Geodesy and Cartography
ISSN 2029-6991 / eISSN 2029-7009
2023 Volume 49 Issue 3: 142–148
https://doi.org/10.3846/gac.2023.16007

UDC 528.94

ASSESSMENT OF LAND DEGRADATION USING REMOTE SENSING APPROACH

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Received 23 November 2021; accepted 15 September 2023

Abstract. Land degradation leads to the alteration of ecological and economic functions due to a decrease in the productivity and quality of the land. Land degradation over Minna, Niger State, was assessed using geospatial techniques. Studies between the rainfall and NDVI used on human-induced and climate-induced land degradation were correlated. Landsat imageries on a decadal scale (2000–2019) were processed and classified using a maximum likelihood classifier. NDVI trends are not by rainfall dynamics to human actions. Averagely low, about 24.14%, correlation was found between the observed land degradation and the precipitation factor, yielding more than 50% congruence in degradation induced by human activities. The study discovered that the built-up and bare surfaces are increasing. The long-term changes in built-ups were 96% between 2000 and 2019; conversely, a sharp decrease in vegetative lands at about –19.38%. Based on the terrain analysis, locations have less steep and moderate slopes in the study area due to continuous urban expansion and demographic pressure. Consequentially, over time, available lands not degraded within the study areas would be reduced. The study recommended a proper land management system of land use allocation and land cover activities.

Keywords: land degradation, remote sensing and GIS techniques, rainfall dynamics, NDVI, human-induced, climate-induced and precipitation factor.

Introduction

Land degradation is the persistent reduction of the land's biological and economic production capacity (Vogt et al., 2011). Land degradation happens through natural and anthropogenic phenomena where the former cannot altered and adaptation of the latter, can be mitigated (Vu et al., 2014). Globally, about 10–20% of drylands are estimated to be land degraded (Millennium Ecosystem Assessment, 2005), and about 12 million hectares are degraded each year (James et al., 2013). Understanding the causes and consequences of land degradation processes on ecosystem functioning, affected areas, and regions at risk (land degradation hotspots) is a prerequisite strategy to mitigate and avoid land degradation (Stellmes et al., 2015; Abdel-Kader, 2019).

Land degradation has been one of the most critical environmental issues of this time, experienced on a global scale. It can be defined as the persistent or long-term reduction of ecosystem services and vegetation productivity on the land as it affects lives. This occurrence encompasses effects, including changes in plant species composition, soil erosion, and a reduction in the land's productive potential. The changes in land degradation are human factors and natural processes. Human causes are otherwise called anthropogenic factors, which include the overuse of land (e.g., overgrazing and deforestation) and other socio-economic factors, such as improper agriculture development policies.

Natural factors include extreme and periodic climatic variations, aridity, and droughts, mainly induced by precipitation and temperature in arid or semi-arid regions (Huang & Kong, 2016). Land degradation can be assessed in terms of Land Degradation Assessment in Drylands (LADA), a unique way of assessing and mapping land degradation at different spatial scales, small to large, at various levels, local to global. It was in drylands, but the methods and tools developed were widely applicable in other ecosystems and diverse contexts with minimal required adaptation (Biancalani et al., 2011).

The genesis and distribution of different land degradation processes depend on climate, topography, vegetative cover, parent material (salty or acidic), and groundwater

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(saline, sodic, or heavy metals or metalloids). Above all, human-induced degradation of land has been increasing recently. These changes in land degradation can be monitored and assessed through geospatial techniques such as remote sensing (RS) and geographic information systems (GIS) with fine spatial and spectral resolution imageries. Advanced techniques such as microwave, hyperspectral, and proximal ground-based sensor data with multivariate statistical algorithms have increased the efficiency of the classification and mapping of degraded lands. Therefore, this study aims to assess the impacts of land degradation in Minna using remote sensing data such as MODIS data, precipitation data, terrain analysis, and Landsat images.

1. Study area

The study area, Minna metropolis, is located within the North central region of Nigeria within the approximate latitude of 90° 25′00″ and 90° 40′00″ north of the equator and longitude 60° 24′20″ and 60° 36′40″ east of the meridian, covering an approximate area of 88 km^2 with a population of 1.2 million. Minna has two local government areas, Bosso and Chanchaga LGA, shown in Figure 1.

The study area is approximated to a total area of 50,338.5 km^2, accounting for 4.7% of the total area of Minna. However, the field observations and the satellite images show several types of land degradation accumulations in the southern part of Chanchaga and the northern part of Bosso within Minna. The land degradation descended from mostly parts of Chanchaga local government and Bosso Local Government areas, and the environmental problems in the study areas are demographic pressure, erosion and rainfall. The region has a tropical climate characterized by two distinct seasons, dry and rainy seasons. The mean annual temperature, relative humidity, and rainfall were 30.20°, 61.00%, and 1334.00 cm, respectively. The vegetation of the study area is a typical Guinea savannah, which comprises tall grasses with a series of tall trees within the vegetation areas.

2. Materials and methods

2.1. Landsat dataset

Landsat imageries of the study area were acquired from the USGS-EROS satellite image database for four epochs (2000, 2010, 2015 and 2019) in Table 1. There was no scene-to-scene variation of the utilised imageries, and it ensures consistency in the spectral characteristics of the study area. The 2000 and 2019 data were downloaded, with 0.00% cloud cover, and 2010 and 2015 with 2.30% and 3.45% cloud cover, which is a tolerable amount. Table 1 shows the details of the images downloaded and used for this study.

Table 1. The properties of the imagery sensors used in this study

Product ID	Sensor type	Date acquired	Cloud cover (%)
LT04_L1TP_189056_20000106_20200917_02_T1	Landsat-4 TM	1988/01/06	0.00
LT05_L1TP_189056_20050213_20200908_02_T1	Landsat-5 TM	1999/02/13	0.00
LE07_L1TP_189056_20100214_20200913_02_T1	Landsat-7 ETM	2008/02/14	3.45
LE07_L1TP_189056_20150124_20200830_02_T1	Landsat-7 ETM	2018/01/24	2.30

Moderate Resolution Imaging Spectroradiometer MODIS-Terra Vegetation Index (VI) product (MOD13Q1, Collection 5) was used as a proxy for vegetation cover dynamics in the study area, covering the time period from January 2000 to December 2019 at a pixel resolution of 250 m by 250 m. Precipitation data was used, in the absence of ground stations, Tropical Rainfall Measuring Mission (TRMM) Time Series Data Sets 2000–2019, 3B43.6/7:20,010,101–20,161,201 in mm/h with a temporal

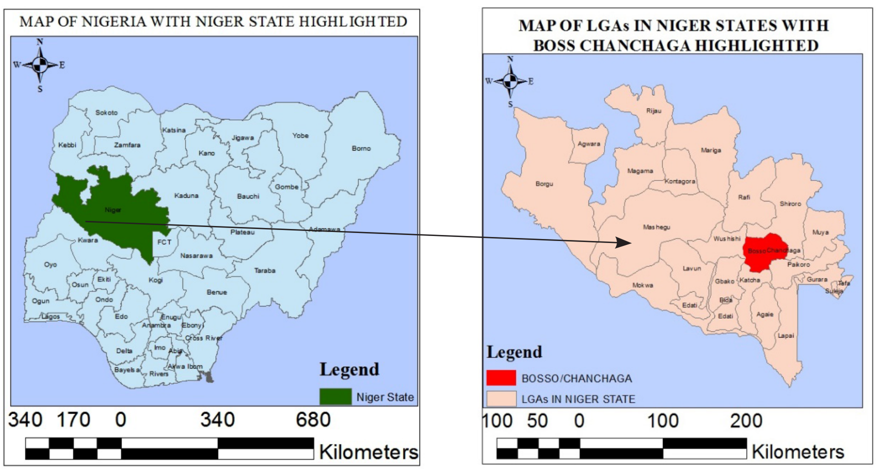


Figure 1. Map of the study area

resolution of one month and a spatial resolution of 0.25 m was used to illustrate the rainfall trends of the study area. The Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) with a 30 m spatial resolution was obtained (CGIAR- CSI, 2005) and used for the terrain analysis. A differential GPS receiver (v30) was used to acquire the data to generate a digital elevation model (DEM) for the study area, and the DEM was a standard value in the validation of the SRTM-DEM for the field observation data.

2.2. Data processing and assessments

2.2.1. NDVI as an indication for land degradation

A 16-day composite of the Normalized Difference Vegetation Index (NDVI) from the MODIS-Terra Vegetation Index (VI) product (MOD13Q1, Collection 5) was adopted as a proxy for vegetation cover dynamics in the study area, covering the period from 2000 to 2019 at a pixel resolution of 250 m by 250 m. The earlier image (2000) pixel values for the baseline image and images (2005, 2010, 2015 and 2019) pixel values were later used by subtracting the values from the baseline image after processing to obtain the results and comparing them against each year to identify the loss/gain in land Net Primary Productivity within the years as presented in Figures 2a–2e. Table 2 shows the comparison of annual NDVI.

The following images from Figures 2a to 2e show the condition of land within the study area concerning NDVI. Based on the estimated MODIS NDVI, the degradation was categorised into four levels as depicted in the legend from 2000 to 2019 in Figures 2ato 2e: non-degraded, no yield (partial degradation), less-degraded, and highly degraded portions, respectively.

Table 2. Comparison of annual NDVI

2000	2005	2010	2015	2019
0	–0.0067	–0.0476	–0.3855	–0.3651
0	–0.0067	–0.0436	–0.3741	–0.3585
0	0.0085	–0.0133	–0.3656	–0.337
0	0.0205	0.0223	–0.3532	–0.3391
0	–0.0195	–0.0089	–0.3898	–0.3788
0	–0.0195	–0.0563	–0.3713	–0.3555
0	–0.0089	–0.0267	–0.3561	–0.3368
0	–0.0018	–0.0092	–0.3512	–0.3339
0	–0.0018	–0.0019	–0.3601	–0.3342
0	–0.0289	–0.0101	–0.3707	–0.3438

Despite the consistency in the month of the data, a high value in the NDVI in the years 2000, 2005, and 2010 was an indicator of higher production in non-degraded lands. Therefore, the current state of land was terrible in 2015, with a slight increase in 2019 due to low net primary production (NNP) as land degrades over time, as shown in Figure 3.

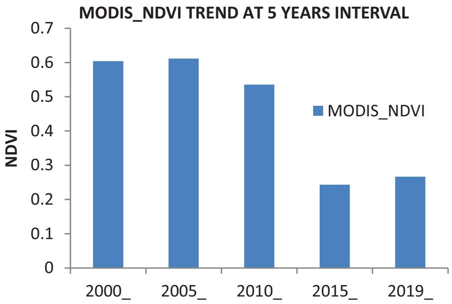
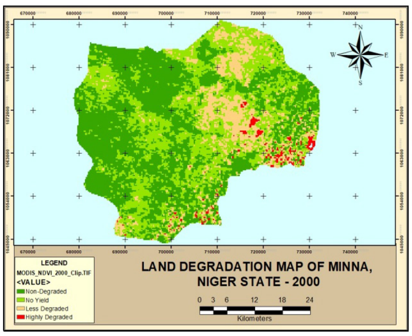
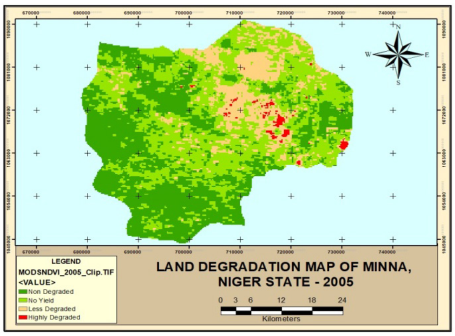


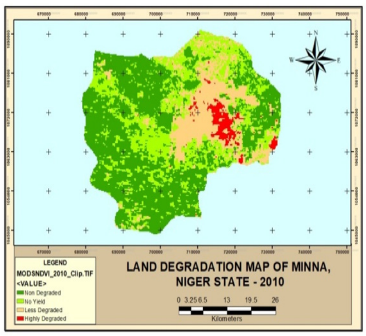
Figure 3. Trend in NDVI via MODIS sat imagery



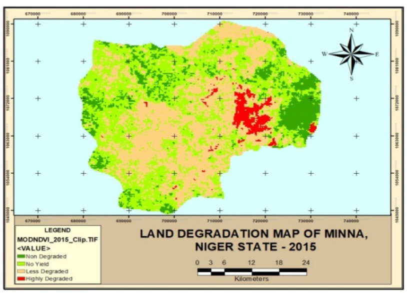
a) 2000



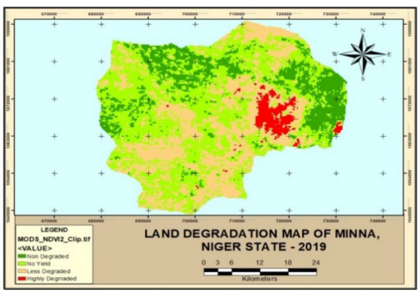
b) 2005



c) 2010



d) 2015



e) 2019

Figure 2. Land degradation maps of Minna

Table 3. NDVI difference versus precipitation

2005		2010		2015		2019	
PPT	NDVI	PPT	NDVI	PPT	NDVI	PPT	NDVI
23.2827	–0.0067	13.7825	–0.0476	42.9733	–0.3855	8.4115	–0.3651
22.427	–0.0067	27.1371	–0.0436	32.7372	–0.3741	4.8795	–0.3585
3.9763	0.0085	–14.3257	–0.0133	31.3308	–0.3656	–2.3962	–0.337
23.2827	0.0205	13.7825	0.0223	42.9733	–0.3532	8.4115	–0.3391
23.2827	–0.0195	13.7825	–0.0089	42.9733	–0.3898	8.4115	–0.3788
23.2827	–0.0195	13.7825	–0.0563	42.9733	–0.3713	8.4115	–0.3555
23.2827	–0.0089	13.7825	–0.0267	42.9733	–0.3561	8.4115	–0.3368
23.6751	–0.0018	49.1733	–0.0092	50.9008	–0.3512	39.8097	–0.3339
22.427	–0.0018	27.1371	–0.0019	32.7372	–0.3601	4.8795	–0.3342

2.2.2. Vegetation response to precipitation

Spatial and temporal differences in NDVI are closely related to climate change in an environment. The difference in the spatial pattern of NDVI response to interannual rainfall in Minna is in Table 3, where the positive numbers mean the generation of land and the negative numbers mean land degradation. So, in an attempt to separate human-induced and climate-driven vegetation productivity dynamics, the correlation between interannual vegetation productivity (expressed as NDVI) and rainfall over Minna was assessed between 2000–2019 using Pearson's correlation coefficient for all 31,117 pixels mapped (Table 3). Therefore, the NDVI for 2005, 2010, 2015 and 2019 are 0.1075, 0.3725, 0.4285 and 0.5527 shown in Figure 4. The correlation between the NDVI and precipitation typifies a very low coefficient, which signifies a low impact of climatic conditions on land degradation.

2.2.3. Terrain analysis

Utilised was the research slope map for susceptibility to land degradation alongside Terrain. The accuracy assessment of the SRTM data was assessed and found to be between 10 and 11.5 m. The slope, as expressed, was categorised into five classes based on cartographic standards. An extreme slope was determined in part of Chanchaga, Luka, behind the airport, Gidan kwano, with large artificial holes in the ground where stone and sand, dug on the site is made up of heavy mountains, the locations observed to have a steep slope are few and more to have a moderate slope, as shown in Figure 5. Furthermore, based on the slope analysis, a susceptibility map was generated for the study area, as shown in Figure 6, where steeper slope regions are more susceptible to land degradation, according to Wubie and Assen (2020).

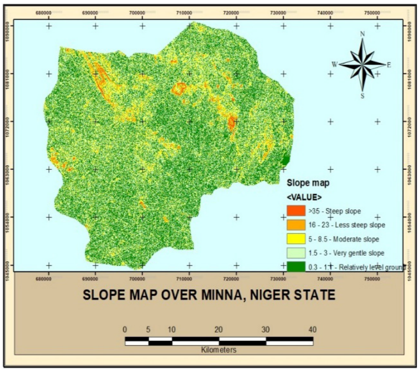


Figure 5. Slope map

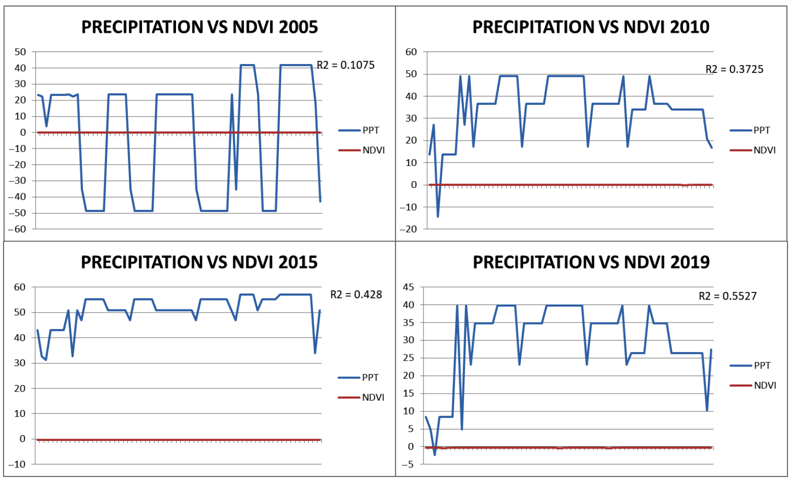


Figure 4. NDVI response to precipitation dynamics (2000–2019)

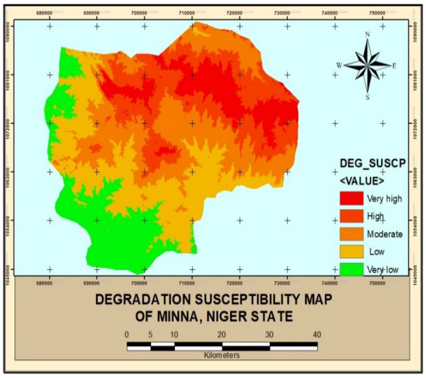


Figure 6. Susceptibility map

2.2.4. Land cover classification

The land use land cover as classified using the supervised maximum likelihood algorithm in ENVI 5.0 remote sensing software is displayed in Figure 7, which shows the land use land classification from 2000 to 2019.

2.2.5. Accuracy assessment

The accuracy of classified maps in ENVI 5.1 software was assessed using a stratified random sampling technique called ROI-based ground truthing, with the Kappa coefficient test evaluating the accuracy of the classified map.

2.2.6. Change detection analysis

A post-classification thematic change detection scheme was used for this analysis to evaluate the level of change in land classes over the years.

3. Discussion of results

The MODIS image was used to compare the annual NDVI of the study area concerning land degradation. The annual NDVI values were generated from the pixel values of the MODIS images used from 2000 to 2019, respectively, which show areas that are highly degraded and areas that have had a little bit of restoration over the years. The result of the analysis identifies the loss in net primary productivity of the lands, most especially in 2015, as a result of anthropogenic factors therein, and a slight increase in 2019, 2000, 2005, and 2010 recorded to have less degradation within the years due to indicators of higher degradation in non-degraded lands.

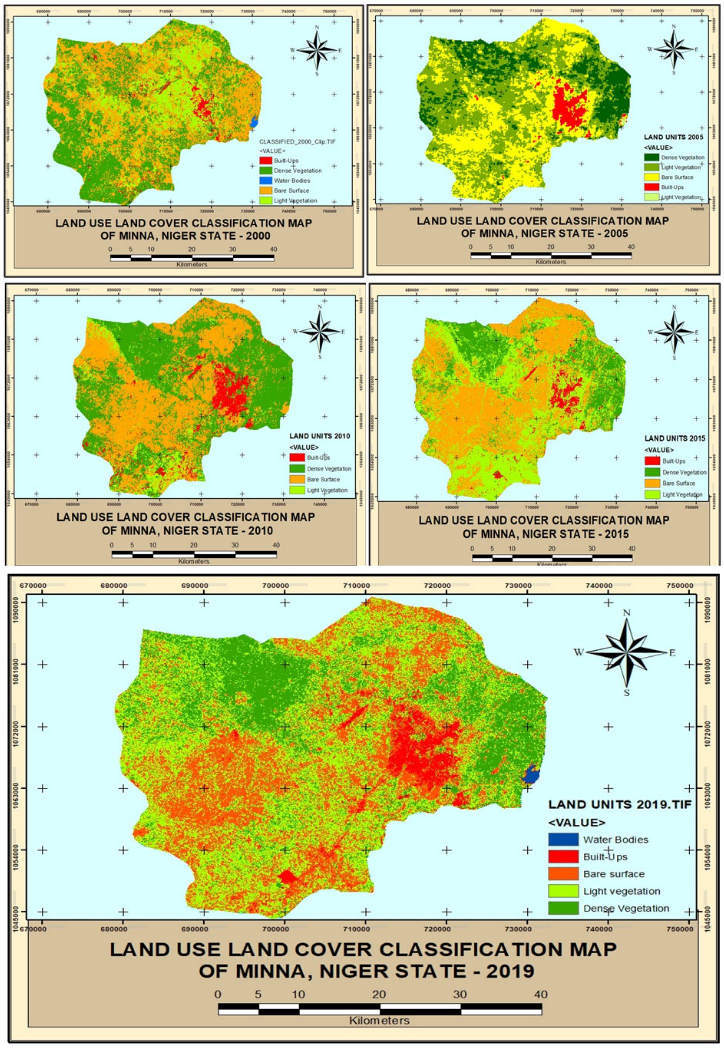


Figure 7. Land use/land cover classification maps of Minna from 2000 to 2019

The vegetation dynamics are closely related to climate change on many lands. MODIS NDVI was separated from inter-annual rainfall in the study area, where positive and negative numbers, as depicted in Table 3, where positive numbers mean the generation of the land and negative ones mean the degradation of the land, respectively. The relationship between vegetation productivity and precipitation to separate or analyse the more terrible factor between human and climatic factors affecting land, leading to land degradation using Pearson's correlation, which shows that human factors have more impact than climatic factors due to the low coefficient values of precipitation and anthropogenic pressure on the lands. Previous studies have shown that vegetation activity and precipitation have high correlations in the arid and semi-arid regions. The vegetation will rise in a year that has more rainfall. When low precipitation occurs in the year, the NDVI and vegetation are lower. The inter-annual variations of precipitation and NDVI were analysed from 2000 to 2019. The inter-annual variation precipitation was parallel with that of NDVI. In 2000, 2005, and 2010, the NDVI was relatively high, coinciding with the peak precipitation.

The slope map of the study area was generated and analysed for susceptibility to land degradation alongside Terrain. The accuracy assessment of the SRTM data was assessed and found to be between 10 and 11.5 m. The slopes were five classes ascertained in most parts of Chanchaga and Bosso, including the Luka area, behind the airport area and Gidan kwano areas with large holes and erosion phenomena. A field survey testified to the accuracy of the SRTM slope analysis, which corresponds with the field survey data obtained on those sites.

The land use and land cover as classified using the supervised maximum likelihood algorithm in ENVI 5.0 remote sensing software are in Figure 7, which is the land use and land classification from 2000 to 2019, respectively, which shows that the amount of land used occurred in 2015 and 2019 with the most buildups. Accuracy assessments were generated in ENVI 5.1 using a stratified random sampling technique. The technique is ROI-based ground truthing. For the respective images, 2000 for 90 points, 2005 for 100 points, 2010 for 103 points, 2015 for 105 points and 2019 for 109 points were randomly generated. Ground truth determines the accuracy of the classified maps. The Kappa coefficient test measures the accuracy of the classified map as it considers all the elements in the error matrix. Agricultural land increased from 58.94% to 79.11% from 2000 to 2010. The built-up area rose from 0.81% in 2000 to 4.06% in 2019. Vegetal cover shows variation between the study periods; it was 60.79% in 2000, 64.32% in 2005, 55.77% in 2010, 37.85% in 2015 and 5.45% in 2019 in change detection analysis.

Conclusions

In conclusion, this study has successfully assessed land degradation in Minna, Niger State, based on the soil's net primary productivity (as indicated by MODIS NDVI). Taking the year 2000 as the baseline, the negative variation obtained by comparing the NDVI of the subsequent years indicates depreciation in vegetation productivity, and random positive values obtained indicate regions where land regeneration occurs, as indicated in Table 3.

The study concluded that the land degradation experienced within the study area is primarily due to anthropogenic factors, as indicated by the low correlation between vegetation (by the NDVI difference) and precipitation. On the other hand, the results from the study show that land mass is subjected to infrastructural development. Consequently, it will reduce the availability of land over time.

Based on the study, slope and meteorological data were observed. Further studies should look into other indicators and more meteorological perspectives.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Funding

This study did not receive any financial assistance or grant from the public, private or not-for-profit sectors.

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