assessed and the Kappa coefficient was used as a statistical parameter in this study [34]. A random selection of pixels from the ground truth (Google Earth) was compared with satellite images classified as recommended in the reference in order to estimate the errors [34,35]. This approach made it possible to reclassify the land cover data in a different way, following the step proposed in the studies [35,36] and also used later [32].

In addition, the total accuracy of a classified image was obtained by dividing the sum of the good predictions by the total predictions.

$$\text{Total Accuracy} = \frac{\text{Number of corrected pixels}}{\text{Total number of elected pixels}} \text{ X } 100 \quad (1)$$

Thus, a classification is acceptable when it has an accuracy percentage of 85%. The Kappa coefficient is a discrete multivariate technique used to assess the accuracy of thematic maps. It is also an effective approach for deriving information from an image via the confusion matrix. If $K > 0.80$, it means that it is strong and has good accuracy, from 0.40–0.80, it is average, and < 0.40, it is weak [24]. The Kappa was obtained using the following equation:

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{i+1})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{i+1})} \quad (2)$$

where N: Total prediction, X_{ii}: Good prediction, x_{i+} : Field reality,x_{i+1} : Total reference point of a class.

The statistics of the changes found were obtained by simply comparing the area of each class after evaluating the degree of accuracy of each classified image. Thus, the percentage loss and gain from 1990 to 2020 for each class was calculated.

2.3.2. Temperatures, rainfall, and extreme indices

CHIRPS (mean precipitation) and CHIRTS (maximum and minimum temperature) data were used to calculate climate indices (Table 1). Climate indices are generated values that can be used to reflect the state of variations in the climate system. They enable the statistical study and comparison of time series, extremes, trends, and averages [37,38]. These indices also describe the particular characteristics of extreme precipitation, including the frequency, amplitude, and persistence of rainfall events [24]. In addition, climate indices enable us to see the evolution of phenomena (flooding, landslides, and UHI) that are caused by changes in land use.

Extreme precipitation indices are total precipitation (PRCPTOT), number of wet days (RR1), maximum number of consecutive wet days (CWD), maximum number of consecutive dry days (CDD), very wet days (R95p), extremely wet days (R99p), and simple daily intensity (SDII). Extreme temperature indices are relatively warm days (TX90p), relatively warm nights (TN90p), relatively cold days (TX10p), relatively cold nights (TN10p), and the Warm Sequence Duration Indicator (WSDI).

The CWD, RR1, R95p, R99p, and SDII indices show the impact of precipitation on flooding and landslides. However, the TX90p and WSDI indices show the impact of temperature on energy consumption and health. TX90p, TN90p, TX10p, and TN10p show the influence of urban heat pockets (UHIs).

Table 1. Indices of daily precipitation and temperature extremes and their descriptions.

Index	Names	Definition	Units
Precipitation			
PRCPTOT	Total annual precipitation	Sum of daily PR ≥ 1.0 mm	mm
RR1	Annual number of wet days	Number of rainy days (PR ≥ 1 mm)	days
CWD	Consecutive wet days	Maximum annual number of consecutive wet days (when PR ≥ 1.0 mm)	days
CDD	Consecutive dry days	Maximum annual number of consecutive dry days (when PR < 1.0 mm)	days
R95p	Very wet days	Annual sum of daily PR > 95th percentile	mm
R99p	Extremely wet days	Annual sum of daily PR > 99th percentile	mm
SDII	Simple daily intensity index	Annual total PR divided by the number of wet days (when total PR ≥ 1.0 mm)	mm/ days
Temperature			
TX10p	Number of cool days	Percentage of days when TX < 10th percentile	%
TN10p	Number of cold nights	Percentage of days when TN < 10th percentile	%
TX90p	Number of hot days	Percentage of days when TX > 90th percentile	%
TN90p	Number of warm nights	Percentage of days when TN > 90th percentile	%
WSDI	Warm spell duration indicator	Annual number of days contributing to events where 6 or more consecutive days experience TX > 90th percentile	days

In addition, indices per year were averaged over the period from 1990 to 2020 for extreme precipitation indices, and over the period from 1990 to 2016 for extreme temperature indices, in order to analyze trends.

Several methods are used for the statistical analysis of trends in many studies, namely linear trend analysis [39], linear trend analysis combined with a t-test [40,41], the non-parametric Kendall tau test with linear least squares trends [42,43], and the sen slope estimator with non-parametric Mann-Kendall (MK) test [44–46]. The non-parametric Mann-Kendall test is a non-parametric test based on rank to examine the significance of a trend [47,48]. It is widely used in hydrology and climatology to detect trends [34]. This test makes no assumptions regarding the distribution of the data or the linearity of the trends [26,49]. Parametric trend tests, on the other hand, require the data to be both normally distributed and independent. Non-parametric trend tests do not require the data to be independent [26]. The MK was performed in our study to examine the statistical significance of the trends because of its robustness and insensitivity to outliers in the time series [26].

The MK test was carried out over the period from 1990 to 2020 for precipitation and for temperatures from 1990 to 2016. However, a trend is considered to be statistically significant if the p-value is less than or equal to 5%, which is equivalent to a confidence level of 95%.

2.3.3. Correlation matrix between indices and LULCC

The correlation matrix was used to analyze the level of change in one variable as a result of the change in the other. A high correlation indicates a strong relationship between the two variables, while a low correlation means that the variables are weakly related. Two Excel files were created and saved in CSV format, containing the data required for this analysis.

The first file contains the following columns: years, water, forest or crop, scrub or fallow, built-up areas, precipitation, PRCPTOT, RR1, CWD, CDD, SDII, R95p, R99p, and population. The data for water, forest or crop, scrub or fallow, and built-up areas are the surface areas. The second file contains the following columns: years, water, forest or crop, scrub or fallow land, built-up areas, TN10p, TN90p, TX10p, TX90p, WSDI, maximum temperature, minimum temperature, mean temperature, and population. These files were used to examine the relationships between land cover and the other parameters listed above.

For the occupancy and population class data, linear interpolation was used to determine the intermediate values between two dates. This was obtained using the following formula:

$$V_t = V_{start} + \frac{V_{end\_}V_{start}}{N} \tag{3}$$

where V_t: Values to be interpolated to a year *t*; $V_{début}$: Values observed at the beginning of the period; V_{fin}: Values observed at the end of the period; *N*: Number of years between the two observations.

This linear interpolation method was also applied to the population of Bingerville. From this annual difference, the value for each intermediate year was calculated by adding it to the value for the previous year.

The correlation was carried out using Rstudio software, using the “cor” function. This function is used to select the correlation method (Pearson, Spearman, and Kendall). The Pearson correlation method was used in our study and the calculations were made as a function of time. The Pearson correlation was used by several authors to assess the impact of climate extremes on land use [50]. It has also been used in [51] to see the correlation between extreme climate indices and land surface phenology.

3. Results

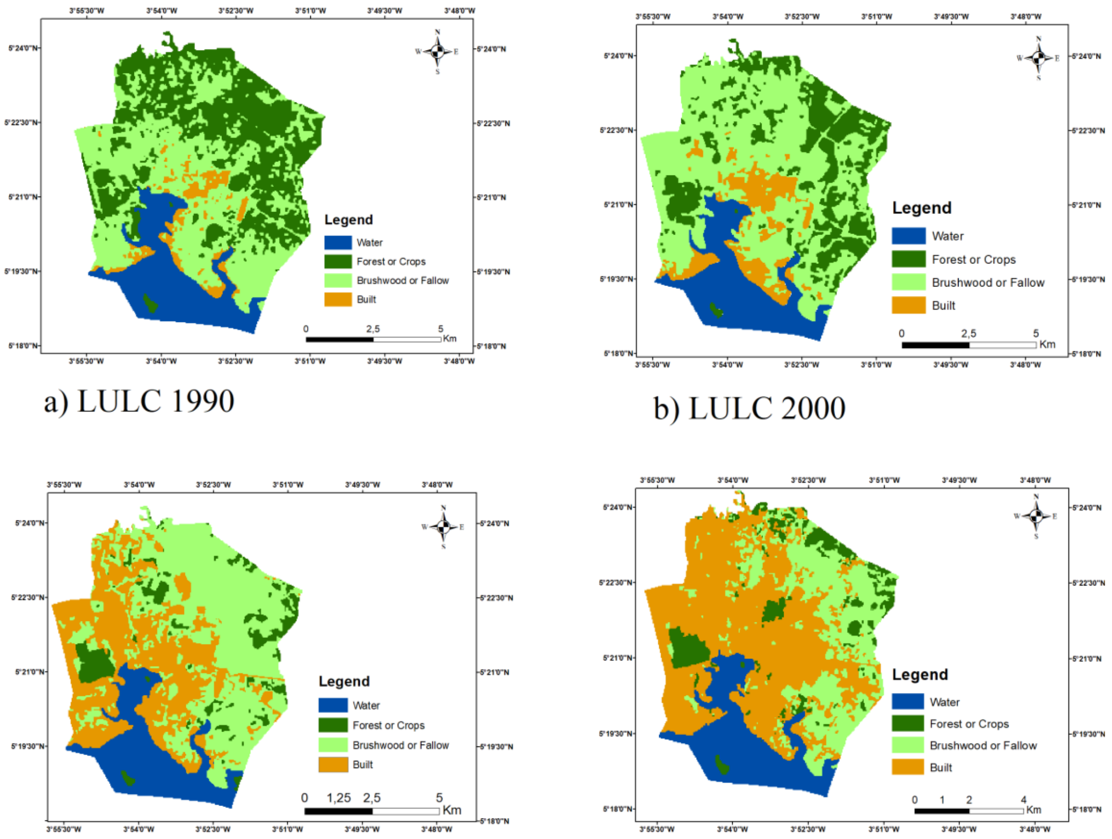
3.1. Land use dynamics

Figure 3 shows the results of satellite image processing for the years 1990, 2000, 2015, and 2020. Land use has been grouped into four classes: water, forest or crop, scrub or fallow, and built-up areas. In 1990, forest or crops occupied the north and east, while built-up areas were in the center and around the Ebrié lagoon. By 2020, however, the forest or farmland occupied more of the northeast and the built-up areas occupied the west, center and a little east of the city. However, from 1990 to 2000, there was a slight increase in built-up areas, with forest or crops being replaced more by scrubland or fallow land and built-up areas. The proportion of scrubland or fallow land is high in Bingerville during this period.

In the period from 2000 to 2015, there was a major process of change. Forests and crops declined considerably, while scrubland and fallow land decreased slightly. Built-up areas, on the other hand, increased significantly over this 15-year period. As a result, built-up areas are taking up more space in the town of Bingerville.

In the period from 2015 to 2020, we saw a big change in the built environment over these five years. Urbanization increased considerably. Built-up areas and forest or crops increased, and scrubland or fallow land decreased. We also note a great change in the urban landscape of the town of Bingerville from 1990 to 2020, showing a rapid and continuous replacement of natural space (water, forest or crops, scrubland or fallow land) by built-up areas. This natural area shrunk enormously in surface area. Forest or crops and scrub or fallow land almost disappeared. The evolution of built-up areas has been from south to north, occupying the whole of the west. In 1990, the surface area of the natural environment was very visible compared to that of the built-up area. In 2020, the opposite was true, with a marked reduction in the natural environment.

Analysis of the statistical report on land use dynamics in the town of Bingerville shows that between 1990 and 2000, the built-up area increased by 3.35 km², or 95.98%. For a surface area of 3.49 km² in 1990, the area doubled in 2000, reaching 6.84 km². Table 2 also shows a considerable drop in forest or crop area of 9.67 km² (38.48%). Between 1990 and 2000, the surface area of water and scrub or fallow land increased by 0.02 km² (0.17%) and 6.25 km² (20.36%), respectively. Between 2000 and 2015, the area of built-up land increased by 15.94 km² (233.04%). Table 2 also shows a decline in the area of forest or crops, down by 10.09 km² (65.26%), which has been converted to other uses (buildings, scrubland or fallow). Bush or fallow land and water decreased by 0.71 km² (6.02%) and 5.07 km² (13.72%), respectively. As for the statistics on changes in land use between 2015 and 2020, we see that the built-up area increased by a further 12.85 km², or 56.40% of the surface area. Forest or crops and water increased slightly, by 0.73 km² (13.59%) and 0.58 km² (5.23%), respectively. The surface area of scrubland or fallow land continued to decrease, by 14.15 km² (44.40%). The statistical report on the overall land use of the town of Bingerville from 1990 to 2020 highlights a large increase in the built-up area, i.e., 32.11 km² (920%). However, this is the only class that has seen an increase in surface area over the period from 1990 to 2020. Forest and crops have decreased considerably, by 19.09 km² (75.73%). Water and scrub or fallow land have also decreased, by 0.11 km² (0.93%) and 13.21 km² (43.04%), respectively.



a) LULC 1990

b) LULC 2000

c) LULC 2015

d) LULC 2020

Figure 3. Bingerville land use dynamics in 1990, 2000, 2015, and 2020.

Table 2. Statistical ratio of detected changes in land use between 1990 and 2020.

Land use type	Change 1990–2000		Change 2000–2015		Change 2015–2020		Change 1990–2020	
	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Water	0.02	0.17	−0.71	−6.02	0.58	5.23	−0.11	−0.93
Forest or Crops	−9.67	−38.48	−10.09	−65.26	0.73	13.59	−19.03	−75.73
Brushwood or Fallow	6.25	20.36	−5.07	−13.72	−14.15	−44.4	−12.97	−42.26
Built	3.35	95.98	15.94	233.04	12.82	56.27	32.11	920.06

However, the global accuracy values show that the Landsat images were well classified and exceeded the minimum global accuracy requirement of 85%. Thus, the overall accuracy of the classified images varies between 89% and 93%. This means that the majority of classes have been well discriminated. The accuracy of a map results from the variability of the classes to be mapped [36]. The 1990 Landsat image shows an accuracy of 89.06%, with a Kappa coefficient of 85.41%. As for the Landsat images of 2000 and 2015, we have an overall accuracy of 90.60% with a Kappa coefficient of 87.5%. However, the 2020 Landsat image shows a good classification with an overall accuracy of 95.31% and a Kappa coefficient of 93.98% (Table 3).

Table 3. Accuracy and Kappa coefficient from 1990 to 2020.

Year	Accuracy	Kappa Coefficient
1990	0.89	0.854
2000	0.906	0.875
2015	0.906	0.875
2020	0.953	0.939

3.2. Temporal analysis

Climate changes rapidly over time in general, and in Bingerville in particular. The indices calculated have provided an annual trend for the town of Bingerville (Figure 4). This annual trend also shows the evolution of the climate in Bingerville.

However, the Mann-Kendall test shows an upward trend for the extreme precipitation indices, but these are statistically insignificant. The regression curve in red shows an upward trend for all indices, except for SDII and R95p, which show a downward trend. The fitting curve in blue also shows an increase in total precipitation (PRCPTOT) from 1990 to 1998 and from 2015 to 2020, and a decrease from 1999 to 2015. Consecutive rainy days (CWD) increased from 1990 to 2000 and from 2006 to 2020. Falls occurred from 2001 to 2005. As for consecutive dry days (CDD), we observe an increase from 1990 to 2002, and a decrease from 2003 to 2020. For rainy days (RR1), they show an increase between 1990 and 2005 and between 2013 and 2020. Rainy days (RR1) decrease between 2006 and 2012. However, rain intensity (SDII) increases from 1990 to 2000 and decreases between 2001 and 2020. The adjustment curve for very wet days with precipitation above the 95th percentile (R95p) shows an increase from 1990 to 2000 and a fall from 2001 to 2020. Extremely wet days with precipitation above the 99th percentile (R99p) show an increase from 1990 to 2000, a decrease from 2001 to 2010, and a further increase from 2011 to 2020. The PRCPTOT, RR1, CWD, and R99p indices show two break dates, respectively, (1999 and 2015), (2007 and 2012), (2001 and 2006), and (2001 and 2011).

As for extreme temperature indices, most show a statistically insignificant trend, except for cold days (TX10p) and hot days (TX90p), which show a statistically significant trend with 0.005 and 0.019, respectively.

The regression curve generally shows an upward trend in all extreme temperature indices, except for TX10p and warm nights (TN90p), which show a downward trend.

The fit line shows a decrease in TX10p from 1990 to 2005 and from 2011 to 2016, and an increase between 2006 and 2010. However, for TX90p, we note an increase from 1990 to 2006 and a decrease from 2007 to 2016. As for cold nights (TN10p), we observe a decrease from 1990 to 1997, 2004 to 2007, and 2014 to 2016, and an increase between 1998 and 2003 and 2007 and 2014. While TN90p increased from 1990 to 1998 and decreased from 1999 to 2016, it sometimes remained constant in certain years. The consecutive warm day index (WSDI) shows a decrease between 1990 and 2000 and between 2010 and 2016. The WSDI increases between 2001 and 2009 (Figure 4).

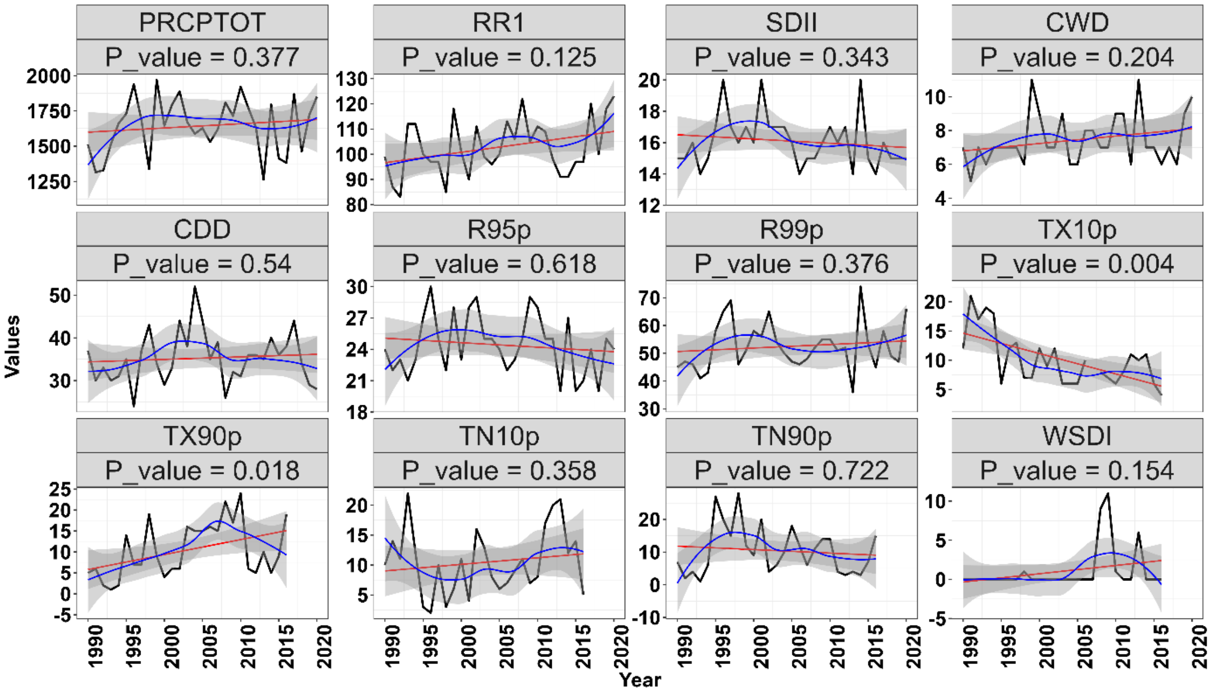


Figure 4. Interannual variability of PRCPTOT (mm), RR1 (days), SDII (mm), CWD (days), CDD (days), R95p (mm), R99p (mm), TX10p (days), TN90p (days), TX10p (days), TX90p (days), WSDI (days) indices from 1990–2020. The red line corresponds to the linear regression line, the blue curve corresponds to the smoothing curve, and the grey area gives the proportion of bridges on the plot that influence smoothing at each value.

3.3. Autocorrelation between indices, other variables, and the LCLU

The correlation matrix was constructed between land cover classes and extreme temperature indices (TN10p, TN90p, TX10p, TX90p, and WSDI), Bingerville population (pop), maximum (Tmax), minimum (Tmin), mean (Tmean) temperature, and the years of our study period on the one hand. On the other hand, it is between land use classes and extreme precipitation indices (PRCPTOT, RR1, CWD, CDD, SDII, R95p, and R99p), the Bingerville population, average precipitation, and the years of our study period. This enabled us to assess the relationship between land cover classes and the above variables. The land use classes are water, forest or crop (F or C), scrub or fallow (B or F), and built-up area.

However, population and years are significantly and strongly correlated with buildings. Population, buildings, and years are slightly correlated with the number of rainy days (RR1) and consecutive rainy days (CWD). Brush or fallow land is slightly correlated with consecutive dry days.

Water and forest or crop are not correlated with extreme precipitation indices and precipitation. In the end, buildings are correlated with RR1 and CWD, and bush or fallow land is correlated with CDD (Figure 5A).

As for Figure 5B, population and years are also significant and strongly correlated with buildings. Buildings are slightly correlated with cold nights (TN10p) and consecutive hot days (WSDI). Maximum temperature (Tmax) is correlated with buildings, years, and population. Hot days (TX90p) are slightly correlated with buildings, years, and population. Cold days (TX10p) are correlated with forest or crop (F or C) and slightly correlated with water. Scrubland or fallow land is slightly correlated with mean and minimum temperature and warm nights (TN90p).

Overall, all land use classes are correlated with temperature indices, maximum, minimum, and average temperature. This means that land use classes have an impact on temperature.

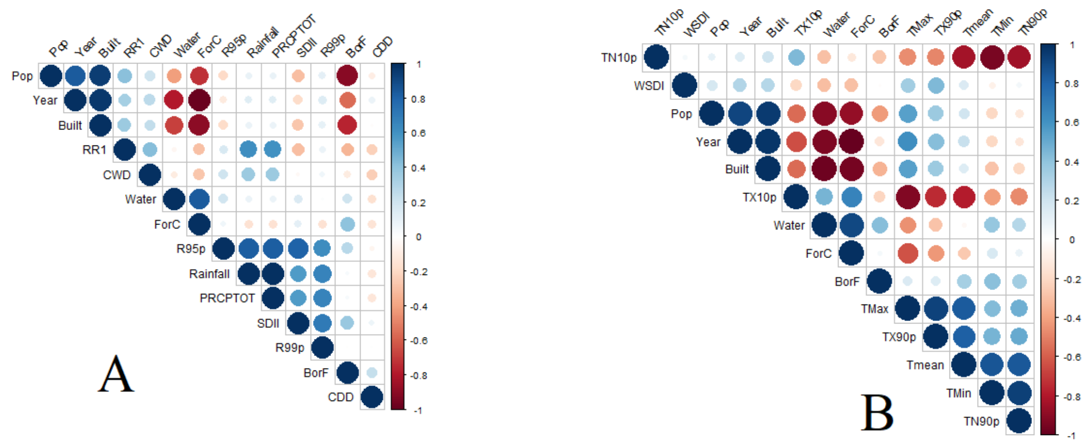


Figure 5. Correlation between land use and: (A) extreme precipitation indices, (B) extreme temperature indices.

4. Discussion

4.1. Urban dynamics

The analysis of changes in the land of the town of Bingerville between 1990 and 2020 in this study shows an increase in built-up areas and a decrease in forest or crops, scrubland or fallow land, and water. [52] states that urban sprawl leads to the conversion of agricultural land, wetlands, and lakes into urban areas. Thus, the town of Bingerville is experiencing a major change in its natural environment through the increase in built-up areas over the period from 1990 to 2020, even though the area has many slopes.

The periods from 1990 to 2000 and 2000 to 2015 show that the built-up area has tripled, rising from 3.35 km² to 15.94 km² in twenty-five years. In five years, from 2015 to 2020, the built-up area was 12.82 km². These results also show the strong growth in urbanization, which has increased in size in five years rather than twenty-five. In addition, built-up areas are more concentrated to the west and east in 2020, which are areas with steep slopes. Urbanization took up more space between

1989 and 2014, increasing from 400 hectares to 10,200 hectares (INS, 2014). This is in line with the thesis [20] and article [53].

This sharp increase in built-up areas to the detriment of the natural landscape has led to rapid urbanization due to strong demographic growth, with the population rising from 28,741 in 1988 to 204,656 in 2021. From 1990 onward, the town experienced strong demographic growth, rising from 47,180 inhabitants in 1998 to 59,690 in 2010 and 9,131 in 2014. The town of Bingerville is home to numerous educational institutions and vocational training centers [54]. In addition, the annual growth rate was estimated at 2.96% between 1988 and 1998, and then 3.2% between 1998 and 2014. Between 2014 and 2021, the rate had jumped to 4.4%, demonstrating the intensification of urbanization and the growing attractiveness of the city. Another factor in this growth is the political crisis that hit Côte d'Ivoire in 2010. This crisis led the population of Abidjan to move to Bingerville because of the security that remained there. Land prices were also lower at the time. Urban development plans were created, but not respected (Ministry of Construction, Housing, Sanitation, and Urban Development).

The rapid growth of the city of Abidjan has also led to a growing demand for housing. The impossibility of meeting this demand for housing is forcing Abidjan workers to live in neighboring towns such as Bingerville. One-fifth of Abidjan’s workers live in Bingerville [55]. The lack of land for development in Abidjan and the availability of land for development in Bingerville are two causes of this urban growth. The town of Bingerville is also a meeting place for a large number of property developers, especially in the western part of the town, as well as individual builders. This rapid urban growth in recent years can be explained by the urbanization of the commune of Cocody, which is now merged with the town of Bingerville.

4.2. Extreme temperatures

Temperatures in the city of Bingerville from 1990 to 2016 show decreasing cold days and nights and increasing hot days and nights, as well as consecutive hot days. This is in line with articles [26,37]. Researchers in Morocco and South Africa have confirmed that relatively cold days and nights are decreasing and relatively warm days and nights are increasing [56,57].

This decrease in cold days and nights has also been reported by other authors [27,58]. In fact, these warm nights show that there is an urban heat island (UHI) effect, because UHI occurs when an urban center is warmer than its surroundings [59,60]. This is in line with [61], which states that urban heat islands are more noticeable at night after the release of solar heat absorbed by streets and buildings during the day.

However, prior to the 2000s, consecutive warm days (WSDI) were stable, warm days and nights were increasing, and cold days and nights were decreasing in the town of Bingerville. This may be due to low urban growth, as its effect on the climate was moderate. During this period, warm conditions existed, but as urbanization was slow, this was not strongly felt.

From 2001 to 2010, apart from TX10p and TN90p, which were decreasing, TX90p, TN10p, and WSDI were increasing, indicating a marked warming of the local climate. This increase is consistent with that of [26], which states that this period was the warmest in the Zanzan region. This warming has occurred in several countries around the world [62]. The increase in WSDI is similar to that of the study [26,63], which stated the same in south-west Côte d’Ivoire. This increase is due to urbanization, which has started to increase. These results show the importance of urban dynamics in changing the local climate after the 2000s.

All the temperature indices fell except TN10p from 2011 to 2016. Despite the increase in urbanization, there has been an attenuation of the climate with the presence of cold nights. The decrease in cold days (TX10p) was observed throughout the study period, especially from 2000 onward. This is in line with the article [38].

On the other hand, the study by [64] states that cold days and nights have a statistically significant downward trend while days and nights have a considerable upward trend. TX10p and TX90p show a significant trend. This is similar to [38]. This trend confirms our results of increasing warm days and decreasing cold days. These changes may be due to global warming created by climate change. The decrease in cold nights could affect the health of the population, as studies [13] in Côte d'Ivoire, [65] in Niger, and [66] in Nigeria show. In this case, children and the elderly are the most vulnerable. These changes in temperature are due to natural and human factors, especially greenhouse gas (GHG) emissions [67]. This rise in temperature is also caused by the reduction in vegetation around buildings.

In addition to urbanization, which increases temperature, the increased use of man-made materials and the increase in anthropogenic heat production are also causes of UHI [68]. However, urbanization and the reduction of vegetation are the factors of change to the south of the town of Bingerville.This results in high temperatures despite the presence of the Ebrié lagoon, which runs through its neighborhoods. These temperature changes can have an impact on energy consumption, as fans and air conditioners are used much more frequently to combat the heat.

4.3. Extreme precipitation

The town of Bingerville will experience an increase in annual rainfall (PRCPTOT) from 1990 to 2020 due to a slight increase in the number of rainy days (RR1), although consecutive wet days (CWD) will be shorter and consecutive dry days (CDD) longer. Extremely wet days (R99p) are high although CWD is short. This change is in agreement with the authors [69] who show that several parts of Ivory Coast are affected by increasing and severe changes, especially those in the coastal zone. The general decrease in rainfall, which varies from region to region in Ivory Coast, is also noticeable in the town of Bingerville, as both SDII and R95p have decreased. This is in line with article [26], which confirms the drop in SDII in the Zanzan region. These decreases in rainfall in Ivory Coast, and particularly in Bingerville, are mainly due to ongoing deforestation [40].

Furthermore, the non-significance of the rainfall indices is in line with [25,70], which state that the trends in the Expert Team on Climate Change Detection and Indices (ETCCDI) indices over the period from 1981 to 2010 relating to extreme or intense rainfall, rainfall frequency, and wet and dry spells are not significant along the Guinean coast. This lack of significance is partly linked to the increase in rainfall, which came to a halt in the 1990s, but also to the greater interannual variability in rainfall [25]. Non-significant trends may also be due to the strong oscillations produced by certain climatic indices from one year to the next. The La Nina and El Nino phenomena and Atlantic Multidecadal Oscillation (AMO) may be at the origin of non-significant trends, as they influence decadal variability in West Africa. The duration of 31 years and 27 years may also be a reason because while it is an acceptable length, it may be a short time to find significant trends in the context of climate change. The spatial resolution of the town of Bingerville may also be a reason, as it is small.

From 2000 onward, the PRCPTOT and the SDII experience a decline until 2020. This is in line with studies by [26], which states that these indices have decreased in the Zanzan region, [71], which confirms the decrease in the PRCPTOT of 788 mm between 1984 and 2013 in the central-west region of Ivory Coast, and [63], showing the decrease in the south-west region of Ivory Coast. According to [72], the decrease in PRCPTOT was in the south of Ivory Coast from 2001 to 2020. The decline in the PRCPTOT and SDII is a problem for agriculture in the town of Bingerville, and has been confirmed by the technical department of the Bingerville town hall. PRCPTOT and SDII have fallen in northern Cameroon [45]. In contrast, rainfall intensity increased in Kenya [46]. CWD and CDD have increased, but with a drop in CDD from 2005.

The increase in CWD is smaller than that in CDD. The increase in CDD indicates the presence of drought, which is a worrying situation for the town of Bingerville, as it threatens water resources. The increase in the CWD is a flood risk for the town of Bingerville. The increase in CWD is in line with studies [63] in Daloa. The opposite is true for [71] and [63], which state that the CWD is decreasing in Gagnoa and central western Ivory Coast, respectively. For these authors, CDD is still on the rise. For the studies on Ghana and Niger, respectively, [73] and [74] found that CDD was increasing and CWD decreasing. The increase in CWD is global, as [75] showed an increase in South Africa, East Asia, and South America in their paper on rainfall and temperature extremes since the beginning of the 20th century.

R99p has increased in the town of Bingerville while R95p has decreased. This increase is due to RR1 and CWD, which have increased. R99p is the cause of flooding and landslides. [76] noted that R99p has also increased in Gagnoa. The central and west African Sahel are experiencing an increase in extremely rainy days as per [77]. In the Tigray region of Ethiopia, R99p has decreased. This can be explained by climate change, which is showering some regions with rain and leaving others without.

However, there was no flooding from 2000 to 2011, because R99p was falling. However, from 2011 to the present day, this city has experienced flooding, as the R99p has increased, as have the PRCPTOT, RR1, and CWD. During this period, flooding occured in the town centers. This is supported by officials from the technical department of the Bingerville Town Hall, who say that in the town centers, some property developers or private individuals have built in the ravines and basins without prior planning and without taking account of the town construction plan drawn up by the Ivory Coast government [18]. Data received from the Town Hall shows that there have been many floods from 2011 to the present day. The most serious was that of June 16 and 21, 2022, which destroyed houses and roads and affected 367 households, including four deaths among 10- and 11-year-olds (Groupement Militaire des Sapeurs-Pompiers de Bingerville).

4.4. Relationship between land use classes and extreme weather indices

The Pearson correlation shows a correlation between years, population, and buildings. This also suggests that buildings develop as the years progress and the population increases. The correlation of buildings with rainy days (RR1) and consecutive rainy days (CWD) was between 0.2 and 0.4. This may be due to their respective increases of 0.375 days/year and 0.034 days/year. During periods of urban development, these indices also increased. It can be concluded that urban development has an impact on the precipitation regime.

The low correlation of WSDI with buildings is due to consecutive warm days that have not changed. The high correlation of buildings with populations and maximum temperatures is due to the growth in urbanization. This is in agreement with [78], which states that high density areas have high temperatures. TX90p is weakly correlated with buildings and population because of the decline in this index from 2011 to 2016 and the slope of sen, which is 0.36 days/year. In addition, TX90p hot days increase in inhabited areas more than in vegetated areas as the years go by. This is consistent with the study by [23], which states that urbanization affects urban climatic comfort, as concrete surfaces, asphalt, and parquet flooring that lack vegetation are sources of heat. Vegetated areas, on the other hand, reduce perceived temperatures by up to 20%. The strong correlation of TX10p with forest or farmland is justified by the decrease in forest or farmland to the detriment of built-up areas. The presence of the lagoon is a source of coolness, which shows the correlation between water and minimum temperatures and the TN90p.

It can be concluded that urbanization has an impact on climate and climate change. It is in this sense that [14] state that urbanization has a significant effect on climate change in Iran.

5. Conclusions

The overall aim of this study is to assess the impact of land use on precipitation, temperature, and extreme indices (PRCPTOT, RR1, SDII, CWD, CDD, R95p, R99p, TN10p, TN90p, TX10p, TX90p, and WSDI) in the city of Bingerville from 1990 to 2020 through the temporal variability of these indices. To achieve our objective, land cover mapping for the years 1990, 2000, 2015, and 2020 was done first to see the evolution of the land surface in the city of Bingerville. Next, the evolution of the climate was analyzed by calculating the indices and the evolution of their trend. Finally, the correlation between land use classes and population, years, precipitation, temperatures, and their extreme indices was carried out in order to see the relationship between land use classes and these climatic indices.

However, analysis of the evolution of surface conditions in Bingerville shows an increase in built-up area from 3.35 km^2 between 1990 and 2000 to 12.82 km^2 between 2015 and 2020. This has led to a reduction in water, forest or crop land, and scrub or fallow land. On the other hand, extreme precipitation indices show an increase in PRCPTOT, RR1, CWD, CDD, and R99p and a decrease in SDII and R95p from 1990 to 2020. But after 2010, when urbanization began to increase exponentially, indices such as RR1, CWD, and R99p increased more. This increase in these three indices shows that the town of Bingerville is at risk of increased flooding and landslides. This is in line with the information gathered by Bingerville's Technical Department. In addition, the buildings are correlated with RR1 and CWD. This further confirms the likelihood of flooding due to urban development.

The correlation of built-up areas with maximum temperature and TX90p shows that changes in land use affect temperature through the urban heat island phenomenon. Extreme temperature indices also show an increase in TN10p, TX90p, and WSDI and a decrease in TX10p and TN90p over the period from 1990 to 2016.

Despite the 27 years used for the temperature trend, TX10p and TX90 were statistically significant. This is in line with the studies of [79] asserting a statistically significant decrease in annual concentrations from 1997 to 2010 using the Mann-Kendall test. [25] showed that precipitation indices were not significant over 29 years and we had the same results.

In addition, the results of our study show that the growth of urban built-up areas affects rainfall and temperatures. Thus, this growth in urbanization in the town of Bingerville has adverse effects on the climate, well-being, and health of the population.

Furthermore, unsystematic, rapid, and unplanned urbanization threatens the sustainability of the development process by adversely affecting certain environmental components such as rainfall and temperature. To avoid this problem, municipal decision-makers in the town of Bingerville should put in place policies and practices to slow down the negative impacts of urbanization on the climate and also promote urban sustainability. They should also create heat island management programs, such as creating more green spaces and planting trees to reduce high temperatures. This will help to design rainwater management systems to limit the risk of flooding.

However, Landsat data has a resolution of 30 meters which can be affected by cloud cover and creates classification errors. Data for the period from 2001 to 2010 cannot be used in the study area because of the features on these images. Despite the methods available for making these features disappear, we were unable to make the data usable. The use of data from local weather stations could help and complement the CHIRPS and CHIRTS data used, which have a resolution of 5 km, in order to improve the accuracy of the analyses. These data are not able to detect microclimatic variations in urban areas.

We therefore recommend an in-depth study, taking into account the La Nina phenomenon, El Niño, and the presence of the lagoon and building materials, which also have an impact on the climate. New methods will be used, such as the cellular automata (CA) model to deal with spatio-temporal heterogeneity studies on the partitioning of land use changes and ENVI Met to characterize the microclimates of the town of Bingerville, the Markov-FLUS model to predict the spatial pattern of land use, and finally the XGBoost model to see how the thermal environment evolves through urban heat islands. The correlation between land use and climate indices has yet to be compared using artificial intelligence methods, which are much more robust and take into account several data sources at once.

Use of AI tools declaration

The authors declare that they have not used any AI tools.

Acknowledgments

The authors would like to thank LMI NEXUS and the Centre National de Calcul de Haute Performance de Côte d’Ivoire for providing the facilities and equipment required for this study.

Author contributions

Conceptualization and methodology: TRAORE Kinanlie Sandrine, OBAHOUNDJE Salomon, DIEDHIOU Arona, and HAUHOUOT Asseypo Celestin; Formal analysis, investigation, and data curation: TRAORE Kinanlie Sandrine, OBAHOUNDJE Salomon; Visualization: TRAORE Kinanlie

Sandrine, OBAHOUNDJE Salomon; Validation: OBAHOUNDJE Salomon and DIEDHIOU Arona; Writing—original draft preparation: TRAORE Kinanlie Sandrine; Supervision: DIEDHIOU Arona and HAUHOUOT Asseypo Celestin. All authors contributed to the writing, review, and editing.

Funding

The research leading to this publication is co-funded by the Ministry of Higher Education and Scientific Research and IRD (Institut de Recherche pour le Développement; France) grant number "UMR IGE Imputation 252RA5".

Conflict of interest

The authors declare no conflict of interest.

References

1. Li X, Stringer LC, Dallimer M (2022) The Impacts of Urbanisation and Climate Change on the Urban Thermal Environment in Africa. *Climate* 10: 164. https://doi.org/10.3390/cli10110164
2. Denis E (2020) More Urban Constructions for Whom? Drivers of Urban Built-Up Expansion Across the World from 1990 to 2015, In: D Pumain, Ed., *Theories and Models of Urbanization*, Berlin, Springer, 235–258. https://doi.org/10.1007/978-3-030-36656-8_13
3. Ahmed HA, Singh SK, Kumar M, et al. (2020) Impact of urbanization and land cover change on urban climate: Case study of Nigeria. *Urban Clim* 32: 100600. https://doi.org/10.1016/j.uclim.2020.100600
4. Cahiers de l'Afrique de l'Ouest, Dynamiques de l'urbanisation africaine 2022, le rayonnement économique des villes africaines, OCDE, Nation Unis, 2022, 204. https://doi.org/10.1787/20743556
5. OECD, United Nations Economic Commission for Africa, African Development Bank (2022) New evidence on Africa's urban economy, *Africa's Urbanisation Dynamics 2022: The Economic Power of Africa's Cities*, OECD Publishing: Paris, France.
6. Zhang M, Chen E, Zhang C, et al. (2024) Multi-Scenario Simulation of Land Use Change and Ecosystem Service Value Based on the Markov–FLUS Model in Ezhou City, China. *Sustainability* 16: 6237. https://doi.org/10.3390/su16146237
7. Foissard X, Quenol H, Dubreuil V (2013) Analyse et spatialisation de l'ilot de chaleur urbain dans l'agglomération rennaise, XXVIème colloque de l'Association Internationale de Climatologie, 242–247. Available from: https://www.academia.edu/27969446/Analyse_et_spatialisation_de_lilot_de_chaleur_urbain_dans_lagglom%C3%A9ration_rennaise.
8. Yao X, Wang Z, Wang H (2015) Impact of urbanization and land-use change on surface climate in middle and lower reaches of the Yangtze River, 1988–2008. *Adv Meteorol* 10. http://dx.doi.org/10.1155/2015/395094

9. Xu Z, Zhao G (2016) Impact of urbanization on rainfall-runoff processes: case study in the Liangshui River Basin in Beijing, China. *Proc Int Assoc Hydrol Sci* 373: 7–12. https://doi.org/10.5194/piahs-373-7-2016
10. Jeune Afrique-Economique, Ville et Climat : Abidjan traque les pluies diluviennes. Dossier article de presse «Comment les villes africaines font face au risque climatique», 2020. Available from: https://www.jeuneafrique.com/dossiers/comment-les-villes-africaines-font-face-au-risque-climatique/.
11. Kouamé KM, Kouadio BH, Yao JC, et al. (2023) Cartographie du risque d'inondation à cocody et abobo-abidjan (Côte d'Ivoire). *Éditions Francophones Universitaires d'Afrique*, 430–447.
12. IPCC, Changements climatiques 2014: Rapport de synthèse. Contribution des Groupes de travail I, II et III au cinquième Rapport d'évaluation du Groupe d'experts intergouvernemental sur l'évolution du climat. GIEC, Genève, Suisse, 2014, 161.
13. Ymba M (2022) Analyse des effets des îlots de chaleur urbains sur la santé des populations de la ville d'Abidjan (Côte d'Ivoire). *Les Papiers de la Fondation* 46: 24.
14. Luo XY, Chen MX (2019) Research progress on the impact of urbanization on climate change. *Adv Earth Sci* 34: 984. https://doi.org/10.11867/j.issn.1001-8166.2019.09.0984
15. Chen Y, Yang J, Yu WB, et al. (2020) Relationship between urban spatial form and seasonal land surface temperature under different grid scales. *Sustain Cities Soc* 89: 104374. https://doi.org/10.1016/j.scs.2022.104374
16. Zhang R, Yang J, Ma XY, et al. (2023) Optimal allocation of local climate zones based on heat vulnerability perspective. *Sustain Cities Soc* 99: 104981. https://doi.org/10.1016/j.scs.2023.104981
17. Xu D, Gao J, Lin W, et al. (2021) Differences in the ecological impact of climate change and urbanization. *Urban Clim* 38: 100891. https://doi.org/10.1016/j.uclim.2021.100891
18. Eba AEL, Ake GE, Gouadou DF, et al. (2021) Evaluation de la VulnÃ©rabilite Ã lâ€™Inondation des Communes Ã ProximitÃ© des Grandes Villes Ouest Africaines : Cas de la Commune de Bingerville (Est dâ€™Abidjan â€“ CÃ´te dâ€™Ivoire). *Eur Sci J* 17: 277. https://doi.org/10.19044/esj.2021.v17n14p277
19. Brou AL (2018) Les stratégies des résidents des quartiers précaires d'Abidjan face au politique de l'urbanisation; cas de Yaoséhi, Kennedy Clouétcha et Washington, Thèse Unique, 387.
20. Koutoua AJP (2019) *Planification urbaine et développement du grand Abidjan: cas des villes d'Anyama, de Bingerville et de Grand-Bassam,* Thèse unique, 342.
21. Suman P, Satiprasad S, Pulak M, et al. (2018) Impacts of urbanization on land use /cover changes and its probable implications on local climate and groundwater level. *J Urban Manage* 7: 70–84. https://doi.org/10.1016/j.jum.2018.04.006
22. He F, Yang J, Zhang Y, et al. (2023) Does partition matter? A new approach to modeling land use change, Computers, Environment and Urban Systems. *Comput Environ Urban* 106: 102041. https://doi.org/10.1016/j.compenvurbsys.2023.102041
23. Zhang, M, Yiĝit I, Adigüzel F, et al. (2024) Impact of Urban Surfaces on Microclimatic Conditions and Thermal Comfort in Burdur, Türkiye. *Atmosphere* 15: 1375. https://doi.org/10.3390/atmos15111375

24. Obahoundje S, Ofosu E, Akpoti K, et al. (2017) Land use and Land Cover Changes under Climate Uncertainty: Modelling the Impacts on Hydropower Production in Western Africa. *Hydrologie* 4: 2. https://doi.org/10.3390/hydrology4010002
25. Sacré Regis MD, Mouhamed L, Kouakou K, et al. (2020) Using the CHIRPS Dataset to Investigate Historical Changes in Precipitation Extremes in West Africa. *Climate* 8: 84. https://doi.org/10.3390/cli8070084
26. Kouman KD, Kabo-bah AT, Kouadio BH, et al. (2022) Spatio-Temporal Trends of Precipitation and Temperature Extremes across the North-East Region of Côte d'Ivoire over the Period 1981–2020. *Climate* 10: 74. https://doi.org/10.3390/cli10050074
27. Yapi AF, Kpan OJG, N'guessan BVH, et al. (2024) Analyse des extrêmes de températures de la région de la Marahoué (Centre-Ouest de la Côte d'Ivoire) de 1980–2013. *Afr Sci* 25: 32–45.
28. Obahoundje S, Bi VHN, Kouassi KL, et al (2020) Validation of Three Satellite Precipitation Products in Two South-Western African Watersheds: Bandama (Ivory Coast) and Mono (Togo). *Atmos Clim Sci* 10: 597–613. https://doi.org/10.4236/acs.2020.104031
29. Bassin DL, Du A, Idrissa N, et al. (2018) Variabilité spatiale et tendance de précipitations sur la période 1981–2016 dans le bassin actif du Niger, Centre Béninois de la Recherche Scientifique et Technique, Lettres, Sciences Humaines et Sociales. *Cahiers du CBRST* 11: 37–56. Available from: https://www.researchgate.net/publication/322641224_VARIABILITE_SPATIALE_ET_TENDANCE_DE_PRECIPITATIONS_SUR_LA_PERIODE_1981-2016.
30. Henri-Joel AO, Agoh DAP (2022) Exploitation de données chirps et terraclimate pour l'étude des pluies urbaines sur le district autonome d'Abidjan (Côte d'Ivoire). Editions Francophones Universitaires d'Afrique, 32–61.
31. Phiri D, Morgenroth J (2017) Développements dans les méthodes de classification de la couverture terrestre de Landsat: Une revue. *Remote Sens* 9: 967. https://doi.org/10.3390/rs9090967
32. Kouamé YM, Obahoundje S, Diedhiou A, et al. (2019) Climate, Land Use and Land Cover Changes in the Bandama Basin (Côte D'Ivoire, West Africa) and Incidences on Hydropower Production of the Kossou Dam. *Land* 8: 103. https://doi.org/10.3390/land8070103
33. Obahoundje S, Diedhiou A, Ofosu EA, et al (2018) Assessment of Spatio-Temporal Changes of Land Use and Land Cover over South-Western African Basins and Their Relations with Variations of Discharges. *Hydrologie* 5: 56. https://doi.org/10.3390/hydrology5040056
34. Akpoti K, Antwi E, Kabo-bah A (2016) Impacts of Rainfall Variability, Land Use and Land Cover Change on Stream Flow of the Black Volta Basin, West Africa. *Hydrology* 3: 26. https://doi.org/10.3390/hydrology3030026
35. Foody GM (2002) Status of land cover classification accuracy assessment. *Remote Sens Environ* 80: 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4
36. Congalton RG, Green K (2008) *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, CRC Press. Boca Raton, Floride, USA, 200. https://doi.org/10.1201/9781420055139
37. Barry AA, Caesar J, Klein Tank AMG, et al. (2018) West Africa Climate Extremes and Climate Change Indices. *Int J Climatol* 38: e921–e938. https://doi.org/10.1002/joc.5420

38. Bedoum A, Biona CB, Pierre BJ, et al. (2017) Évolution des indices des extrêmes climatiques en république du Tchad de 1960 à 2008. *Atmos-Ocean* 55: 42–56. https://doi.org/10.1080/07055900.2016.1268995
39. Kruger AC, Shongwe S (2004) Temperature Trends in South Africa: 1960–2003. *Int J Climatol* 24: 1929–1945.
40. Balliet R, Saley MB, Eba ELA, et al. (2016) Évolution Des Extrêmes Pluviométriques Dans La Région Du Gôh (Centre-Ouest De La Côte d'Ivoire). *Eur Sci J* 12: 74. http://dx.doi.org/10.19044/esj.2016.v12n23p74
41. Kruger AC, Rautenbach H, Mbatha S, et al. (2019) Historical and Projected Trends in near Surface Temperature Indices for 22 Locations in South Africa. *S Afr J Sci* 115. https://doi.org/10.17159/sajs.2019/4846
42. Croitoru AE, Chiotoroiu BC, Ivanova Todorova V, et al. (2013) Changes in Precipitation Extremes on the Black Sea Western Coast. *Global Planet Change* 102: 10–19. https://doi.org/10.1016/j.gloplacha.2013.01.004
43. New M, Hewitson B, Stephenson DB, et al. (2006) Evidence of Trends in Daily Climate Extremes over Southern and West Africa. *J Geophys Res Atmos* 111. https://doi.org/10.1029/2005JD006289
44. Berhane A, Hadgu G, Worku W, et al. (2020) Trends in Extreme Temperature and Rainfall Indices in the Semi-Arid Areas of Western Tigray, Ethiopia. *Environ Syst Res* 9: 3. https://doi.org/10.1186/s40068-020-00165-6
45. Vondou DA, Guenang GM, Djiotang TLA, et al. (2021) Trends and Interannual Variability of Extreme Rainfall Indices over Cameroon. *Sustainability* 13: 6803. https://doi.org/10.3390/su13126803
46. Gebrechorkos SH, Hülsmann S, Bernhofer C (2019) Changes in Temperature and Precipitation Extremes in Ethiopia, Kenya, and Tanzania. *Int J Climatol* 39: 18–30. https://doi.org/10.1002/joc.5777
47. Obahoundje S, Diedhiou A, Kouassi KL, et al (2022) Analysis of hydroclimatic trends and variability and their impacts on hydropower generation in two river basins in Côte d'Ivoire (West Africa) during 1981–2017. *Environ Res Commun* 4: 19. https://doi.org/10.1088/2515-7620/ac71fa
48. Kendall M, Gibbons JD (1938) *Méthodes de corrélation des rangs*, Londres: Oxford University Press.
49. Davis CL, Hoffan MT, Roberts W (2016) Recent Trends in Climate of Namaqualand, a Megadiverse Arid Region of South Africa. *S Afr J Sci* 112: 9. https://doi.org/10.17159/sajs.2016/20150217
50. Zhao L, Zhang C, Wang Q (2024) Climate extremes and land use carbon emissions: Insight from the perspective of sustainable land use in the eastern coast of China. *J Cleaner Prod* 452: 142219. https://doi.org/10.1016/j.jclepro.2024.142219
51. Wu L, Zhao C, Li J, et al. (2023) Impact of extreme climates on land surface phenology in Central Asia. *Ecol Indic* 146: 109832. https://doi.org/10.1016/j.ecolind.2022.109832

52. Suckall N, Fraser E, Forster P, et al. (2015) Using a migration systems approach to understand the link between climate change and urbanisation in Malawi. *Appl Geogr* 63: 244–252. https://doi.org/10.1016/j.apgeog.2015.07.004
53. Oura KR, Kanga KMJ (2017) L'agriculture urbaine face au défi de l'urbanisation de Bingerville dans le Sud-Est d'Abidjan, en Côte d'Ivoire. *Dynamiques des territoires et développement* 16: 260–280.
54. Loba ADFV (2010) Les déterminants de la dynamique spatiale de la ville de Bingerville (sud de la Côte d'Ivoire) de 1960 à nos jours. *EchoGéo*.
55. BNETD, Projet de développement des communes côtières, communes de Bingerville, 1993, 55.
56. Aoubouazza M, Rajel R, Essafi R (2019) Impact Des Phénomènes Climatiques Extrêmes Sur Les Ressources En Eau et l' Agriculture Au Maroc. *Rev Mar Sci Agron Vét* 7: 223–232.
57. Van der Walt AJ, Fitchett JM (2021) Exploring Extreme Warm Temperature Trends in South Africa: 1960–2016. *Theor Appl Climatol* 143: 1341–1360. https://doi.org/10.1007/s00704-020-03479-8
58. Bambara D, Compaore H, Bilgo A (2018) Évolution des températures au Burkina Faso entre 1956 et 2015: cas de Ouagadougou et de Ouahigouya. *Physio-Géo Géographie physique et Environnement* 12: 23–41.
59. Tam BY, Gough WA, Mohsin T (2015) The impact of urbanization and the urban heat island effect on day to day temperature variation. *Urban Clim* 12: 1–10. https://doi.org/10.1016/j.uclim.2014.12.004
60. Chen L, Frauenfeld OW (2016) Impacts of urbanization on future climate in China. *Clim Dyn* 47: 345–357. https://doi.org/10.1007/s00382-015-2840-6
61. Kalnay E, Cai M (2003) Impact of urbanization and land-use change on climate. *Nature* 423: 528–531. https://doi.org/10.1038/nature01675
62. Coumou D, Rahmstorf SA (2012) A decade of weather extremes. *Nature Clim Change* 2: 491–496. https://doi.org/10.1038/nclimate1452
63. Atcheremi KND, Jourda JPR, Saley MB, et al. (2018) Study of the evolution of the rainfall extremes and temperature extremes in davo river basin (south- western of cote d'ivoire) from some indices of the software rclimdex. *Larhyss J* 36: 99–117.
64. Ghohoui YP, Hountondji YC, De Longueville F, et al. (2018) Appercu synoptique de la variabilité des extremes climatique du Bénin (1960–2016). *Risques ClimatiquesAIC*, 98–102.
65. Karimou BM, Ambouta K, Sarr B, et al. (2015) Analyse Des Phénomènes Climatiques Extrêmes Dans Le Sud-Est Du Niger. XXVIIIe Colloque de l'Association Internationale de Climatologie: Liège, Belgium, 537–542. Available from: https://orbi.uliege.be/bitstream/2268/184575/1/087-KARIMOU_BARKE-537-542.pdf.
66. Abatan AA, Abiodun, BJ, Lawalc KA, et al. (2016) Trends in extreme temperature over Nigeria from percentile-based threshold indices. *Int J Climatol* 36: 2527–2540. https://doi.org/10.1002/joc.4510
67. IPCC, Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Parry ML, Canziani OF, Palutikof JP, et al., Eds., Cambridge University Press: Cambridge, UK, 2007. Available from: https://www.ipcc.ch/site/assets/uploads/2018/03/ar4_wg2_full_report.pdf.

68. Mohajerani A, Bakaric J, Jeffrey-Bailey T (2017) The urban heat island effect, its causes, and mitigation, with reference to the thermal properties of asphalt concrete. *J Environ Manage* 197: 522–538. https://doi.org/10.1016/j.jenvman.2017.03.095
69. Goula BTA, Soro EG, Kouassi W, et al. (2012) Trends and abrupt changes in daily extreme rainfalls of Ivory Coast (West Africa). *Hydrol Sci J* 57: 1067–1080. https://doi.org/10.1080/02626667.2012.692880
70. Sanogo S, Fink AH, Omotosho JA, et al. (2015) Spatio-temporal characteristics of the recent rainfall recovery in West Africa. *Int J Climatol* 35: 4589–4605. http://dx.doi.org/10.1002/joc.4309
71. Allechy FB, Ta MY, Bi VHG, et al. (2020) Trend of Extreme Precipitations Indices in West-central Côte d'Ivoire: Case of the Lobo Watershed. *Eur J Eng Res Sci* 5: 1281–1287.
72. N'guessan HBV, Arona D, Adjakpa T, et al. (2015) Apport de la télédétection à l'analyse spatio-temporelle de l'évolution des extrêmes pluviométriques dans le district d'abidjan au sud de la cote d'ivoire. *Mélanges en hommages aux Professeurs Houssou CS, Houndagba CJ Thomas* 3: 364–378.
73. Larbi I, Hountondji FCC, Annor T, et al. (2018) Spatio-Temporal Trend Analysis of Rainfall and Temperature Extremes in the Vea Catchment, Ghana. *Climate* 6: 87. https://doi.org/10.3390/cli6040087
74. Ozer P, Manzo L, Tidjani AD, et al. (2017) Evolution Récente Des Extrêmes Pluviométriques Au Niger (1950–2014). *Geo-Eco-Trop: Revue Internationale de Géologie, de Géographie et d'Ecologie Tropicales* 41: 375–383.
75. Donat MG, Alexander LV, Yang H, et al. (2023) Updated Analyses of Temperature and Precipitation Extreme Indices since the Beginning of the Twentieth Century: The HadEX2 Dataset. *J Geophys Res Atmos* 118: 2098–2118. https://doi.org/10.1002/jgrd.50150
76. Balliet R (2017) Impacts du changement climatique et de la pression anthropique sur l'environnement naturel et humain de la région du Gôh (Centre-ouest de la Côte d'Ivoire): analyse de mesures endogènes d'adaptation. Thèse unique, Université Félix Houphouët Boigny, 193.
77. Panthou G, Vischel T, Lebel T (2014) Recent Trends in the Regime of Extreme Rainfall in the Central Sahel. *Int J Climatol* 34: 3998–4006. https://doi.org/10.1002/joc.3984
78. Mobio ABH, Dré KF, Kouamé AKD, et al. (2017) Contribution de la Télédétection à l'étude de la Distribution spatiale de la Température en fonction du relief et du mode d'occupation du Sol: Cas de la ville d'Abidjan (Côte d'Ivoire). *Int J Eng Sci Invent* 6: 48–55.
79. Drápela K, Drápelová I (2011) Application du test de Mann-Kendall et des estimations de la pente de Sen pour la détection des tendances dans les données de dépôt de Bílý Kříž (Monts Beskydy, République tchèque) 1997–2010. *Base de Donnée CABI* 4: 133–146.

Appendix

Appendix 1: Dynamics of land use in the town of Bingerville, 1990–2020

Dynamics of land use in the town of Bingerville, 1990–2020

The appendix shows the statistics for changes in land cover in Bingerville over the period from 1990 to 2020. During this period, forest or crops and scrub or fallow land, which occupied a large area in 1990, disappeared by 2020. Built-up areas were taking up more and more space. Thus, the period from 2015 to 2020 shows a major change in built-up areas compared with the periods from 1990 to 2000 and from 2000 to 2015. The town of Bingerville is changing more and more as the years go by.