

1 Time series analysis and impact assessment of the temperature 2 changes on the vegetation and the water availability: A case study 3 of Bakun-Murum Catchment Region in Malaysia

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15 Abstract

16 The Bakun-Murum (BM) catchment region of the Rajang River Basin (RRB), Sarawak,
17 Malaysia, has been under severe threat for the last few years due to urbanization, global
18 warming, and climate change. The present study aimed to evaluate the time series analysis and
19 impact assessment of the temperature changes on the vegetation/agricultural lands and the
20 water availability within the BM region. For this purpose, the Landsat data for the past thirty
21 years (1990-2020) were used. Remote sensing techniques for estimating the surface
22 temperatures and variation within the vegetation and water bodies were utilized, and validation
23 was done using on-ground weather stations. Google Earth Engine (GEE) and other RS & GIS
24 tools were used for analyzing the time series trends of land surface temperature (LST),
25 normalized difference vegetation index (NDVI), and normalized difference water index
26 (NDWI). The results exposed an overall rise of 1.06°C in the annual mean temperatures over
27 the last thirty years. A maximum annual mean NDVI of 0.48 was recorded for 2018 and 2019.
28 The lowest annual mean NDVI (0.27) was observed in 2005. The annual mean NDWI
29 increased to 0.48 in 2018 and 2019, respectively. The statistical correlation results revealed the
30 coefficient of determination (R^2) of 0.09 and 0.13 for the annual mean LST and annual mean
31 NDVI and the annual mean LST and annual mean NDWI, respectively. Moreover, the Mann-
32 Kendall trend test for the annual mean temperature series indicates a slightly increasing trend

33 with Sen's slope of 0.03°C/year. It is found that there is a positive trend in the annual mean
34 rainfall patterns, as Sen's slope indicates a yearly increase of 50.58 mm/year. This study found
35 significant changes in the LST, NDVI, and NDWI of the BM catchment region during the last
36 thirty years, demanding the concerned authorities' instant attention to alleviate the adverse
37 effects of such changes to protect the ecosystem.

38 **Keywords:** Time series analysis; google earth engine; remote sensing & GIS; impact
39 assessment; land surface temperature

40 1. Introduction

41 The LST usually determines the current urban environment's ecological health (Patz et al.,
42 2005; Grimm et al., 2008; Huang et al., 2009; Du et al., 2016; Liu et al., 2018; Oad et al., 2020).
43 Urbanization is a fast human-induced process primarily based on urban area expansion, and
44 land transformation (Guha et al., 2020) has not only decreased the agricultural lands and
45 contributed to the increased temperature. The remote-sensing normalized difference indices are
46 usually used to identify ecological shifts within natural resources (Chen et al., 2006; Govil et
47 al., 2019; He et al., 2019; Govil et al., 2020; Guha et al., 2020). Remote sensing also provides
48 the TIR structure of the wavelengths, which is also very useful in assessing the variability of
49 LST temporally and spatially. Remote sensing is widely implemented in every field of earth
50 science (Wen et al., 2017; Ferrelli et al., 2018; Alexander, 2020; Nimish et al., 2020; Sultana
51 & Satyanarayana, 2020). The spatial heterogeneity of the LST is due to the variation in
52 roughness and reflectance of the ground surface (Grimm et al., 2008). The LST has risen due
53 to global climate change impacts on the meteorological parameters, affecting water resources,
54 land cover, land use, and vegetated areas. It is claimed that different environmental problems
55 are responsible for such changes (Chan & Yao, 2008; Choudhury et al., 2019). Using satellite
56 imagery, shortwave infrared (SWIR), visible and near-infrared (VNIR), and thermal infrared
57 (TIR) bands allow us to monitor ecological changes (Chan & Yao, 2008; Mondal et al., 2011;
58 Das et al., 2013; Alexander, 2020). Land surface temperature represents the Earth's surface
59 temperature and is one of the critical parameters that influence surface-energy balance, heat
60 fluxes, energy exchanges, and regional climates (Wan & Dozier, 1996; Dash et al., 2002;
61 Karnieli et al., 2010; Meng et al., 2017; Fang et al., 2018; Zhou et al., 2018; Martin et al.,
62 2019).

63 The effects of LST on various subjects have been investigated by several researchers,
64 including surface heat island (SHI), geological and geothermal studies (Coolbaugh et al., 2007;

65 Eskandari et al., 2015; Mia et al., 2018; Sekertekin & Arslan, 2019), evapotranspiration
66 (Elnashar et al., 2021), forest fire monitoring (Maffei et al., 2018), and urban climate studies
67 (Sekertekin et al., 2016; Naughton & McDonald, 2019; Simwanda et al., 2019). LST has also
68 been acknowledged as one of the essential criteria for the International Geosphere and
69 Biosphere Program (IGBP) (Townshend et al., 1994; Li et al., 2013). Meteorological stations
70 estimate air Temperatures from radiance measurements. However, as it is a point-based
71 measurement, it does not necessarily allow extensive monitoring on a larger scale (Hale et al.,
72 2011). On the other hand, remotely sensed TIR data enables large-scale, even global, temporal,
73 and spatial LST observation (Gao et al., 2013). It is crucial for meteorologists, agronomists,
74 and hydrologists to know the different terms that interact with the surface energy balance. The
75 LST, however, is one of the key parameters that play a significant role in the interaction
76 processes of the atmosphere, hydrosphere, and biosphere (Douglas & Aochi, 2008). The LST
77 is also used throughout many fields, such as the hydrological cycle, evapotranspiration,
78 vegetation, climate change, etc. (Douglas & Aochi, 2008). It is the critical factor influenced by
79 the properties of the Earth's surface, such as landscape, land cover, vegetation, land usage, and
80 permeability of the soil surface (Khandelwal et al., 2018). Many studies have been conducted
81 to detect LST variations because of land use, vegetation, and land cover differences. Most
82 research studies (Chan & Yao, 2008; Choudhury et al., 2019) have reported a negative
83 correlation between natural vegetation and LST, referring to the reduction of LST in crop
84 cover. The LST can be quantified using the traditional method and remote sensing (RS)
85 technique. The LST is determined through meteorological stations as temperature using
86 traditional methods, whereas RS allows assessing it through the energy balance's surface model
87 (Daou et al., 2012). It is suggested that LST is a vital microclimate variable and that radiation
88 is transmitted within the atmosphere. Remote sensing and geographical information system
89 tools, alongside ground-truthing data collected, are suggested for evaluating the spatiotemporal
90 changes in the LST.

91 Various vegetation indexes are known to examine differences in the vegetative zone.
92 Among the most accurate, most extensive, and most widely used indexes is NDVI (Sruthi &
93 Aslam, 2015). It is possible to calculate the changes in vegetation in a specific area using
94 NDVI. Several researchers using GIS and Remote Sensing techniques are currently exploring
95 the inverse relationship between LST and NDVI (Chen et al., 2010). Researchers identified
96 that satellite imagery thermal bands can calculate the LST (Dagliyar et al., 2015). Using the
97 OLI/TIRS data acquired, Dagliyar et al., 2015 identified the LST in Erzurum, Turkey.

98 Rajendran et al., 2015 focused on LST using the Landsat 8 thermal bands; OLI/TIRS images
99 show that LST is a feature of vegetative cover and soil water content in India. Using satellite
100 data, Crawford et al., 2006 observed the relationships between NDVI and LST in China's
101 Shanghai region. It stated that GIS and RS techniques helped determine the climate change
102 impacts on the ecosystem. Rapid changes in land use and land cover patterns have resulted in
103 major LST shifts.

104 The normalized difference water index (NDWI) is the most common index for surface
105 water abstraction that is often implemented in land use and LST-related analyses (Yuan et al.,
106 2017). In addition, the nature of the LST-NDWI relationship is not linear and marginal in an
107 urban climate. Temperature, precipitation, plants, barren land, environmental effluence, warm
108 or cold soil, an organic layer, various human-made products, and other influences affect it
109 (McFeeters, 1996; Ghobadi et al., 2015). NDWI and LST's relationship has been established
110 using TIR remote sensing in various current research studies (Chen et al., 2006; Choudhury et
111 al., 2019; Govil et al., 2019; Solangi et al., 2019). But, in subtropical Malaysia, the seasonal
112 study of the LST-NDWI relationship is unusual. Owing to the seasonal variations in air
113 temperature, moisture content, precipitation, evaporation, etc., NDWI and LST's nature has
114 changed. Consequently, in Malaysia's subtropical climate, a constant evaluation of the LST-
115 NDWI relation is crucial (Hussain et al., 2018).

116 The study focused on evaluating the impact of variations in the LST on vegetation and
117 water bodies and assessing the correlations between them for the Bakun-Murum catchment
118 region in Sarawak, Malaysia. The Bakun-Murum region was selected because it has been
119 severely affected by climatic conditions. The following specific objectives achieved the
120 primary goal:

- 121 • Firstly, the data was collected from the respective repositories and departments.
- 122 • Secondly, the satellite data were analyzed using the Google Earth Engine code editor
123 to determine the trends in the LST, NDVI, and NDWI.
- 124 • Finally, XLSTAT and R statistical tools were used for the Pearson correlation analysis
125 of annual mean LST with mean NDVI, annual mean NDWI, annual mean temperature,
126 and annual mean rainfall.

127 Due to the limitations and unavailability of cloud-free Landsat satellite imageries for the
128 selected years, we conducted this study using GEE as the available Landsat data specifically
129 for the BM region is of no use because of the cloud covers. The results of this research would

130 be helpful for future urban and country planners, policymakers, environmentalists, and farmers
131 in the region to take remedial steps to reduce the impacts of climate change in the study area.

132 **2. Materials and Methods**

133 **2.1 The Study Area**

134 Figure 1 shows the location map of the study area developed with the help of the shapefiles
135 and digital elevation model (DEM) using ArcGIS 10.8. The required shapefiles for the study
136 area map were created using Google Earth Pro, and the administrative boundaries shapefile of
137 Malaysia was downloaded from DIVA-GIS <http://www.diva-gis.org/download>.

138 Malaysia's Sarawak state is covered by thick tropical rainforests and is rich in water
139 resources (Hussain et al., 2018). It also has a perfect hydropower development landscape
140 (Hussain et al., 2018). Sarawak is located at 1.5533° N, and 110.3592° E. The Southwestern
141 monsoon (May to September) and the North-easterly monsoon (October to April) are the two
142 monsoon seasons in Sarawak (Hussain et al., 2018). In this region, the Southwestern monsoon
143 has less rainfall than the Northeastern monsoon (Hussain et al., 2018). The minimum rainfall
144 periods are June to August, and the months from December to February are the rainiest each
145 year (Hussain et al., 2018). Throughout Malaysia's Sarawak state, the Rajang River Basin
146 (RRB) is the primary river in agricultural and economic development (Hussain et al., 2018).
147 RRB is located on Borneo Island (2.1245° N, 111.2181° E), the largest island in Asia and the
148 third largest island worldwide. It drains fifty thousand square kilometres of Sarawak's tropical
149 rainforest, accounting for 40% of the state's total area (Oad et al., 2020). In the RRB area,
150 annual precipitation varying from 3000 to 5200 millimetres is plentiful, and the river is very
151 well recognized for the hazards of high soil erosion (Hussain et al., 2018). In the upper portion
152 of the RRB, the catchment elevations range from sea level to about 2016 meters on the west
153 coast. This river is the largest in Malaysia, with an overall length of 563 kilometres. RRB
154 originated from the mountains of Iran (Nakisa et al., 2014; Hussain et al., 2018).

155 The geographical features of the study area are shown in Figure 2, including slope
156 (Figure 2a), aspect ratio (Figure 2b), and hillshade (Figure 2c). They were evaluated from the
157 Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global digital elevation model
158 (DEM) of a 30 m by 30 m resolution. The DEM was downloaded from the USGS Earth
159 Explorer <https://earthexplorer.usgs.gov/>. A slope map shows a region's topography and an
160 overview of topographical characteristics that have affected and may continue to impact land
161 creation (Oad et al., 2020). The slope of the study area ranged from 7.48% to 63.59% in figure

162 2(a). The aspect and degree of slope for the study area are shown simultaneously by an aspect-
 163 ratio map in figure 2(b). Hues (e.g., orange, yellow, red, etc.) symbolize aspect groups, and the
 164 degree of slope classes are mapped with saturation such that the steeper ones are lighter.
 165 Hillshading is a method for making relief maps; shading (points of grey) displays the
 166 topographical form of hills and mountains, suggesting relative slopes and mountain edges, not
 167 total height. A topographical map showing the contour lines of the shape of the ground's
 168 surface, the comparative space of the lines representing the surface's relative angle.

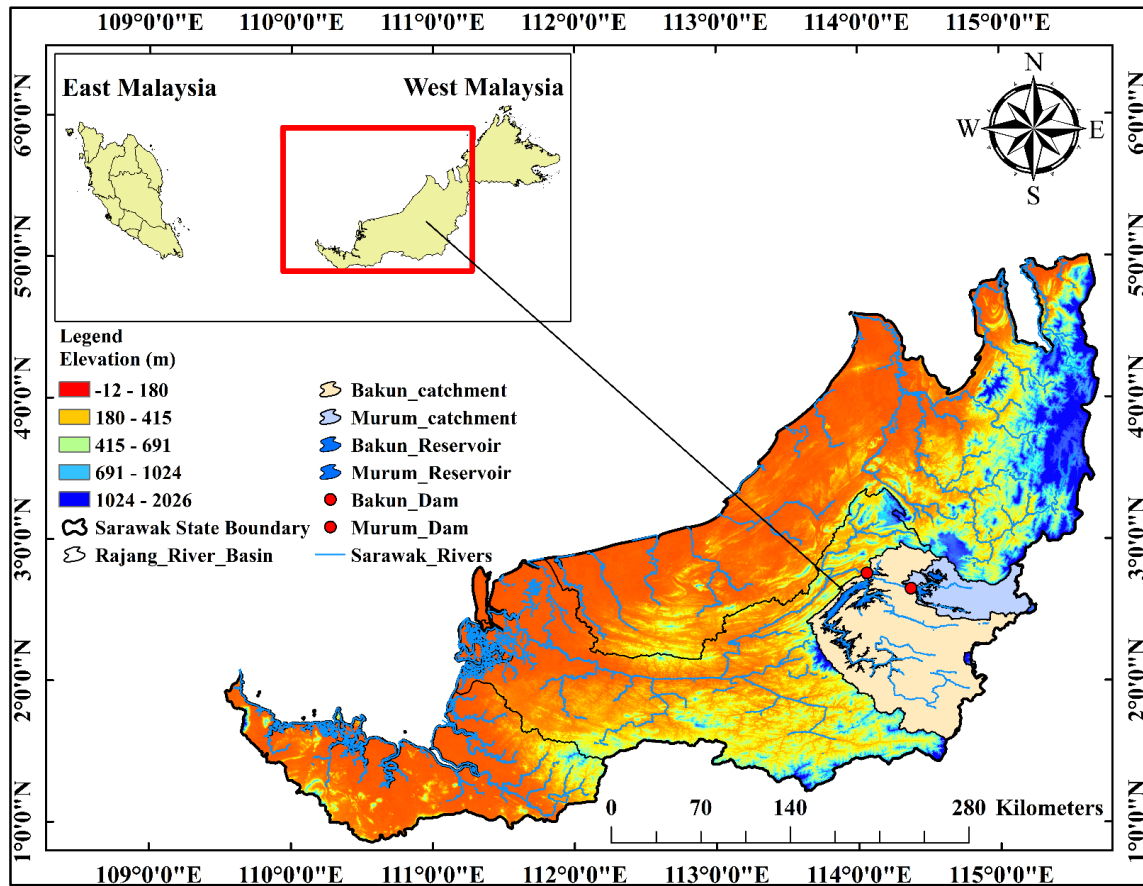
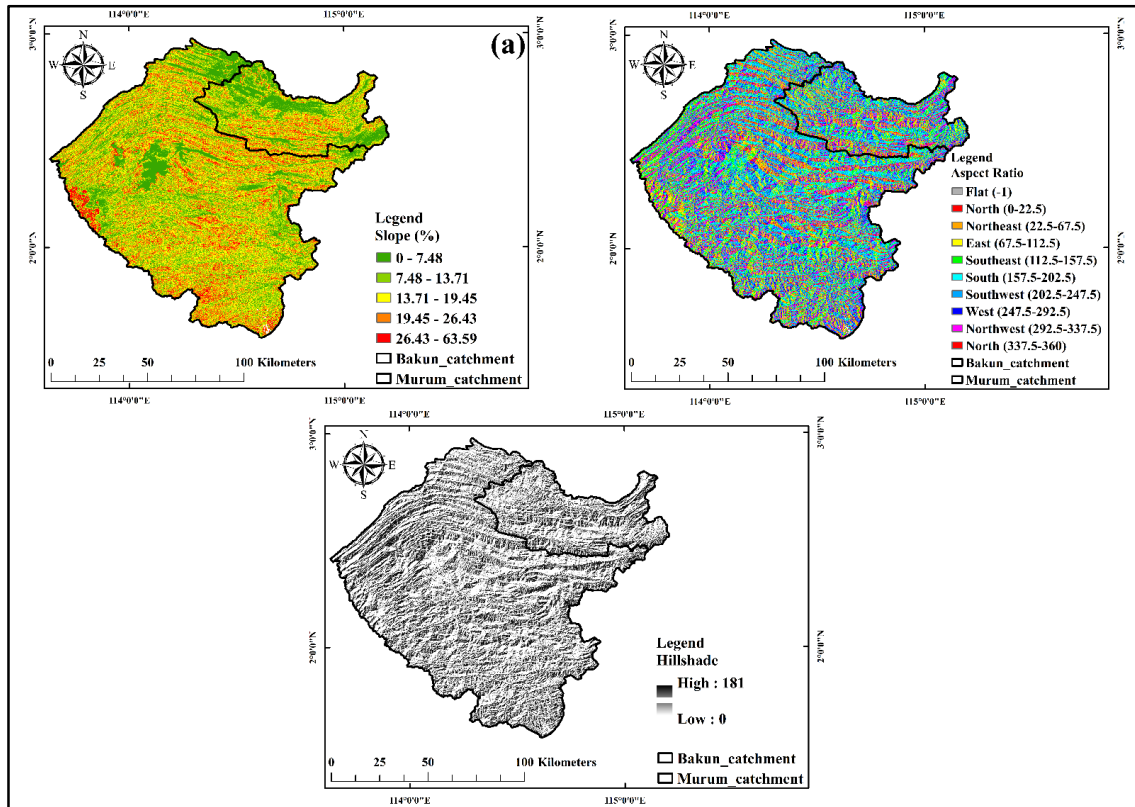


Figure. 1. Map of the study area.



171

172 Figure. 2. Geological features of the study area (a) slope, (b) aspect ratio, and (c) hillshade.

173 **2.2 Description of Datasets**

174 Google Earth Engine code editor (<https://code.earthengine.google.com/>) was used to acquire
 175 the level 2 surface reflectance of Landsat 5 and 8 images from 1990 to 2020. Only cloud-free
 176 images (less than 10% clouds) were processed. As discussed in the later sections, the respective
 177 bands from each image were later used in the estimation of NDVI and NDWI. The description
 178 of the datasets may be obtained from [https://developers.google.com/earth-](https://developers.google.com/earth-engine/datasets/catalog/landsat)
 179 [engine/datasets/catalog/landsat](https://developers.google.com/earth-engine/datasets/catalog/landsat).

180 **2.3 Land Surface Temperature**

181 LST was estimated by using an open-source code developed and described by Ermida et al.,
 182 (2020) to estimate the LST from the Landsat series and ASTER emissivity using the GEE code
 183 editor. The script to calculate the LST using GEE is attached at
 184 https://code.earthengine.google.com/cbc91b8ed4af97453106b5bacc003970?accept_repo=use
 185 [rs%2Fvipinkoad%2FRSPaper](https://code.earthengine.google.com/cbc91b8ed4af97453106b5bacc003970?accept_repo=use).

186

187 **2.4 Determination of Vegetation Cover**

188 The normalized difference vegetation index (NDVI) was evaluated using the GEE code editor
189 to determine the temporal changes in the vegetative cover. This index was determined using
190 the NIR (near-infrared) and red (R) bands, as described in Equation 1 (Choudhury et al., 2019).
191 Numerous scholars worldwide have used this index as an indicator of green vegetation. For
192 Landsat 5, bands 3 and 4 were used, but for Landsat 8/OLI, bands 4 and 5 were used to calculate
193 NDVI. The index's values vary from -1 to +1. A value of -1 represents a non-vegetated area,
194 while +1 indicates a vegetative area (Yuan et al., 2017). The script to estimate the NDVI using
195 GEE is attached at
196 https://code.earthengine.google.com/e2c4d973d24e8c4a672631647252dfc3?accept_repo=user%2Fvipinkoad%2FRSPaper.
197

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \quad (1)$$

198 **2.5 Determination of Water Index**

199 The normalized difference water index (NDWI) was used as a stable normalized difference
200 spectral index in the current research analysis to test the correlation of water bodies with LST.
201 The NDWI defined in Equation 2 (McFeeters, 1996; McFeeters, 2013) was calculated using
202 green (G) and near-infrared (NIR) bands. For the TM data, band two was used as a green band,
203 and band four was used as the NIR band, comparatively. For OLI/TIRS data, bands 3 and 5
204 were used as green and NIR, respectively. The NDWI value ranges from -1 to +1 (Yuan et al.,
205 2017). A negative NDWI value implies that there are no water bodies in the region and that the
206 land is dry, while a positive NDWI value indicates water surfaces and plants. The google earth
207 engine script to estimate the NDWI is attached at
208 https://code.earthengine.google.com/888ef20dfacb8076d39e0f397064d132?accept_repo=user%2Fvipinkoad%2FRSPaper.
209

$$\text{NDWI} = \frac{\text{G} - \text{NIR}}{\text{G} + \text{NIR}} \quad (2)$$

210 **2.6 Climate Data**

211 The meteorological data for Malaysia's Sarawak state for the years 1990 to 2020 was obtained
212 from the Malaysian Meteorological Department. The data are the annual mean temperature in
213 degrees Celsius (°C) and the annual mean rainfall in millimetres (mm). The annual mean
214 temperature and annual mean rainfall series data were analyzed for trend interpretation and

215 shifts in the trend slope. Trend identification was achieved using the Mann-Kendall non-
216 parametric test and Sen's estimator's trend slope. It's a distribution-free test that doesn't use
217 normally distributed data (Ahmad et al., 2018; Arfan et al., 2019; Tayyab et al., 2019; Waseem
218 et al., 2020). Sen's estimator lists the N values' time series from most minor to largest and
219 computes them. Sen's slope estimator is the median of these N values (Oad et al., 2020).

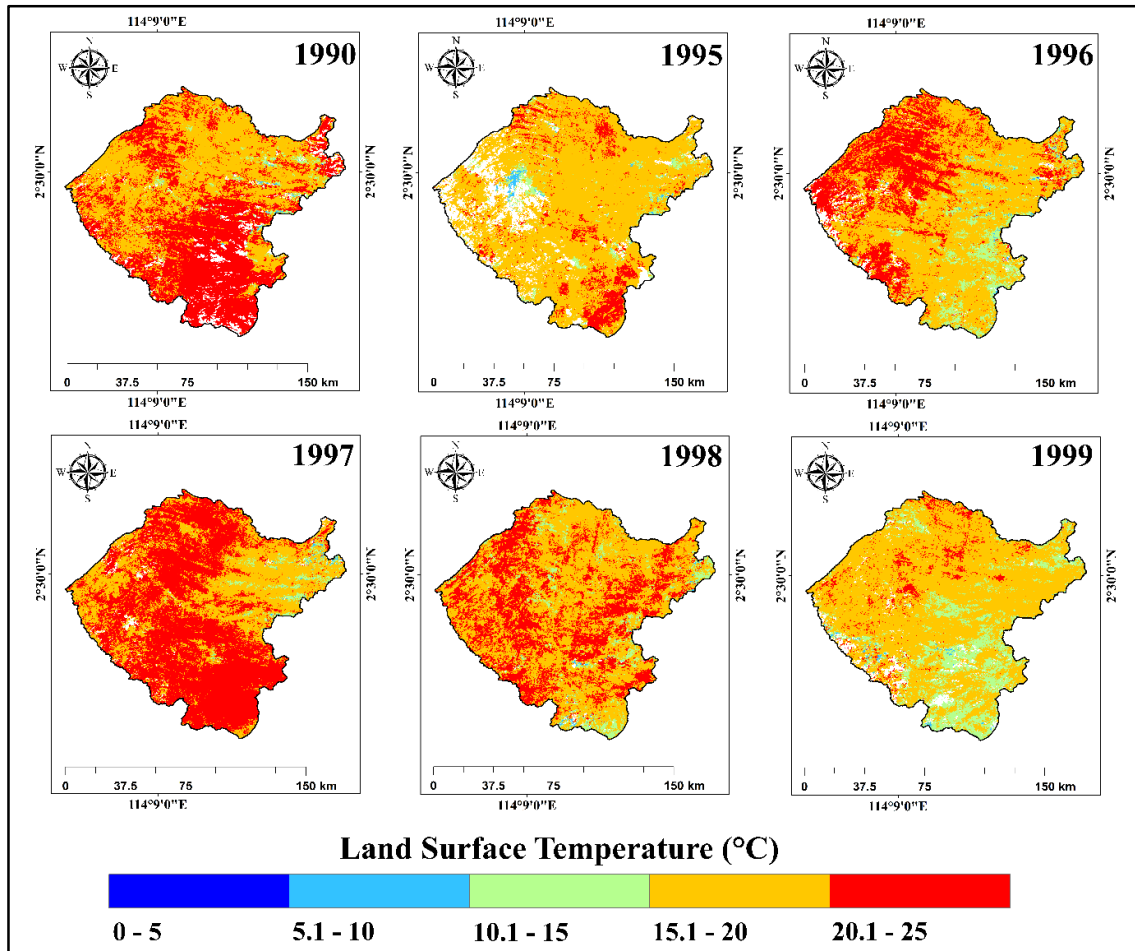
220 **2.7 Statistical Analyses**

221 As Choudhury et al., 2019 described, the LST was integrated with NDVI and NDWI to see the
222 influence of the LST on the vegetative cover and water resources of the Bakun-Murum
223 catchment area of the Rajang River basin. Pearson correlation analysis was used to illustrate
224 how the evolving LST has influenced the region's vegetative cover and water resources.

225 **3. Results and Discussion**

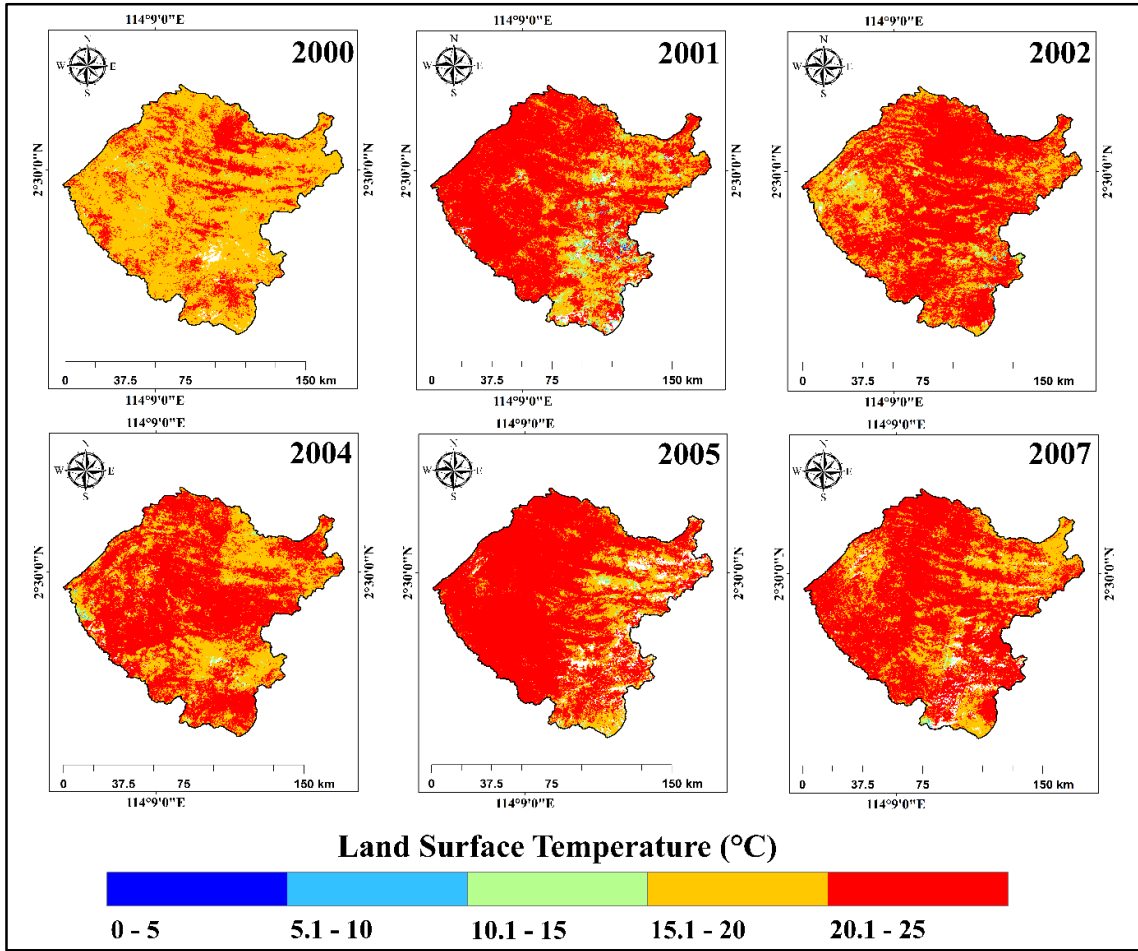
226 **3.1 Dynamics of land surface temperature (LST)**

227 Figures 3a, 3b, and 3c depict the temporal changes in the annual mean land surface temperature
228 of the Bakun-Murum catchment area from 1990 to 2020. It was observed that the regions of
229 water and trees have lower LST than towns and barren lands. The LST and its causative factors
230 have realistic and empirical consequences for advanced crop growth management systems in
231 an arid and semi-arid climate. Figure 3a shows a decrease in the LST from 19.87°C in 1990 to
232 17.09°C in 1999. A slight increase was found from 19.87°C in 1990 to 19.96°C in 1997.
233 Moreover, Figure 3b showed a rise from 19.42°C in 2000 to 21.02°C in 2005, and a slight
234 decrease was observed at 20.43°C in 2007. Furthermore, from Figure 3c, an increasing LST
235 trend can be seen from 19.95°C in 2013 to 22.10°C in 2014. Again, a decreasing trend from
236 2014 to 2017 in Figure 3d was observed. From 2017 to 2019, an increasing LST was observed;
237 from 2019 to 2020, it slightly decreased. Finally, an overall increase of 1.06°C in the mean
238 LST has been found from 1990 to 2020 in Figure 3d.



239

240 Figure. 3 (a). Temporal variations of the study area's annual mean land surface temperature
 241 (1990, 1995, 1996, 1997, 1998, and 1999).

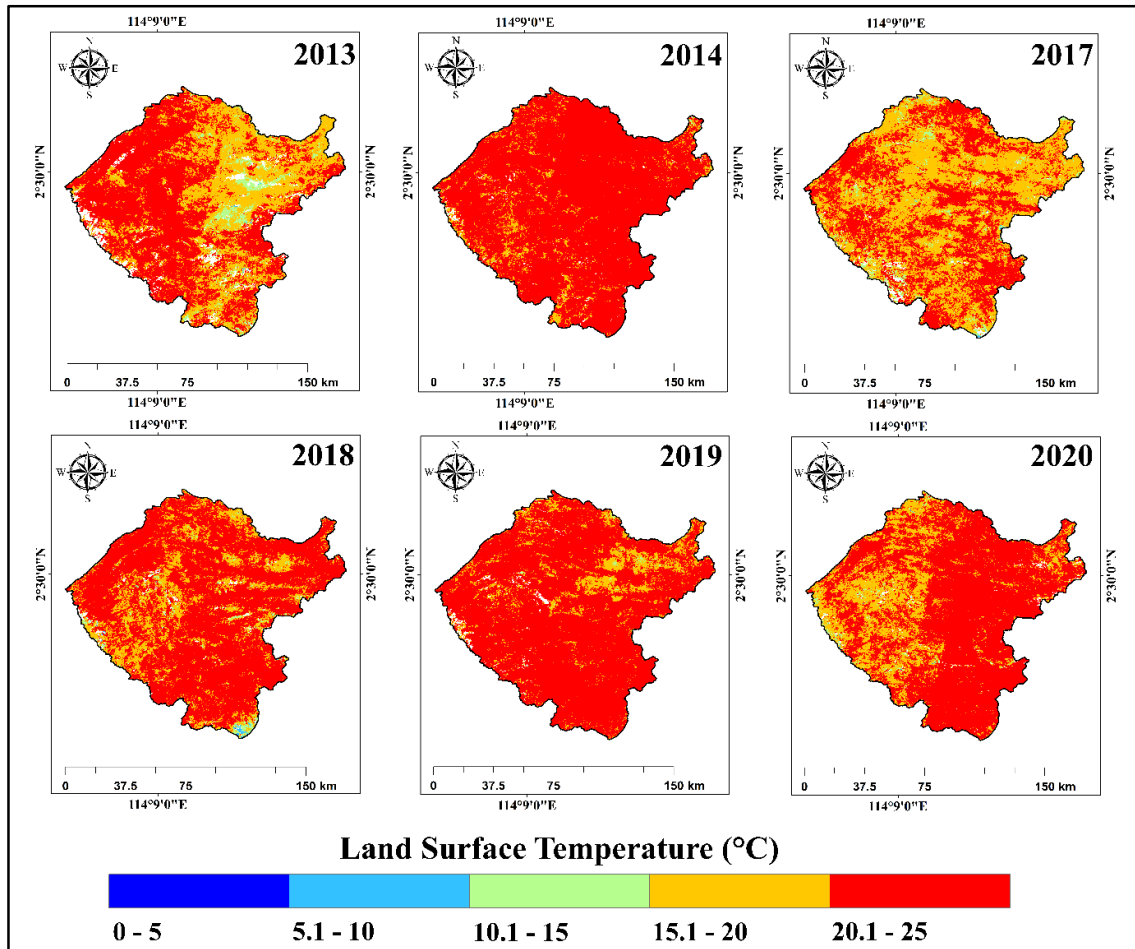


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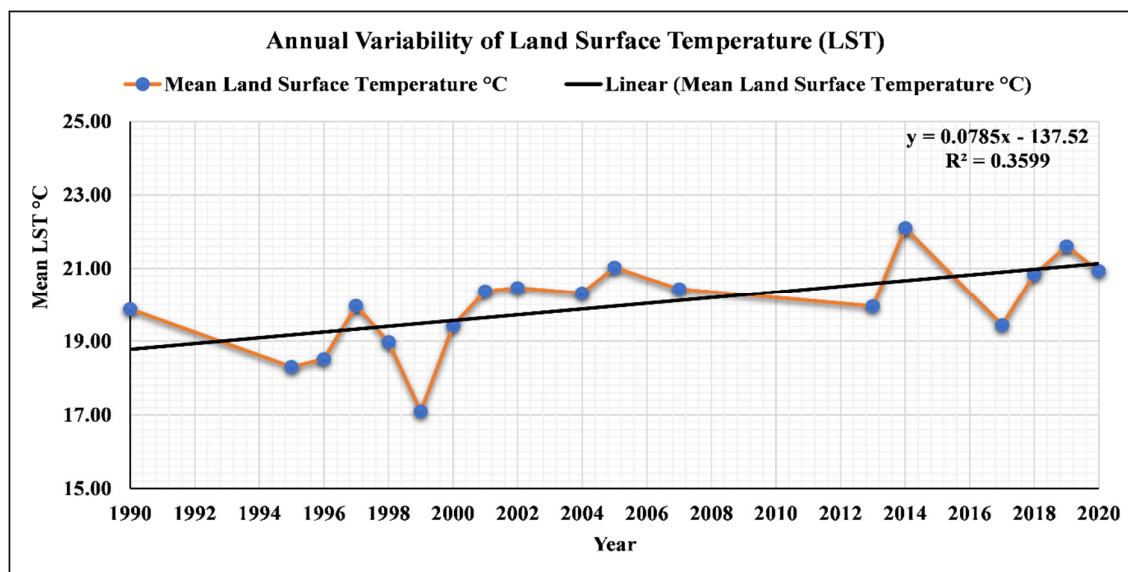
Figure. 3 (b). Temporal variations of the study area's annual mean land surface temperature (2000, 2001, 2002, 2004, 2005, and 2007).



245

246 Figure. 3 (c). Temporal variations of the study area's annual mean land surface temperature
 247 (2013, 2014, 2017, 2018, 2019, and 2020).

248 For several factors, increasing LST patterns have a more significant impact on crop
 249 growth. Figure 3d indicates time-based changes in the LST of the study area under several
 250 ranges of temperature. Shifts in the LST are more prominent in the Rajang River Basin's
 251 Bakun-Murum catchment area. It is because of climate change and changes in the region's
 252 hydrological characteristics due to the developmental growth of the late 1990s. Several factors,
 253 such as increased housing areas and overall global climate change, can lead to a temporal
 254 increase in LST.



255

256

Figure. 3 (d). Annual variability of land surface temperature from 1990 to 2020.

257

3.2 Temporal variations in the vegetation index (NDVI)

258

Figures 4a, 4b, and 4c indicate chronological changes in the vegetative cover of the Bakun-

259

Murum catchment zone. The annual variability of the annual mean normalized difference

260

vegetation index is shown in Figure 4d. It can be observed from Figure 4a that the NDVI

261

decreased from 0.42 in 1990 to 0.36 in 1995. From 1995 to 1996, an increase of 0.04 in NDVI

262

was found. A decreasing trend of 0.08 NDVI was observed from 1998 to 1999. Figure 4b

263

depicts a continuous increasing trend in the NDVI from 0.32 in 2000 to 0.38 in 2002. Moreover,

264

a decrease of 0.11 NDVI was found from 2002 to 2005. Then from 2005 to 2007, a considerable

265

increase was observed from 0.27 to 0.45. Furthermore, from 2007 to 2013, an increasing trend

266

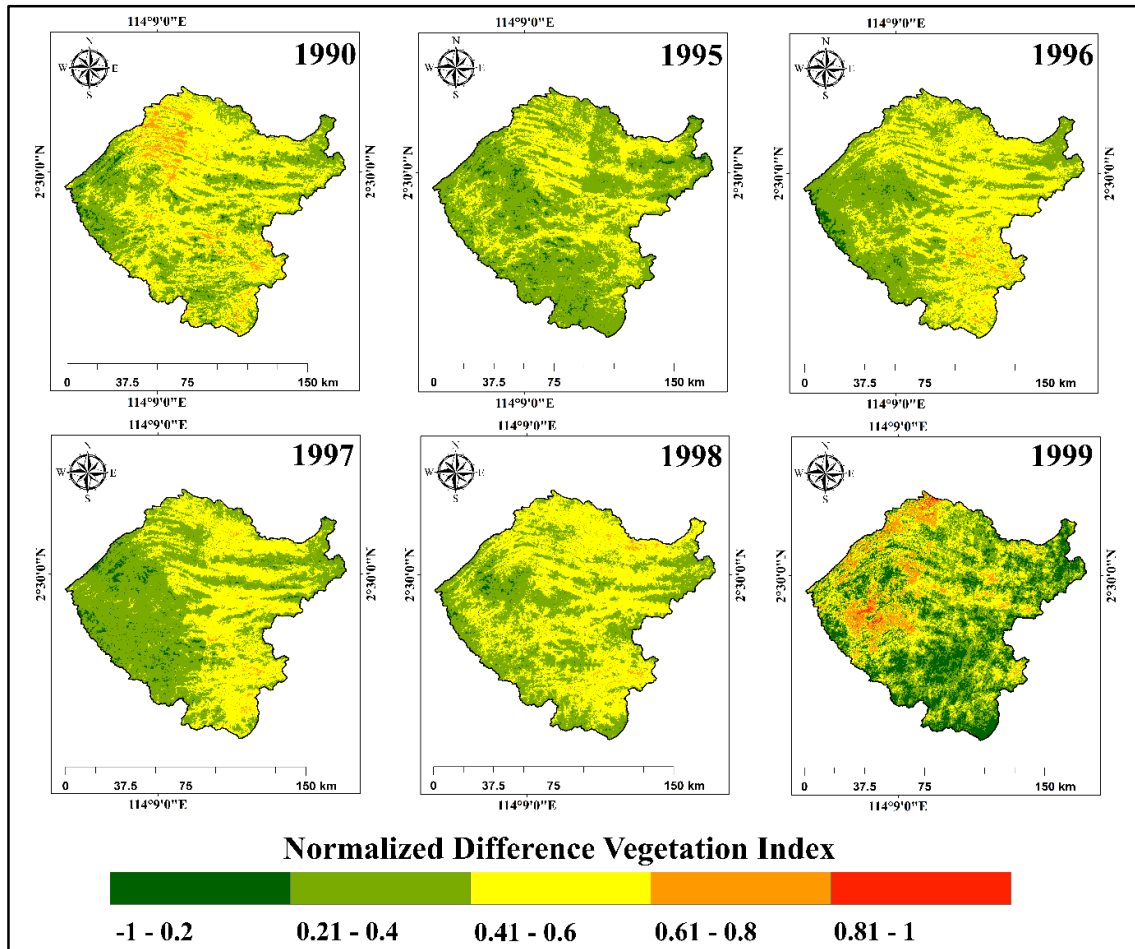
continued, while a slight decrease of 0.03 NDVI was found from 2013 to 2014; again, a rising

267

trend continued from 2014 to 2020. Finally, an overall increase of 0.05 NDVI has been found

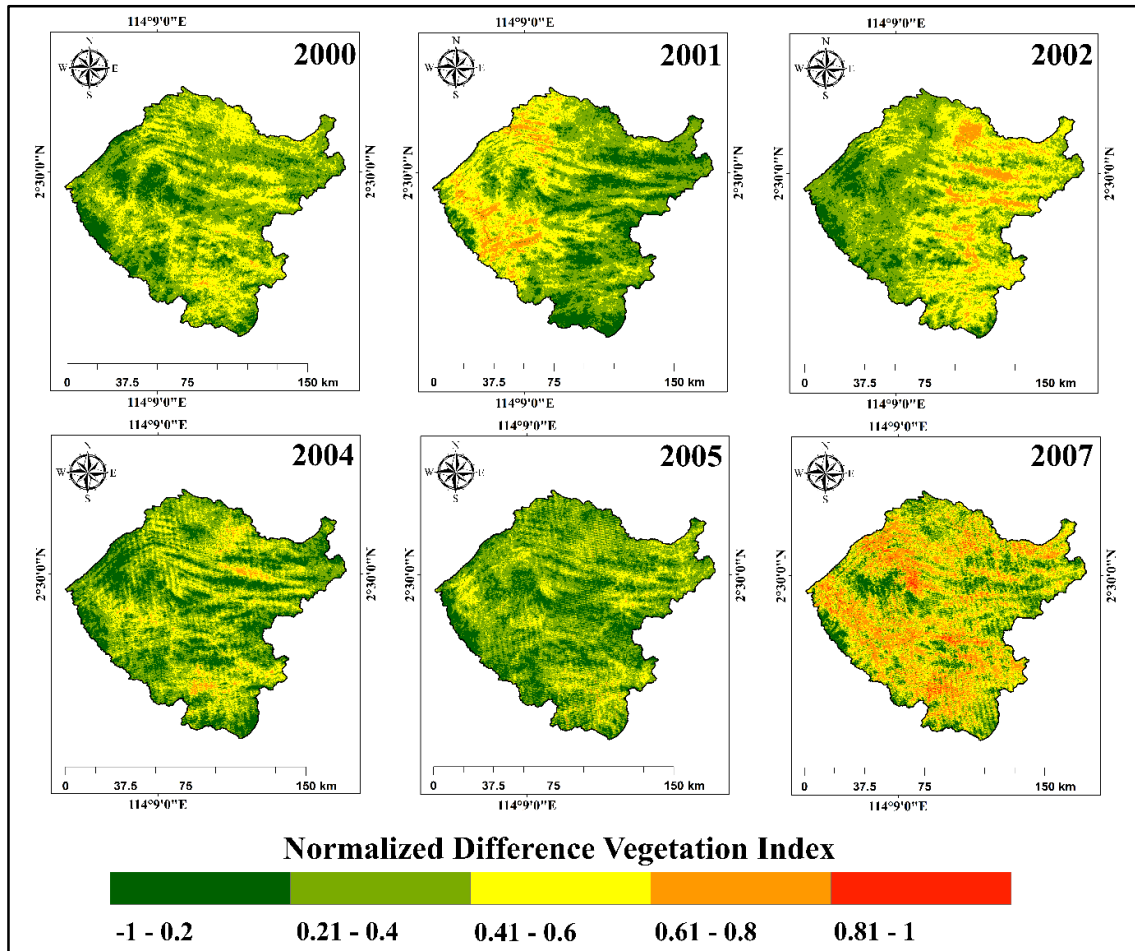
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from 1990 to 2020.



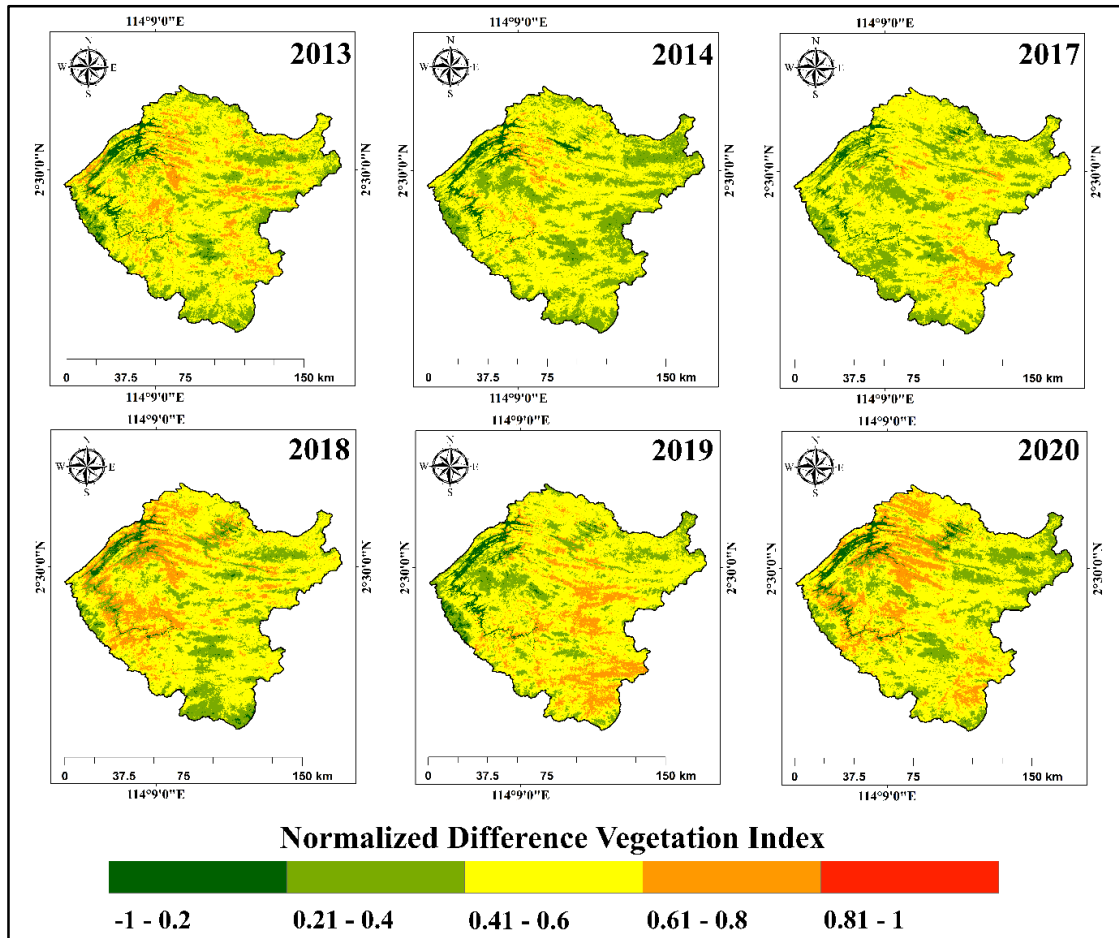
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270 Figure. 4 (a). Temporal variations of the study area's annual mean normalized difference
 271 vegetation index (1990, 1995, 1996, 1997, 1998, and 1999).



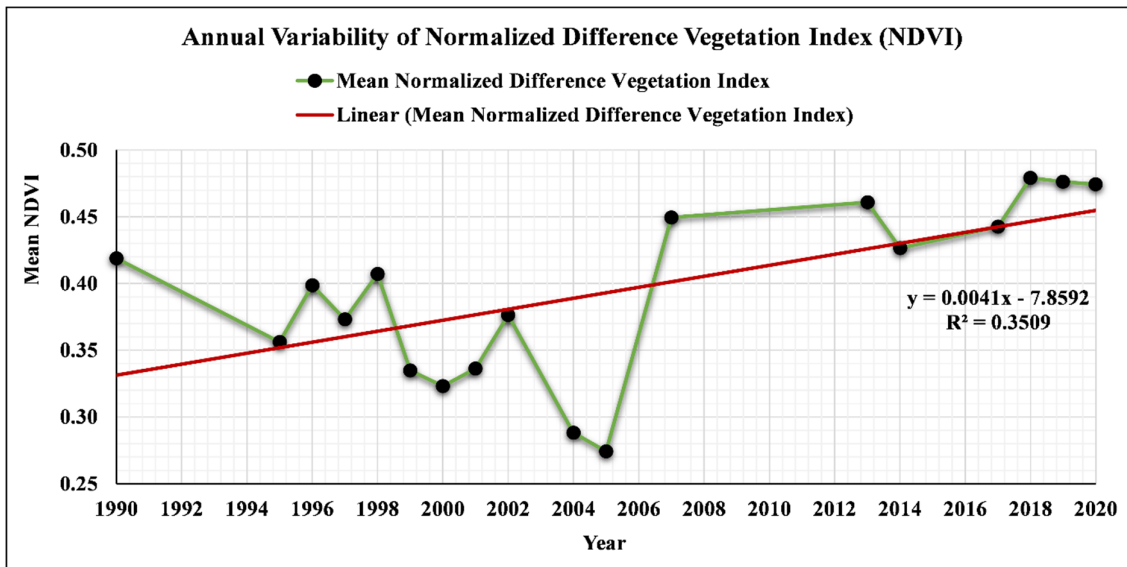
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273 Figure. 4 (b). Temporal variations of the study area's annual mean normalized difference
 274 vegetation index (2000, 2001, 2002, 2004, 2005, and 2007).



275

276 Figure 4. (c). Temporal variations of the study area's annual mean normalized difference
 277 vegetation index (2013, 2014, 2017, 2018, 2019, and 2020).



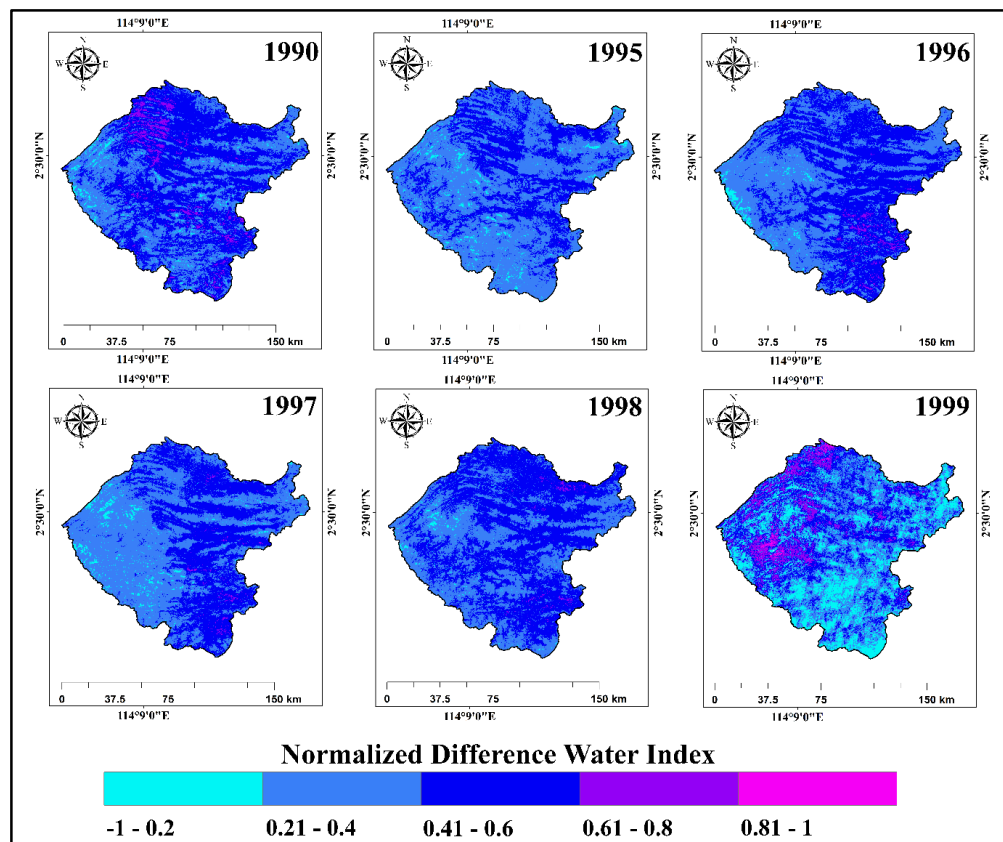
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279 Figure 4 (d). Annual variability of normalized difference vegetation index from 1990 to
 280 2020.

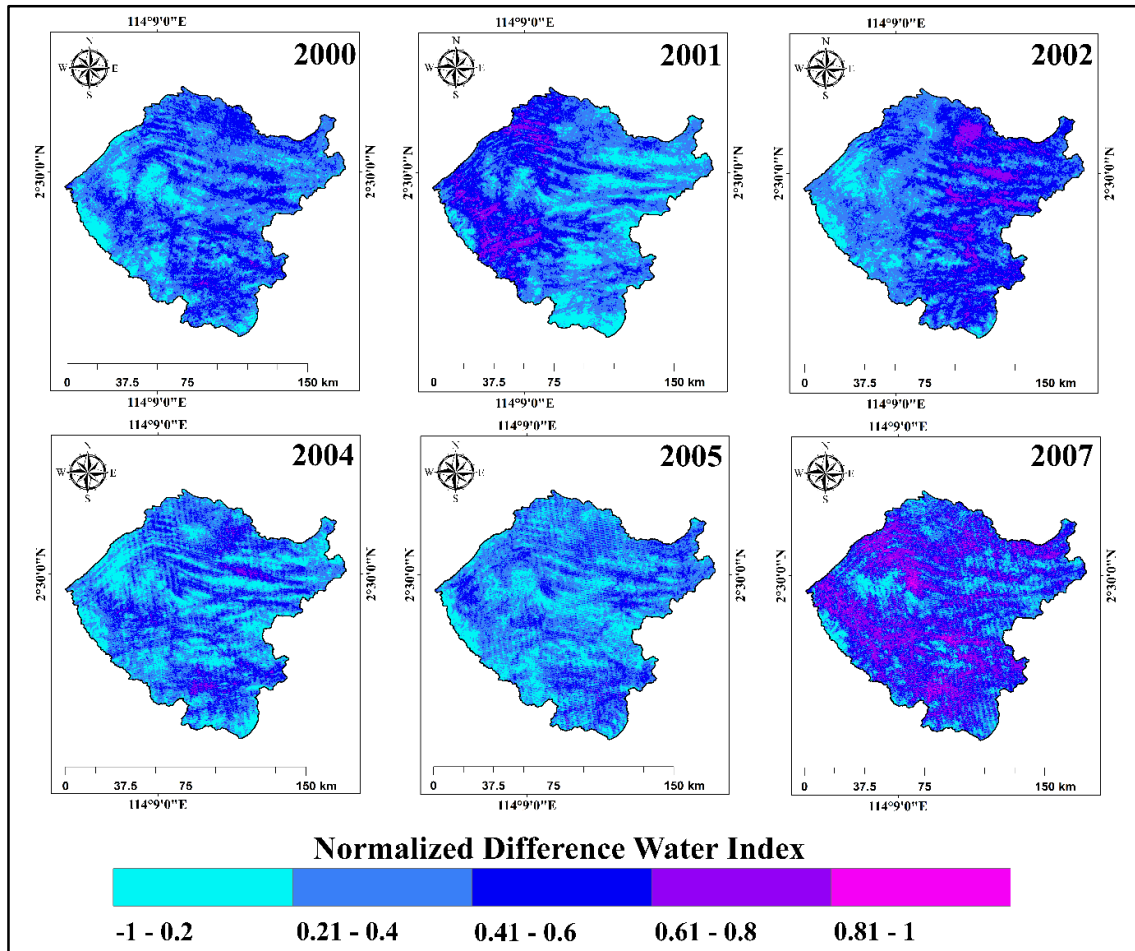
281 Several factors, such as the increase in the developmental areas, increasing LST, and
282 overall global climate change, may lead to a temporal reduction in the NDVI.

283 3.3 Temporal variations in the water index (NDWI)

284 Figures 5a, 5b, and 5c indicate sequential changes in the water bodies of the Bakun-Murum
285 catchment zone. The annual variability of the annual mean normalized difference water index
286 is shown in Figure 5d. It can be observed from Figure 5a that the NDWI decreased from 0.39
287 in 1990 to 0.34 in 1995. From 1995 to 1996, an increase of 0.04 in NDWI was found. A
288 decreasing trend of 0.05 NDWI was observed from 1998 to 1999. Figure 5b depicts a
289 continuous increasing trend in the NDWI from 0.32 in 2000 to 0.38 in 2002. Moreover, a
290 decrease of 0.11 NDWI was found from 2002 to 2005. Then from 2005 to 2007, a considerable
291 increase was observed in NDWI from 0.27 to 0.45. Furthermore, from 2007 to 2013, an
292 increasing trend continued, while a slight decrease of 0.03 NDWI was found from 2013 to
293 2014; again, a rising trend continued from 2014 to 2020. Finally, an overall increase of 0.08
294 NDWI has been found from 1990 to 2020.

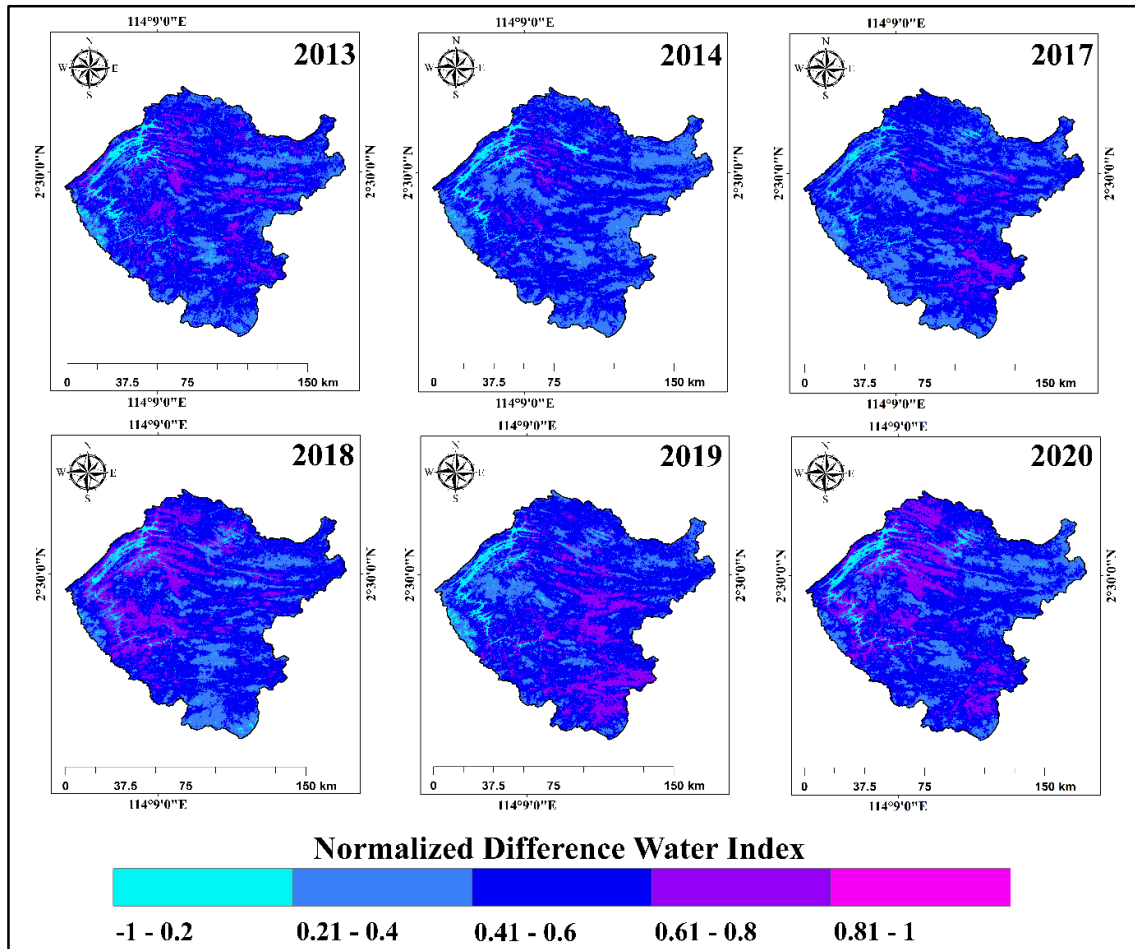


296 Figure. 5 (a). Temporal variations of the study area's annual mean normalized difference
297 water index (1990, 1995, 1996, 1997, 1998, and 1999).



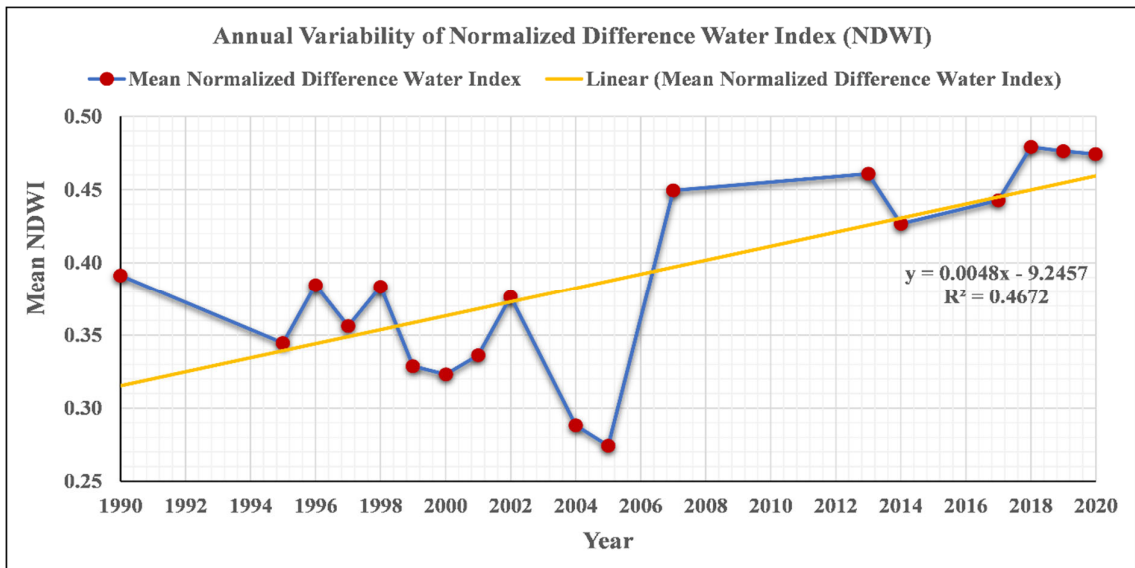
298

299 Figure. 5 (b). Temporal variations of the study area's annual mean normalized difference
 300 water index (2000, 2001, 2002, 2004, 2005, and 2007).



301

302 Figure. 5 (c). Temporal variations of the study area's annual mean normalized difference
 303 water index (2013, 2014, 2017, 2018, 2019, and 2020).



304

305 Figure. 5 (d). Annual variability of normalized difference water index from 1990 to 2020.

306 **3.4 Correlation among annual mean NDVI, NDWI, LST, Temperature, and Rainfall**

307 Pearson Correlation among annual mean NDVI, NDWI, LST, temperature, and rainfall
 308 was assessed using XLSTAT statistical tool. Table 1 shows the Pearson correlation matrix of
 309 the abovementioned variables. Table 1 shows that the NDVI and NDWI significantly correlate
 310 with a Pearson correlation matrix (r) of 0.99. A negative relationship between LST and NDVI
 311 is found with (r) of 0.30. A weak relationship with (r) of 0.36 between LST and NDWI is also
 312 observed. The correlation between annual mean temperature and land surface temperature is
 313 found at (r) of 0.39. A negative relation (r) of -0.09 between annual mean rainfall and land
 314 surface temperature is observed. Furthermore, a correlation is observed between the annual
 315 mean temperature and NDWI (r) of 0.50 and the annual mean temperature and NDVI (r) of
 316 0.46. In contrast, a negative relation between annual mean rainfall and other variables is found.

317 Table 2 represents the statistical correlation of annual mean LST with annual mean
 318 NDVI with a coefficient of determination of (R^2) of 0.09 is very weak and considered negative.
 319 Thus, as stated by (Yue et al.,2007; Huang & Ye, 2015; Dong et al., 2018), the NDVI of the
 320 region decreases with an increase in LST. Annual mean LST and annual mean NDWI also
 321 show a weak relation (R^2) of 0.13. Furthermore, annual mean LST and annual mean
 322 temperature show a modest relationship with (R^2) of 0.15.

323 In Shanghai, China, Yue et al.,2007 also observed an inverse relationship between the
 324 land surface temperature and the NDVI. In the Asansol Durgapur area of West Bengal,
 325 Choudhury et al., 2019 recorded a decreasing greenery pattern in response to rising LST. The
 326 correlation of LST with NDVI in the Karst area was examined by Dong et al., 2018; they found
 327 an inverse relationship between these parameters. Furthermore, Sun et al., 2012 saw a
 328 substantial decrease in Beijing’s LST in the regions surrounding lakes, waterbodies, etc.

329 The relationship of LST with derived factors like NDVI and NDWI in the Asansol-
 330 Durgapur Development Area was discovered by Choudhury et al., 2019; they reported an
 331 inverse relationship between these LST and NDVI. Figure 6 displays the correlation matrix of
 332 the annual mean NDVI, NDWI, LST, temperature, and rainfall developed using R
 333 programming (RStudio).

334 **Table 1.** Pearson Correlation Matrix (r).

Variables	Mean Normalized Difference Vegetation Index	Mean Normalized Difference Water Index	Mean Land Surface Temperature °C	Annual Mean Temperature (°C)	Annual Mean Rainfall (mm)
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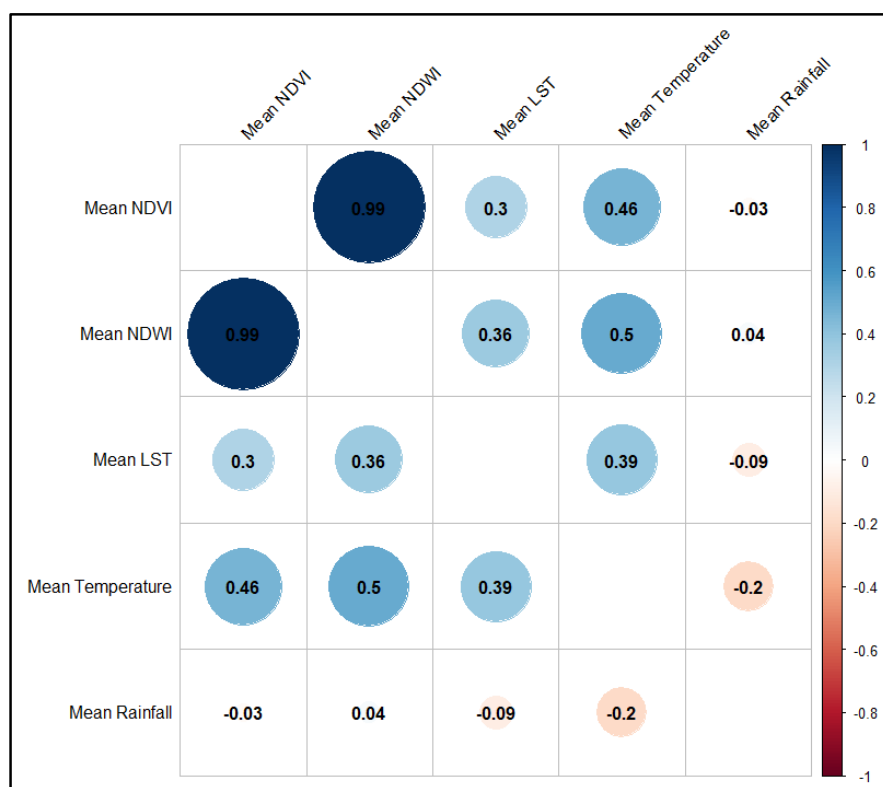
Mean Normalized Difference Vegetation Index	1	0.9902	0.3021	0.4642	-0.0283
Mean Normalized Difference Water Index	0.9902	1	0.3607	0.5042	0.0353
Mean Land Surface Temperature °C	0.3021	0.3607	1	0.3872	-0.0908
Annual Mean Temperature (°C)	0.4642	0.5042	0.3872	1	-0.1971
Annual Mean Rainfall (mm)	-0.0283	0.0353	-0.0908	-0.1971	1

335 * Values in bold are different from 0 with a significance level of alpha=0.05

336 **Table 2.** Statistical Correlation with Coefficients of Determination (R^2).

Variables	Mean Normalized Difference Vegetation Index	Mean Normalized Difference Water Index	Mean Land Surface Temperature °C	Annual Mean Temperature (°C)	Annual Mean Rainfall (mm)
Mean Normalized Difference Vegetation Index	1	0.9806	0.0913	0.2155	0.0008
Mean Normalized Difference Water Index	0.9806	1	0.1301	0.2542	0.0012
Mean Land Surface Temperature °C	0.0913	0.1301	1	0.1499	0.0082
Annual Mean Temperature (°C)	0.2155	0.2542	0.1499	1	0.0388
Annual Mean Rainfall (mm)	0.0008	0.0012	0.0082	0.0388	1

337 * Values in bold are different from 0 with a significance level of alpha=0.05



338

339 Figure. 6. Correlation matrix of the annual mean NDVI, NDWI, LST, temperature, and
340 rainfall.

341 **3.5 Trend analysis of rainfall and temperature**

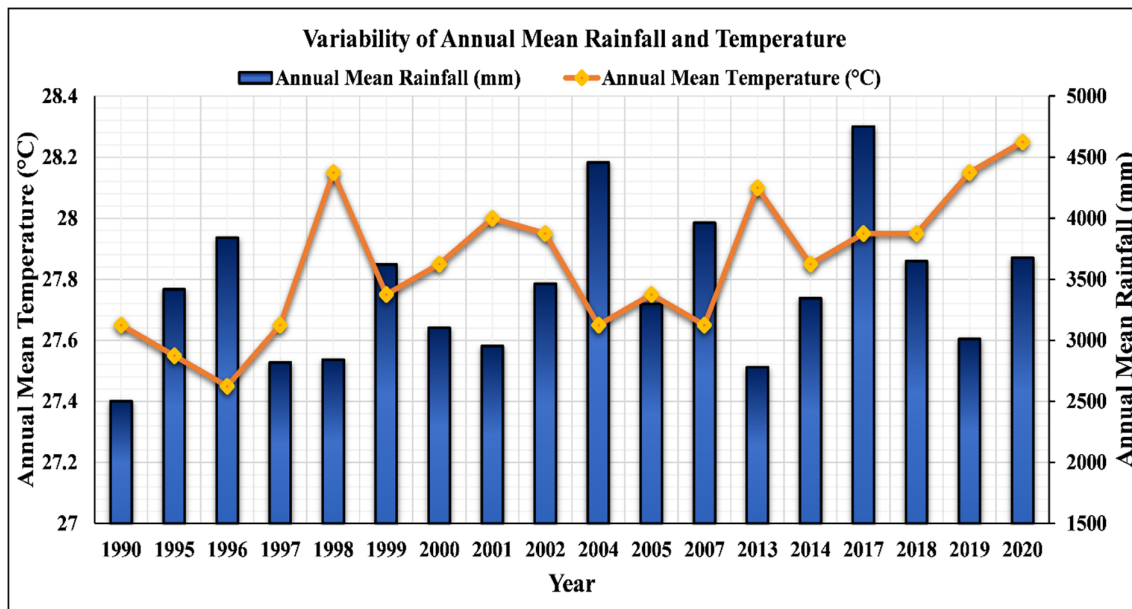
342 The annual mean temperature and rainfall data of the Bakun-Murum Catchment region from
 343 1990 to 2020 were statistically analyzed using Mann-Kendall trend tests every year to identify
 344 temporal changes. The abovementioned climatic parameters are graphically represented in
 345 Figure 7. Table 1 represents Mann-Kendall trend test statistics.

346 The Mann-Kendall trend test for the annual mean temperature series indicates a slightly
 347 increasing trend with Sen's slope of 0.03°C/year. From Table 1, it is found that there is a
 348 positive trend in the annual mean rainfall patterns, as Sen's slope indicates a yearly increase of
 349 50.58 mm/year. Furthermore, Kendall's tau for annual mean temperature is recorded as 0.50,
 350 and for annual mean rainfall, it is 0.27. The p-values (Two-tailed) for both abovementioned
 351 parameters are 0.01 and 0.13, respectively. An approximation has been used to compute the p-
 352 value.

353 **Table 3.** Trend analysis of rainfall and temperature.

Test Statistic	Annual Mean Temperature (°C)	Annual Mean Rainfall (mm)
Kendall's tau	0.50	0.27
p-value (Two-tailed)	0.01	0.13
Sen's slope	0.03	50.58

354



355

356 Figure. 7. The trend of annual mean temperature and annual mean rainfall over the selected
 357 years.

358 For the annual mean temperature, as the computed p-value is lower than the significance
359 level $\alpha=0.05$, one should reject the null hypothesis H_0 and accept the alternative
360 hypothesis, H_a . The risk of rejecting the null hypothesis H_0 while true is lower than 0.58%.
361 The continuity correction has been applied. Ties have been detected in the data, and the
362 appropriate corrections have been applied. Moreover, for the annual mean rainfall, as the
363 computed p-value is more significant than the significance level $\alpha=0.05$, one cannot reject
364 the null hypothesis H_0 . The risk of rejecting the null hypothesis H_0 while true is 12.97%. The
365 continuity correction has been applied for this climatic parameter as well.

366 The tendency of air temperature to increase equally affects the LST. (Hu et al., 2019; Ali
367 et al., 2020; Ali et al., 2021; Barreto et al., 2021; Memon et al., 2021) demonstrated that air
368 temperature alone showed 81 to 98 per cent change in LST under the cloudy condition and a
369 cloudless sky.

370 **4. Conclusions**

371 For the last thirty years (1990-2020), variations in the LST of the BM catchment area and its
372 effect on the vegetative cover and water bodies have been studied. The research showed that
373 the study area's LST increased by an average of 1.06°C over the last thirty years. The temporal
374 variations in the region's NDVI showed a maximum NDVI of 0.48 in 2018 and 2019,
375 respectively, followed by an NDVI of 0.47 in 2020. In the year 2005, the lowermost NDVI of
376 0.27 was found. In addition, the region's temporal NDWI variance recorded the highest NDWI
377 of 0.48 in 2018 and 2019, followed by an NDWI of 0.47 in 2020. In the year 2005, the lowest
378 NDWI of 0.27 was observed. An increase in the NDVI shows an increase in vegetation, while
379 an increase in the NDWI shows an increasing amount of water bodies.

380 An inverse relationship between LST and NDVI is found with (r) of 0.30. An opposite
381 relationship with (r) of 0.36 between LST and NDWI is also observed. Furthermore, an inverse
382 correlation is observed between annual mean temperature and NDWI (r) of 0.50 and annual
383 mean temperature and NDVI (r) of 0.46. At the same time, a negative relation between annual
384 mean rainfall and other variables is found. The statistical correlation of annual mean LST with
385 annual mean NDVI with a coefficient of determination of (R^2) of 0.09 is very weak and
386 considered negative.

387 In comparison, annual mean LST and annual mean NDWI show an inverse relation (R^2)
388 of 0.13. Moreover, annual mean temperature and annual mean NDVI also indicate a bad
389 relationship with (R^2) of 0.2155; for annual mean temperature and annual mean NDWI, it is

390 recorded as (R^2) of 0.2542. The Mann-Kendall trend test for the annual mean temperature series
391 indicates a slightly increasing trend with Sen's slope of $0.03^\circ\text{C}/\text{year}$. It is found that there is a
392 positive trend in the annual mean rainfall patterns, as Sen's slope indicates a yearly increase of
393 50.58 mm/year.

394 Research studies like this current work are essential to guide policymakers to take steps
395 to mitigate the adverse environmental effects of climate change and human-induced changes
396 (land-use changes). This study corroborates that a significant difference in vegetation cover
397 and surface water bodies occurred during the last three decades, which calls for the concerned
398 authorities' immediate attention to mitigate the negative impacts of such changes and safeguard
399 the ecosystem. Such environmental and human-induced problems can be tackled by reducing
400 deforestation and planting trees.

401 **Limitations and Recommendations**

402 Based on this present study, we recommend that future studies consider land use land
403 cover changes (LULC) analysis and assess the impacts of the LST on LULC for those study
404 areas for which the Landsat satellite data is available with cloud covers below the 10% for
405 conducting the proper analysis as our study has some data availability limitations that is why
406 LULC was not considered in this study. For the Bakun-Murum Catchment region, the available
407 Landsat satellite data for the LULC analysis have cloud covers over 20% from 1990 to 2020.
408 Therefore, we recommend that advanced machine learning and remote sensing techniques be
409 applied to clear the cloud covers from the abovementioned Landsat satellite images for future
410 studies.

411 **Conflicts of Interest:** The authors declare no conflict of interest.

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