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Relationship between net primary production (NPP) and dust storms in different land cover classes

Ali Shamsoddini *¹, Ali Sadeghnezhad ¹

¹ Tarbiat Modares University, Department of Remote Sensing and GIS, Tehran, Iran

Keywords

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Abstract

Iran has been a prime target of dust storms, mostly with exogenous origins arising from its neighboring countries. Dust storms generally depend on two factors, namely wind speed and soil erosion threshold, the latter being highly dependent on vegetation. Meanwhile, remote sensing data and imagery allow for monitoring vegetation changes in different spatial and temporal scales, particularly through vegetation indices commonly found in the literature. Still, these indices suffer from certain shortcomings such as a lack of quantitative outcomes and sensitivity to greenness. Net primary production (NPP) is a measure of carbon content absorbed by plants through photosynthesis and is not affected by the shortcomings seen in vegetation indices. This study explored the relationship between NPP and dust storms in the Tigris and Euphrates basin. AOD values derived from MODIS data were used to measure dust and NPP values for different land cover types. The research findings showed that the highest correlation between AOD and NPP was found in the evergreen coniferous forest class with a Pearson correlation coefficient of negative 0.5326.

1. Introduction

Most countries located to the west of Iran are covered with vast deserts that serve as potential sources of sand and dust storms (SDS), which sometimes surpass political borders and affect neighboring countries (Al-Dabbas et al., 2012; Griffin et al., 2002). Dust storms are not limited to specific regions or climates and can affect any place with unprotected soil surfaces. Hence, vegetation, water, and rock covers can effectively protect the soil against wind erosion (Qian et al., 2002). Some of the main contributors to wind erosion are drought, low precipitation, rangeland plowing, and land-use change from forest to rangeland or from rangeland to agricultural lands (Haghighi et al., 2018; N. Middleton & Kang, 2017). Vegetation is much more effective than other factors since plants not only strengthen the soil through their roots but also reduce evaporation by providing shading (N. J. Middleton, 1986). Furthermore, plant litter decomposes into organic matter, which can increase the soil's erosion threshold. Vegetation, however, is severely sensitive to drought and low precipitation and more rangelands and forests are being

destroyed with population expansion worldwide (Rivera et al., 2021). In addition, land cover changes can have positive or negative effects on SDS. Overall, forest and tree cover boost soil consistency and prevent wind erosion by reducing wind speed, creating shade, and developing roots (Youlin, 2001). Vegetation monitoring through field surveys is rarely cost-effective and often impossible in certain cases. Satellite data and imagery present a suitable alternative thanks to their regular and long-term acquisitions, allowing for the analysis of land surface phenomena over long periods from the past to the present. The most common remote sensing method for monitoring vegetation is using vegetation indices such as NDVI. This method has also been used for investigating the effect of vegetation on dust events (Li et al., 2020; Ranjbar et al., 2020; Rivera et al., 2021). These indices are not perfect either and suffer from flaws such as lack of quantitative results, sensitivity to greenness, and high dependence on image acquisition angle and time. This study used net primary production (NPP) instead of vegetation indices to overcome these issues. NPP is an indicator of the carbon absorbed by plants through photosynthesis minus autotrophic respiration.

* Corresponding Author

*ali.shamsoddini@modares.ac.ir ORCID ID 0000-0002-4559-7563
alisadeghnezhad@modares.ac.ir ORCID ID 0000-0002-6469-0616

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NPP is a quantitative indicator of vegetation growth and depends on factors such as leaf area, woody/herbaceous plant type, and perennial/annual plant type (Gulbeyaz et al., 2018; Ruimy et al., 1999). These features also affect sand and dust storms and so NPP monitoring can shed light on the relationship between vegetation and SDS. This study used the NPP index to determine the effect of different land cover classes on the amount of dust in the Tigris and Euphrates basin. AOD was used to measure variations in dust levels. Considering that variations in vegetation affect the level of dust at different intervals and with delay, the relationship between AOD and NPP was investigated using different delay intervals.

2. Research Data and Method

2.1. Study area

The Tigris and Euphrates basin with an area of 935,400 km² is located between longitude 36-51° E and latitude 27-40° N. The study area covers parts of Iran, Turkey, Syria, Jordan, Iraq, and Saudi Arabia, located 9 m below sea level at the shallowest and 4305 m above sea level at the highest point. A variety of climates can be seen across the region with the lowest and highest annual precipitation rates recorded at 18 and 376 mm, respectively.

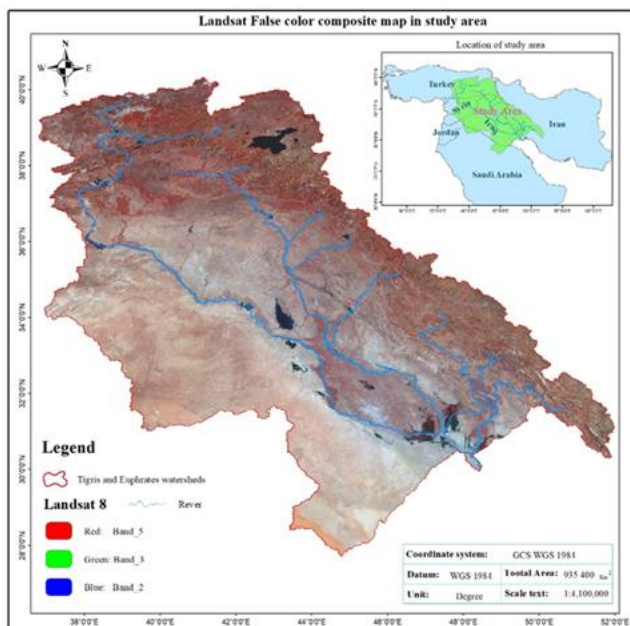


Figure 1. Landsat 8 false-color composite image of the study area (RGB with a band combination of 5, 3, and 2, respectively).

2.2. Research Data

NPP and AOD are among the most commonly used MODIS products for monitoring the carbon cycle and sand and dust storms. NPP is the amount of carbon absorbed by the plant during photosynthesis minus the amount released during respiration. It is called MOD17A3HGF V6 in the Google Earth Engine (GEE), which is a cumulative eight-day composite of MOD17A2H product (i.e., pure photosynthesis). AOD, another MODIS product, is also available in GEE (MCD19A2 V6) and provides daily estimates of optical depth at 0.47 and 0.55

μm wavelengths using the Terra and Aqua sensors. MCD12Q1 V6 product of MODIS supplies six types of global maps of land cover at annual time steps, the fourth being the carbon cycle, which enables NPP monitoring and was used in this study.

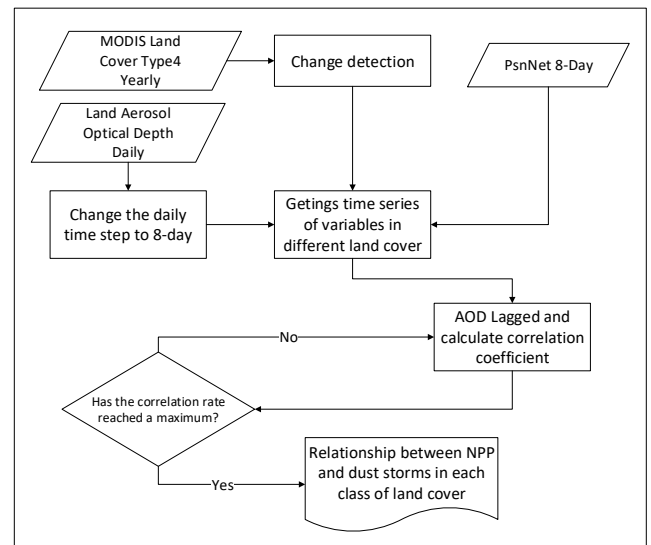


Figure 2. Flowchart of this study

2.3. Methodology

As shown in Figure 2, first, the 20-year MODIS land cover images were retrieved and the changes were enhanced. Then, two classes, namely change from vegetation to other classes and change from one type of vegetation to another vegetation class, were identified. Next, the samples were randomly selected from each class and uploaded to the GEE platform for pre-processing of satellite data and extraction of time series data. After extracting the time series of NPP and AOD samples, the Pearson correlation coefficient values and the time delays were computed in Python.

3. Results

3.1 Twenty-year land cover and land use changes

According to the results, land cover and land use classes in the study area included water bodies, evergreen coniferous forests, evergreen broad-leaved forests, broad-leaved deciduous forests, annual broad-leaved plants, grasslands, barren lands, and built-up lands (eight classes). The highest land use change was from different vegetation classes to barren (112,193 km²) and the lowest from rangeland to built-up (478 km²). The total land use changes over 20 years amounted to 122,000 km². Change from one vegetation class to another was approximately 91,239 km² and from vegetation to other classes stood at about 11,2671 km².

3.2 Area of SDS and monthly NPP over 22 years

AOD measures the optical depth of the atmosphere (i.e., the extent of sunlight prevented from reaching the ground), and AOD values above 0.5 mark the occurrence of a dust event. By retrieving the AOD from the MODIS data in GEE and creating a threshold, areas with an AOD

value above 0.5 were selected and their area was calculated for each month. Figure 3a shows the area of land affected by dust on a monthly basis over a 22-year period. Accordingly, large areas were affected by SDS in the 2000–2002 and 2008–2012 periods.

MODIS NPP is an 8-day product, and the monthly NPP is the cumulative value of each month's images. The total NPP for each month is presented in Figure 3b, showing a declining trend in 2007 and 2008, which is consistent with the significant rising AOD trends.

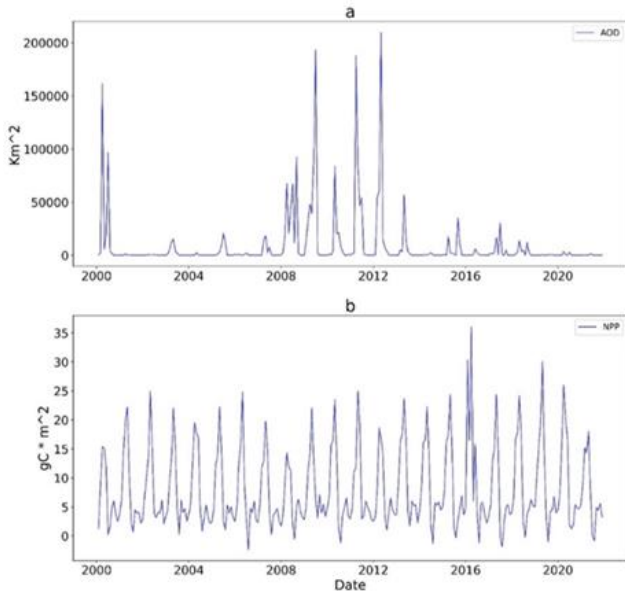


Figure 3. (a) The area of land affected by sand and dust storms per month and (b) the monthly NPP in a 22-year period.

3.3 Relationship between NPP and AOD in each land cover class

Five vegetation land cover classes were found in the study area. After the enhancement of changes, each class was sampled separately and randomly, and the SDS and NPP time series were extracted using GEE. Overall, there were no high correlation coefficients in any of the land use classes, with the highest observed in the evergreen coniferous forest (-0.5326) and the lowest in the evergreen broad-leaved forest class (-0.4320). The highest correlation among all classes was obtained with a 10-month delay, indicating that a rise in dust storms was seen after 10 months since declining NPP trends. An example of the AOD and NPP time series in the evergreen coniferous forest class is presented in Figure 4a. It can be seen that a declining AOD has led to an increasing NPP. Figure 4a shows the correlation coefficient of these variables in 0–25-month time delays. Moreover, 4c and 4d demonstrate the variable scatter plots in zero and 10-month delays. In the 10-month delay, the relationship between the variables was in its most regular state.

Interestingly, in the 10-month delay (4d), no dust storm has occurred with NPP values above 2 since AOD values above 0.5 signal dust storms (Yue et al., 2017). The same result was obtained in other classes except for the evergreen broad-leaved forest class, in which no storms occurred with NPP values above 3.

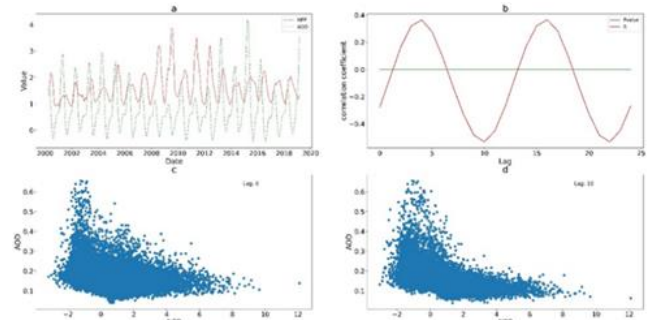


Figure 4. AOD and NPP time series with a 22-year correlation for the evergreen coniferous forest class; (a) the NPP and AOD time series and (b) the correlation coefficient at 0–24-month time delays. Figure 4c and 4d, respectively, show the relationship between the variables in zero and 10-month delays (highest correlation).

4. Discussion

There is an increasing urbanization trend in the Tigris and Euphrates basin (Attiya & Jones, 2020). Over the last 20 years, built-up lands have expanded by 478.25 km² while 112,193.75 km² have turned into barren lands. The vegetation status is changing drastically with 91,239 km² experiencing changes in the vegetation type over the past 20 years, mostly from forests and rangelands to agricultural lands. The research by Xu et al. (2015) revealed that vegetation change from woody to herbaceous led to a severe fall in NPP (Xu et al., 2015). The analysis of the study area showed that in the 20-year period, NPP values were the lowest in 2008 and dust storms were highest from 2008 to 2012 covering large portions of the study area in many months. These findings are consistent with those of many studies (Albarakat & Lakshmi, 2019; Bolorani et al., 2020; Broomandi et al., 2017a, 2017b). Although the fall in NPP cannot be seen as directly affecting the rise in SDS, it can be associated with the rise in AOD considering the effect of vegetation on dust storms as confirmed by previous studies. Zou and Zhai (2004) concluded that former declines in vegetation (e.g., the last summer) can increase dust storms in later times (e.g., the next spring) (Zou & Zhai, 2004). The findings of the present study also showed that the time delay for the highest correlation between the variables was 10 months, which is also consistent with Zou and Zhai (2004).

The separation of land cover classes increased the correlation between NPP and AOD in the evergreen coniferous forest class, whereas a lower correlation was obtained for other tree cover classes due to their low area and distribution.

5. Conclusion

This study used MODIS products, namely AOD, NPP, and land use data to investigate the relationship between AOD and NPP in different land uses and time delays. The research results can be summarized as follows:

- The relationship between NPP and AOD varies in different land cover classes.

- In the study area, the NPP of the evergreen coniferous forest class had the highest correlation with AOD.
- The effect of increasing or decreasing NPP on dust storms reached its highest level 10 months after the land use change.
- A dust storm event is very unlikely if the NPP level has not been less than 2 g of carbon per m² in the previous 10 months.

References

- Al-Dabbas, M. A., Ayad Abbas, M., & Al-Khafaji, R. M. (2012). Dust storms loads analyses—Iraq. *Arabian Journal of Geosciences*, 5(1), 121–131. <https://doi.org/10.1007/s12517-010-0181-7>
- Albarakat, R., & Lakshmi, V. (2019). Monitoring dust storms in Iraq using satellite data. *Sensors (Switzerland)*, 19(17). <https://doi.org/10.3390/s19173687>
- Attiya, A. A., & Jones, B. G. (2020). Climatology of Iraqi dust events during 1980–2015. *SN Applied Sciences*, 2(5). <https://doi.org/10.1007/s42452-020-2669-4>
- Bolorani, A. D., Kazemi, Y., Sadeghi, A., Shorabeh, S. N., & Argany, M. (2020). Identification of dust sources using long term satellite and climatic data: A case study of Tigris and Euphrates basin. *Atmospheric Environment*, 224, 117299. <https://doi.org/10.1016/j.atmosenv.2020.117299>
- Broomandi, P., Dabir, B., Bonakdarpour, B., & Rashidi, Y. (2017a). Identification of the sources of dust storms in the City of Ahvaz by HYSPLIT. *Pollution*, 3(2), 341–348. <https://doi.org/10.7508/pj.2017.02>
- Broomandi, P., Dabir, B., Bonakdarpour, B., & Rashidi, Y. (2017b). Identification of dust storm origin in South - West of Iran. *Journal of Environmental Health Science and Engineering*, 15(1). <https://doi.org/10.1186/s40201-017-0280-4>
- Griffin, D. W., Kellogg, C. A., Garrison, V. H., & Shinn, E. A. (2002). The global transport of dust. *American Scientist*, 90(3), 228–235. <https://doi.org/10.1511/2002.3.228>
- Gulbeyaz, O., Bond-Lamberty, B., Akyurek, Z., & West, T. O. (2018). A new approach to evaluate the MODIS annual NPP product (MOD17A3) using forest field data from Turkey. *International Journal of Remote Sensing*, 39(8), 2560–2578. <https://doi.org/10.1080/01431161.2018.1430913>
- Haghighi, S., Akhzari, D., Attaeian, B., & Bashir Gonbad, M. (2018). The effect of drought in the source area of dust storms on vegetation change (case study: western parts of Iran). *Environmental Resources Research*, 6(2), 195–200.
- Li, J., Garshick, E., Al-Hemoud, A., Huang, S., & Koutrakis, P. (2020). Impacts of meteorology and vegetation on surface dust concentrations in Middle Eastern countries. *Science of the Total Environment*, 712, 136597. <https://doi.org/10.1016/j.scitotenv.2020.136597>
- Middleton, N. J. (1986). Dust storms in the Middle East. *Journal of Arid Environments*, 10(2), 83–96. [https://doi.org/10.1016/s0140-1963\(18\)31249-7](https://doi.org/10.1016/s0140-1963(18)31249-7)
- Middleton, N., & Kang, U. (2017). Sand and dust storms: Impact mitigation. *Sustainability (Switzerland)*, 9(6), 1–22. <https://doi.org/10.3390/su9061053>
- Qian, W., Quan, L., & Shi, S. (2002). Variations of the dust storm in China and its climatic control. *Journal of Climate*. [https://doi.org/10.1175/1520-0442\(2002\)015<1216:VOTDSI>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<1216:VOTDSI>2.0.CO;2)
- Ranjbar, A. A., Imani, A., Abdoosi, V., Fruits, T., Branch, A., Attiya, A. A., Jones, B. G., Yang, B., Bräuning, A., Zhang, Z., Dong, Z., Esper, J., Sun, J., Du, W., Lane, Diana R, Debra P, Lauenroth, & William K, ... Ranjbar, A. A. (2020). The key role of water resources management in the Middle East dust events. *Atmospheric Environment*, 187(5), 139. <https://doi.org/10.1007/978-3-662-45737-5>
- Rivera, J. A., Marianetti, G., Hinrichs, S., Liu, Y., Ju, W., He, H., Wang, S., Sun, R., Zhang, Y. Y., Zhang, N., Hong, Y., Qin, Q., Liu, L., Iwasaka, Y., Minoura, H., Nagaya, K., Bousbih, S., Zribi, M., Pelletier, C., ... Wang, Y. Y. (2021). Light-Use Efficiency Across the Oregon Transect'. *Remote Sensing*, 12(3), 284–295. <https://doi.org/10.1002/ecs2.3578>
- Ruimy, A., Kergoat, L., & Bondeau, A. (1999). Comparing global models of terrestrial net primary productivity (NPP): Analysis of differences in light absorption and light-use efficiency. *Global Change Biology*, 5(SUPPL. 1), 56–64. <https://doi.org/10.1046/j.1365-2486.1999.00007.x>
- Xu, J., Dong, J., Wu, L., Shao, G., & Yang, H. (2015). Land Use/Cover Change and its Impact on Net Primary Productivity in Huangfuchuan Watershed Temperate Grassland, China. *Communications in Computer and Information Science*, 482, 664–683. https://doi.org/10.1007/978-3-662-45737-5_65
- Youlin, Y. (2001). Global Alarm: Dust and Sandstorms from the World's Drylands. *Global Alarm: Dust and Sandstorms from the World's Drylands*, 345. http://www.preventionweb.net/files/1800_VL1022_11.pdf
- Yue, H., He, C., Zhao, Y., Ma, Q., & Zhang, Q. (2017). The brightness temperature adjusted dust index: An improved approach to detect dust storms using MODIS imagery. *International Journal of Applied Earth Observation and Geoinformation*, 57, 166–176. <https://doi.org/10.1016/j.jag.2016.12.016>
- Zou, X. K., & Zhai, P. M. (2004). Relationship between vegetation coverage and spring dust storms over northern China. *Journal of Geophysical Research: Atmospheres*, 109(3), 1–9. <https://doi.org/10.1029/2003jd003913>