

Geospatial analysis of Oktibbeha County of Mississippi, USA

Hafez Ahmad¹ & Your Name^{1,2}

¹ Mississippi State University

² Mississippi State University

Author note

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Correspondence concerning this article should be addressed to Hafez Ahmad, College of Forest Resources, Mississippi State, MS 39762. E-mail: ha626@msstate.edu

Abstract

The Landsat satellite imageries have been analyzed for the vegetation monitoring and estimation of land use from 2020 to 2022, along with land surface temperature and Precipitation in Oktibebe county, Mississippi. Throughout the year, the average land surface temperature (LST) ranges from 9°C to 28°C . January has the coldest LST at 9.16°C , and July has the hottest LST at 28.55°C . According to data recorded between 2010 and 2022, January and December experienced the lowest LST, ranging from -0.5 to -0.3°C , whereas August and June, experienced higher LST, ranging from 35.5°C to 33.77°C .

Keywords: Rmarkdown, GIS, Remote sensing, NDVI, Land use

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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. On the other hand, remote sensing is a 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-up areas, and water. On the other hand, land use 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 adverse 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 extended temporal coverage, remote sensing is an excellent tool for studying LULCC (Jensen, 1986; Berlanga-Robles & Ruiz-Luna, 2002).

Land cover changes can occur as a result of both human and climate drivers. For example, the demand for new settlements often results in the permanent loss of natural land, resulting in changes in the weather patterns, temperature, and precipitation (Hale, Gallo, Owen, & Loveland, 2006; Pielke Sr et al., 2007). Disturbance events such as wildfire and timber harvest are important factors influencing land cover. According to the North American forest dynamic dataset, from 1985 to 2010, forest disturbances affected an average of approximately 11200 square miles per year in the contiguous United States. The forest disturbance rate decreased by about one-third between 2006 and 2010 (Reidmiller et al., 2019).

In this mini-paper, the **objectives** are (a) to present the results of an analysis of the land surface temperature and precipitation data, (b) to quantify the normalized vegetation index for three years and estimate the land use /land cover, (c) to determine the relationship between vegetation and land use.

2 Methods and Materials

2.1 Study area

Oktibbeha County is a micropolitan county in east-central Mississippi, 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.

2.2 Data collection

Landsat8 imageries (land 8-9 OLI /tirs c2 11) from 2020 to 2022 for February and June with less than 10% cloud were downloaded from USGS earth explorer[<https://earthexplorer.usgs.gov/>]. Moreover, an 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.

2.3 NDVI calculation

We used Normalized Difference Vegetation Index (NDVI) for the vegetation analysis. 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

2.4 Correlation analysis

Correlation analysis is a statistical method used to examine the relationship between two or more variables. The correlation coefficients range between -1 and 1. 0 indicates no relationship between variables, -1 indicates negative, and +1 indicates positive correlation. The equation of the Correlation Coefficient is given below.

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^n (X_i - \bar{X}) (Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

2.5 Land surface temperature and precipitation data analysis

2.6 Landsat satellite imageries preprocessing

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.

2.6.1 Radiometric calibration and Atmospheric Correction.

2.6.1.1 Conversion DN values to spectral radiance.

2.6.1.2 Conversion of spectral radiance to reflectance.

3 Results and discussions

3.1 Mapping

3.2 Land surface temperature and Precipitation

3.3 precipitation works

Throughout the year, the average land surface temperature (LST) ranges from 9 °C to 28 °C. January has the coldest LST at 9.16 °C, and July has the hottest LST at 28.55 °C. According to data

recorded between 2010 and 2022, January and December experienced the lowest LST, ranging from -0.5 to -0.3°C , whereas August and June, experienced higher LST, ranging from 35.5°C to 33.77°C (see table 1).

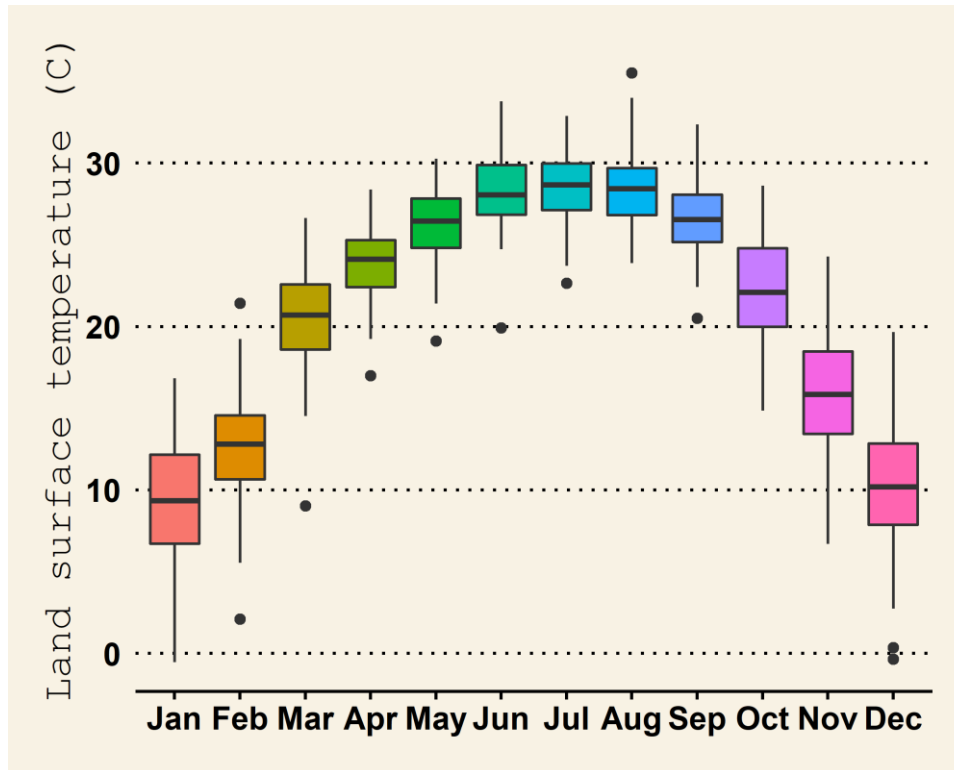


Figure 1. Boxplot of Land surface temperature

The monthly average temperature is 21.00°C and the standard deviation is 2.75

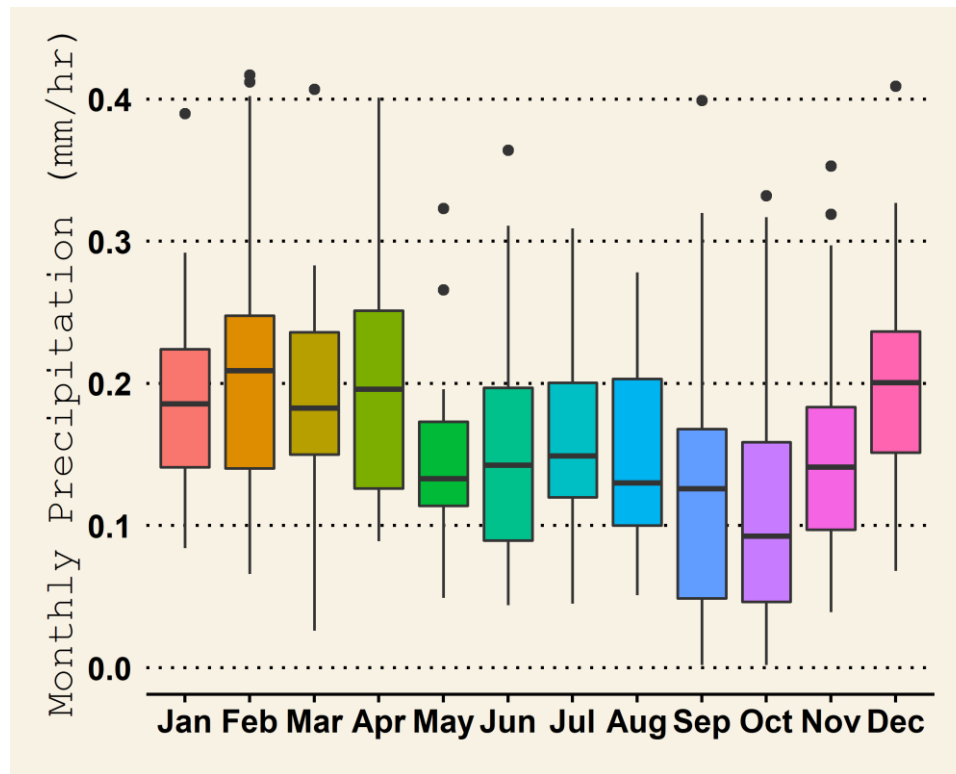


Figure 2. Boxplot of Monthly Precipitation (mm/hr)Table 1. Descriptive statistics of Land surface temperature

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

Month	Mean	Median	Max	Min	SD
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

Monthly precipitation data covered a period of over 20 years. During this period, the average precipitation rate ranged from 0.12 to 0.22 *mm/hr*. These rates remained relatively constant throughout the month. December to April had a higher precipitation rate of around 0.40 *mm/hr*, while August to November had a lower rate ranging from 0.05 to 0 *mm/hr*.

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

Month	Mean	Median	Max	Min	SD
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

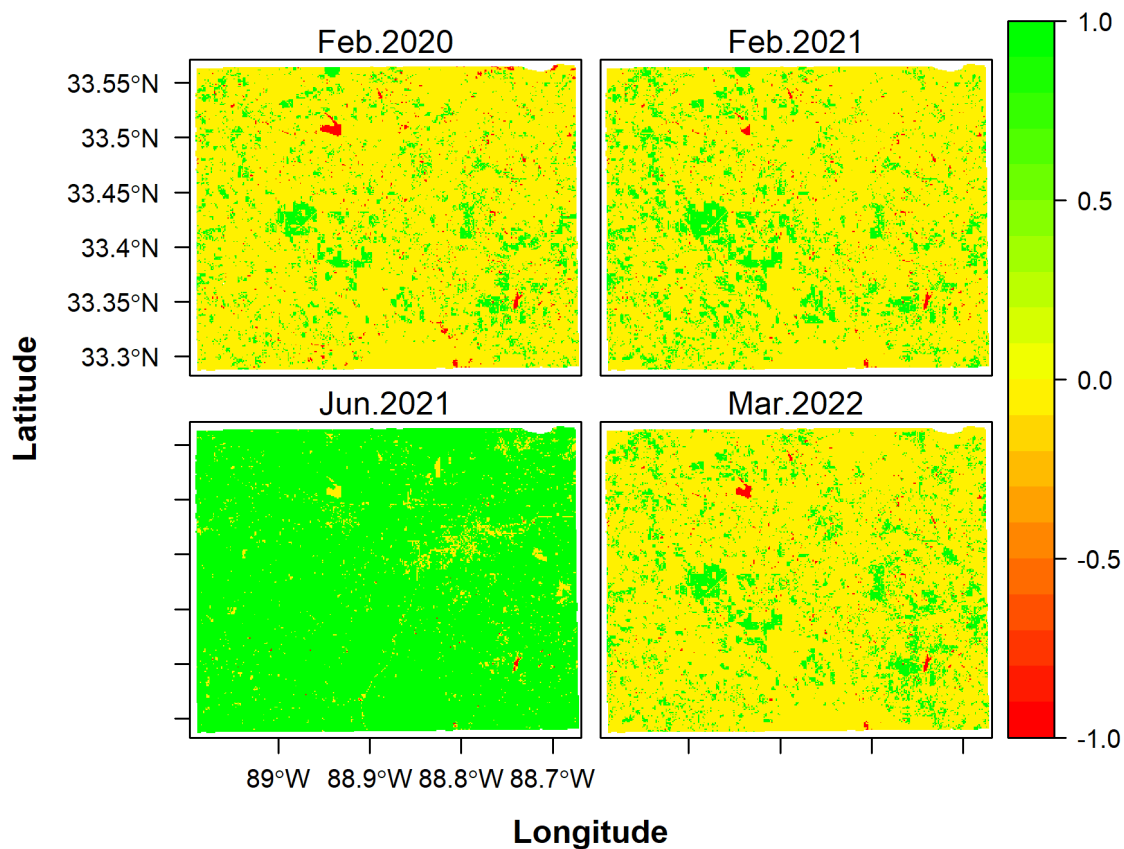


Figure 3. Normalized Difference Vegetation Index Map of Oktibbeha County

Looking at the image, it is understood that the vegetation changes in one place or another every year due to the city's development. The change between red and green is clearly seen in the image.

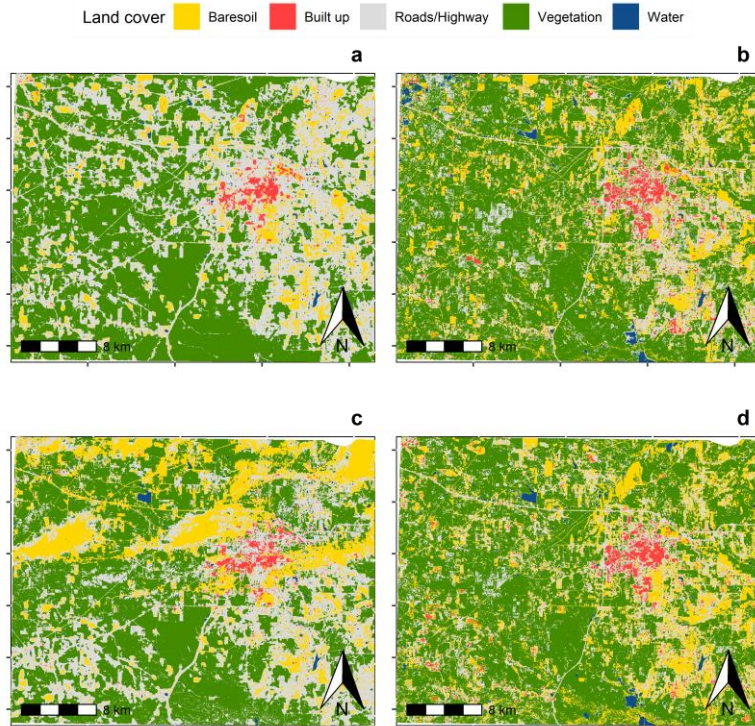


Figure 4. Land cover /land use map of Oktibbeha county

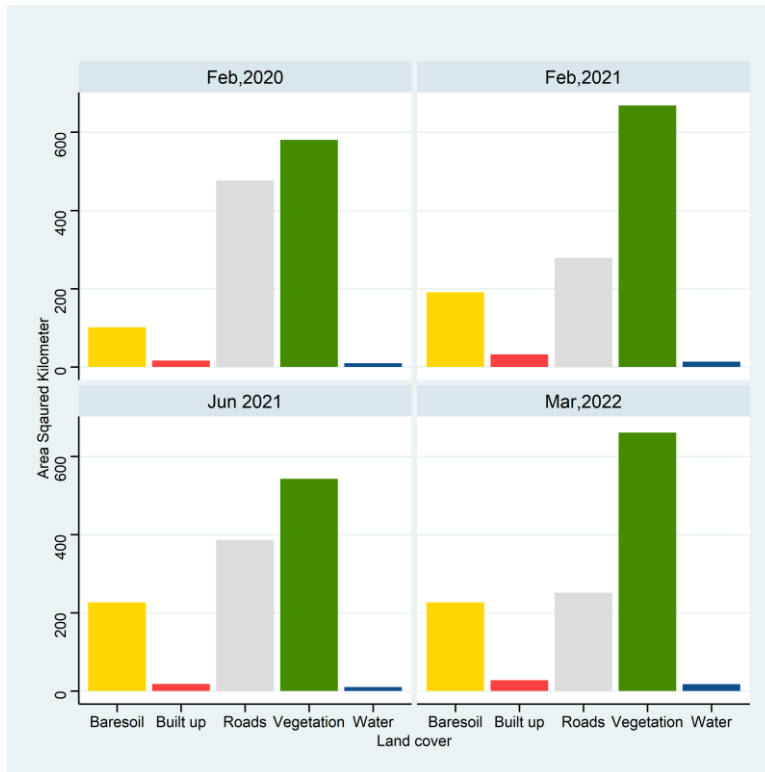


Figure 5. Land cover /land use map of Oktibbeha county

According to figure 5, the most variable land cover classes are bare soil, roads/highways, and vegetation.

4 Conclusion

The Landsat satellite imageries have been analyzed for the vegetation monitoring and estimation of land use from 2020 to 2022, along with land surface temperature and Precipitation in Oktibbeha county, Mississippi. Image classification is so accurate because training samples were very small. The other potential reason is that Feb, march, and June were collected for 30-meter resolution. So satellites images had lower resolution and large cloud coverage. Cloud be removed further advanced analysis, but this study has designated for only Spring 2022.

6 References

- Auguie, B. (2017). *gridExtra: Miscellaneous functions for "grid" graphics*. Retrieved from <https://CRAN.R-project.org/package=gridExtra>
- Aust, F., & Barth, M. (2020). *papaja: Create APA manuscripts with R Markdown*. Retrieved from <https://github.com/crsh/papaja>
- Berlanga-Robles, C. A., & Ruiz-Luna, A. (2002). Land use mapping and change detection in the coastal zone of northwest mexico using remote sensing techniques. *Journal of Coastal Research*, 514–522.
- Bivand, R., Keitt, T., & Rowlingson, B. (2021). *Rgdal: Bindings for the 'geospatial' data abstraction library*. Retrieved from <https://CRAN.R-project.org/package=rgdal>
- Chang, W., Cheng, J., Allaire, J., Sievert, C., Schloerke, B., Xie, Y., ... Borges, B. (2021). *Shiny: Web application framework for r*. Retrieved from <https://CRAN.R-project.org/package=shiny>
- Dunnington, D. (2021). *Ggspatial: Spatial data framework for ggplot2*. Retrieved from <https://CRAN.R-project.org/package=ggspatial>
- Fonji, S. F., & Taff, G. N. (2014). Using satellite data to monitor land-use land-cover change in north-eastern latvia. *Springerplus*, 3(1), 1–15.
- Gannett, H. (1902). The origin of certain place names in the state of mississippi. *Publications of the Mississippi Historical Society*, 6, 339–349.
- Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, 40(3), 1–25. Retrieved from <https://www.jstatsoft.org/v40/i03/>
- Hale, R. C., Gallo, K. P., Owen, T. W., & Loveland, T. R. (2006). Land use/land cover change effects on temperature trends at US climate normals stations. *Geophysical Research Letters*, 33(11).
- Henry, L., & Wickham, H. (2020). *Purrr: Functional programming tools*. Retrieved from <https://CRAN.R-project.org/package=purrr>
- Hijmans, R. J. (2021). *Raster: Geographic data analysis and modeling*. Retrieved from <https://CRAN.R-project.org/package=raster>
- Im, J., & Jensen, J. R. (2008). Hyperspectral remote sensing of vegetation. *Geography Compass*, 2(6), 1943–1961.
- Jensen, J. R. (1986). *Introductory digital image processing: A remote sensing perspective*. Univ. of South Carolina, Columbus.
- Kassambara, A. (2020). *Ggpubr: 'ggplot2' based publication ready plots*. Retrieved from <https://CRAN.R-project.org/package=ggpubr>
- Leutner, B., Horning, N., & Schwalb-Willmann, J. (2019). *RStoolbox: Tools for remote sensing data analysis*. Retrieved from <https://CRAN.R-project.org/package=RStoolbox>
- Müller, K., & Wickham, H. (2021). *Tibble: Simple data frames*. Retrieved from <https://CRAN.R-project.org/package=tibble>
- Pebesma, E. J., & Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, 5(2), 9–13. Retrieved from <https://CRAN.R-project.org/doc/Rnews/>
- Perpiñán, O., & Hijmans, R. (2021). *rasterVis*. Retrieved from <https://oscarperpinan.github.io/rastervis/>
- Pielke Sr, R. A., Adegoke, J., Beltraán-Przekurat, A., Hiemstra, C. A., Lin, J., Nair, U. S., ... Nobis, T. E. (2007). An overview of regional land-use and land-cover impacts on rainfall. *Tellus B: Chemical and Physical Meteorology*, 59(3), 587–601.
- R Core Team. (2021). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>

- Reidmiller, D., Avery, C., Easterling, D., Kunkel, K., Lewis, K., Maycock, T., & Stewart, B. (2019). Fourth national climate assessment. *Volume II: Impacts, Risks, and Adaptation in the United States*.
- Sarkar, D. (2008). *Lattice: Multivariate data visualization with r*. New York: Springer. Retrieved from <http://lmdvr.r-forge.r-project.org>
- Tucker, C. J., Slayback, D. A., Pinzon, J. E., Los, S. O., Myneni, R. B., & Taylor, M. G. (2001). Higher northern latitude normalized difference vegetation index and growing season trends from 1982 to 1999. *International Journal of Biometeorology*, 45(4), 184–190.
- Wickham, H. (2007). Reshaping data with the reshape package. *Journal of Statistical Software*, 21(12), 1–20. Retrieved from <http://www.jstatsoft.org/v21/i12/>
- Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. Retrieved from <https://ggplot2.tidyverse.org>
- Wickham, H. (2019). *Stringr: Simple, consistent wrappers for common string operations*. Retrieved from <https://CRAN.R-project.org/package=stringr>
- Wickham, H. (2021a). *Forcats: Tools for working with categorical variables (factors)*. Retrieved from <https://CRAN.R-project.org/package=forcats>
- Wickham, H. (2021b). *Tidyr: Tidy messy data*. Retrieved from <https://CRAN.R-project.org/package=tidyr>
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., ... Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>
- Wickham, H., François, R., Henry, L., & Müller, K. (2021). *Dplyr: A grammar of data manipulation*. Retrieved from <https://CRAN.R-project.org/package=dplyr>
- Wickham, H., & Hester, J. (2021). *Readr: Read rectangular text data*. Retrieved from <https://CRAN.R-project.org/package=readr>