Geospatial analysis of Oktibbeha County of Mississippi, USA

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Author note

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The authors made the following contributions. Hafez Ahmad: Conceptualization, Writing - Original Draft Preparation, Writing - Review & Editing; Ernst-August Doelle: Writing - Review & Editing.

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1 Introduction

Monitoring vegetation over time is an essential component of geographical resource management applications. On-site monitoring is frequently carried out by taking detailed measurements, such as canopy level measurements. In situ measurements are time-consuming, labor-intensive, and difficult to carry out over large geographic areas. Remote sensing, on the other hand, is a very viable option for monitoring numerous vegetation characteristics using various vegetation indices such as Normalized Difference Vegetation Index, Near-Infrared / Red Ratio, Soil and atmospherically resistant vegetation index (Im & Jensen, 2008). The natural and anthropogenic features found on the Earth’s surface are referred to as land cover. Examples include deciduous forests, wetlands, developed/built areas, grasslands, and water. Land use, on the other hand, describes the activities that take place on the land and indicates the current use of the land. Examples include residential homes, shopping centers, tree nurseries, state parks, and reservoirs. Land cover and land use are frequently studied together in remote sensing studies because satellite imagery and aerial photography can identify land cover, but inferring land use often requires more knowledge of the study region, so a compromise is sometimes made between identifying the variable of interest and inferring land use (Fonji & Taff, 2014).

Local and place-specific global climate change (LULCC) is a type of global climate change, and these changes add up to global climate change. These changes, in turn, have an impact on other components of our earth-atmosphere system, frequently leading to negative outcomes such as biodiversity loss, desertification, and climate change. Several methods exist for tracking or detecting changes in land cover over time. Previously, researchers mapped LULCC over smaller areas using field data and aerial photographs. Because satellite images can cover large geographic areas and have a long temporal coverage, remote sensing is an excellent tool for studying LULCC (Jensen, 1986 ; Berlanga-Robles & Ruiz-Luna, 2002).

Objectives

NDVI, Land surface temperature, Land use

2 Methods

2.1 Participants (First and Last name (Your email))

1. Hafez Ahmad (ha@msstate.edu)

3 Material

3.1 Study area

Oktibbeha County is a micropolitan county in east-central Mississippi that is home to Starkville city and Mississippi State University. The county is located within Mississippi's golden triangle region. The name of the county is derived from a Native American term that means "bloody water" or "icy creek" (Gannett, 1902). According to the 2020 United States Census, the county had 51,788 people, 17,798 households, and 9,263 families.

3.2 Procedure

Data source: Landsat8 imageries from 2020 to 2022 for February and June with less than 10% cloud were downloaded from USGS earth explorer[https://earthexplorer.usgs.gov/]. Moreover, eight-day composite of Precipitation data from 2000 to 2022 was part of "GPM: Monthly Global Precipitation Measurement (GPM)" . Furthermore, Land Surface Temperature was part of “MOD11A2.006 Terra Land Surface Temperature and Emissivity 8-Day Global 1km” . Then Precipitation and land surface temperature data were clipped with the study area. Then they are converted comma separated format for further analysis.

3.3 Vegetation and land-use change and land-cover change [2020_06,2021_02,2021_06,2022_02]

NDVI is a dimensionless index that depicts the difference between the reflectance of vegetation in the visible and near-infrared spectrum.It can be used to assess changes in plant health and vegetation density (Tucker et al., 2001). An NDVI is calculated as a ratio of the red (R) value and the near-infrared (NIR) value. It ranges from -1.0 to 1.0, mainly representing greens, where negative values are mainly made up of clouds, snow, and water, and values close to zero are primarily made up of rocks and bare soil. A very low NDVI value (0.1 or less) corresponds to empty areas of rocks, sand, or snow. Moderate values (between 0.2 and 0.3) represent shrubs and meadows, while large values (between 0.6 and 0.8) indicate temperate and tropical forests.

for the Landsat 8, the formula is given $NDVI = \frac{BAND5 - Band4}{Band5 + Band4}$

Band 5– reflection in the near-infrared spectrum Band 4 – reflection in the red range of the spectrum

3.4 Land use and land cover data

3.4.1 Data analysis.

```
## Rows: 783 Columns: 2

## -- Column specification ----------------------------------------------------
------
```

```
## Delimiter: ","
## chr (1): date
## dbl (1): LST_Day_1km

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.

## Rows: 264 Columns: 2

## -- Column specification ----------------------------------------------------
------
## Delimiter: ","
## chr (1): date
## dbl (1): precipitation

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

3.5 Data preprocessing

3.5.1 land 8-9 OLI /tirs c2 l1.

```
## [1]
"LC08_L1TP_022037_20200612_20200823_02_T1_MTL.txt"
## [2] "LC08_L1TP_022037_20210223_20210303_02_T1_MTL.txt"
## [3] "LC08_L1TP_022037_20210615_20210622_02_T1_MTL.txt"
## [4] "LC08_L1TP_022037_20220210_20220222_02_T1_MTL.txt"
```

```
## [1] "meta_20200612" "meta_20210223" "meta_20210615" "meta_20220210"

## [1] "study<-shapefile('data/raster_vector/Oktibbeha.shp')\nread all raster
files\nrasters_raw<- Sys.glob('data/raster_vector/*.TIF')\nmetafile<-
Sys.glob('data/raster_vector/*.txt')\n# just one file for reprojection
\nnew_Rast<- raster(rasters_raw[1])\n# reproject\nstudy<- spTransform(study,
proj4string(new_Rast)) "

## [1] "rasters_raw<- Sys.glob('data/raster_vector/*.TIF')\n# Raster data
processing \nfor (i in 1:8){\n  new_Rast<- raster(rasters_raw[i])\n cropped<-
crop(new_Rast,extent(study))\n  masked<- mask(cropped,study)\n
writeRaster(masked,paste0('data/raster_vector/',substr(rasters_raw[i],20,62),
'.tif'),overwrite=TRUE)\n}"
```

Landsat sensors capture reflected energy and store data as 8-bit digital numbers (DNs). USGS data includes metadata. The first step is to convert DN to radiance and then radiance to top of reflectance by using provided metadata.

3.5.2 Radiometric calibration and Atmospheric Correction.

1. Conversion DN values to spectral radiance
2. Conversion of spectral radiance to reflectance

4 NDVI calculation

5 Classification

5.1 Statistical analysis

5.2 Land surface temperature and precipitation

5.3 Tests

6 Results

6.1 Mapping

7 used R libraries

We used R [Version 4.1.2; R Core Team (2021)] and the R-packages *dplyr* [Version 1.0.7; Wickham, François, Henry, and Müller (2021)], *forcats* [Version 0.5.1; Wickham (2021a)], *ggplot2* [Version 3.3.5; Wickham (2016)], *gridExtra* [Version 2.3; Auguie (2017)], *lattice* [Version 0.20.45; Sarkar (2008)], *lubridate* [Version 1.8.0; Grolemund and Wickham (2011)], *papaja* [Version 0.1.0.9997; Aust and Barth (2020)], *purrr* [Version 0.3.4; Henry and Wickham (2020)], *raster* [Version 3.5.2; Hijmans (2021); Perpiñán and Hijmans (2021)], *rasterVis* [Version 0.51.0; Perpiñán and Hijmans (2021)], *readr* [Version 2.0.2; Wickham and Hester (2021)], *rgdal* [Version 1.5.27; Bivand, Keitt, and Rowlingson (2021)], *RStoolbox* [Version 0.3.0; Leutner, Horning, and Schwalb-Willmann (2019)], *sp* [Version 1.4.5; Pebesma and Bivand (2005)], *stringr* [Version 1.4.0; Wickham (2019)], *tibble* [Version 3.1.5; Müller and Wickham (2021)], *tidyr* [Version 1.1.4; Wickham (2021b)], and *tidyverse* [Version 1.3.1; Wickham et al. (2019)] for all our analyses.

Table 1:

Descriptive statistics of Land surface temperature

Month	Mean	Median	Max	Min	SD
Jan	9.16	9.33	16.84	-0.53	3.93
Feb	12.53	12.80	21.43	2.11	3.62
Mar	20.44	20.71	26.63	9.03	3.16
Apr	23.78	24.12	28.37	17.00	2.35
May	26.22	26.46	30.28	19.12	2.25
Jun	28.41	28.05	33.77	19.92	2.29
Jul	28.55	28.67	32.88	22.65	2.10
Aug	28.47	28.43	35.53	23.89	2.31
Sep	26.67	26.55	32.36	20.52	2.38
Oct	22.28	22.09	28.62	14.85	3.45
Nov	16.07	15.84	24.29	6.70	3.48
Dec	10.23	10.20	19.67	-0.34	3.87

Note. MOD11A2.006 Terra Land Surface Temperature and Emissivity 8-Day Global 1km

7.1 precipiation works

Table 2:

Descriptive statistics of Precipitation (mm/hr)

Month	Mean	Median	Max	Min	SD
Jan	0.19	0.19	0.39	0.08	0.07
Feb	0.22	0.21	0.42	0.07	0.11
Mar	0.19	0.18	0.41	0.03	0.07
Apr	0.21	0.20	0.40	0.09	0.09
May	0.15	0.13	0.32	0.05	0.07
Jun	0.16	0.14	0.36	0.04	0.09
Jul	0.17	0.15	0.31	0.04	0.07
Aug	0.15	0.13	0.28	0.05	0.07
Sep	0.13	0.13	0.40	0.00	0.10
Oct	0.12	0.09	0.33	0.00	0.10
Nov	0.16	0.14	0.35	0.04	0.08
Dec	0.20	0.20	0.41	0.07	0.08

Note. GPM: Monthly Global Precipitation Measurement (GPM) v6

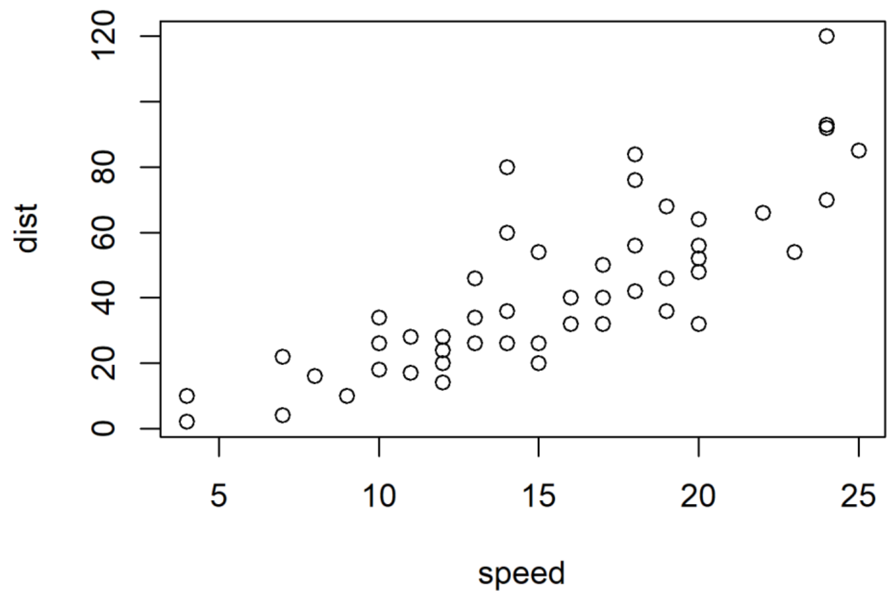

Figure 1. (ref:my-figure-caption)

7.2 Discussion

Monthly average temperature is 21.00 [C] and standard deviation is 2.75

8 Conclusion

9 References

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