Using Google Earth Engine for the complete pipeline of temporal analysis of NDVI in Chitwan National Park of Nepal

RITIKA PRASAI (ritikaprasai3@gmail.com)
Institute of Forestry

Research Article

Keywords: Python API, Thiel Sen regression, satellite imagery, seasonality, NDVI decomposition

Posted Date: May 18th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1633994/v3

Abstract

Advent of cloud computing and Google Earth Engine has completely changed the way we acquire, manage and process large satellite data. Here, we analyze temporal dynamics of vegetation productivity in Chitwan National Park, Nepal (CNP) for the period of 1988 to 2020 using Google Earth Engine (GEE) Python API, without using local computer for data storage or analysis. Specifically, we computed normalized difference vegetation index (NDVI) from Landsat data and analyzed the time-series NDVI using a Thiel Sen estimator and by decomposing it to the trend and season components We completed remote sensing analyses including image retrieval, image analysis, classification and report generation in GEE Python API, which is a free resource. Our results showed that NDVI in CNP increased at the rate of 0.0006/year ($p<0.05$, $R^2= 0.66$). We observed variation in NDVI during pre-monsoon ($p<0.05$, $R^2=0.79$) and monsoon ($p<0.05$, $R^2=0.79$) seasons which were 0.0005/ year and 0.0007/year, respectively. An annual increase in NDVI value in CNP indicates an increase in primary productivity that is assumed to support higher animal species richness. Using NDVI in GEE Python API proved to be an effective and efficient tool for monitoring the primary productivity of ecologically important sites such as protected areas.

1. Introduction

Availability of green vegetation cover is always a desirable component of the terrestrial ecosystems. Increase in green vegetation cover indicates increase in primary productivity that is assumed to support higher animal species richness (Bailey et.al., 2004). This is even more important in the protected areas within the fragmented landscape that are viewed as the ultimate refuge for sustaining biological diversity amid widespread degradation of the natural areas (Connell & Orias, 1964). As biological diversity largely depends on the primary productivity of the terrestrial ecosystems, periodic monitoring of vegetation greenness is essential. Quantification of trends in vegetation productivity is also crucial for understanding the response of ecosystems to the environmental change (Liu et al., 2015), including influences on water resources, agriculture, biodiversity (Xu et al., 2017), and wildlife conservation (Prasai, 2021; Liu et al., 2015). Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation indices (Mlenga & Jordaan, 2020; Baniya et al., 2018;Wilson & Norman, 2018) that is a reliable indicator of vegetation dynamics, and can be derived from satellite imagery (Liu et al., 2015; Tian et al., 2015; Galvão et al., 2011). This index has been extensively used to measure the biotic response to climate change (Tian et al., 2015), monitor drought (Thieme et al., 2020; Baniya et al., 2018; Sarma et al., 2015), understand forest carbon dynamics (Liu et al., 2015), classify land use and land cover (LULC) and LULC change (Schut et al., 2015), and estimate land degradation (Galvão et al., 2011).

Nepal, a hotspot of endangered wildlife with an important eco-tourism industry (Kafley et al., 2019), is an example of a country where ecosystems appear to be rapidly changing due to climate change (Adhikari et.al, 2021; Marino et al., 2019; Baniya et al., 2018) . One of the most impressive collections of wildlife species in the world reside in the Chitwan National Park (CNP) of Nepal (Stapp et.al., 2015). CNP, with the size of 952.63 km2, represents the largest contiguous protected area of the country, and was designated as the world heritage site in 1984 (Figure 1). Researchers have estimated at least 700 different terrestrial

vertebrate species in the park, including several endangered mammals such as the Bengal tiger (*Panthera tigris*), clouded leopard (*Neofelis nebulosa*) (Kafley et al., 2019), one-horned rhinoceros (*Rhinoceros unicornis)*, sloth bear (*Melursus ursinus*), and Indian pangolin (*Manis crassicaudata*) (Plains & Park, 2019). Around 500 species of birds have been documented from the park including threatened and endangered bird species such as the swamp francolin (*Francolinus gularis*) and Bengal florican (*Houbaropsis bengalensis*) (Kafley et al., 2019). Assessing temporal trend of NDVI allows the understanding of patterns and processes of vegetation ecology (Dai et al., 2020). The existing and changing pattern of physical and biological environmental conditions can be determined for efficient environmental management (Krakaeur et al., 2017). Monitoring temporal trends of vegetation indices assist in understanding the ecosystem dynamics to assess whether the ecosystem is restoring or degrading Wasniewski et al., 2020; Moffiet et al., 2006).

NDVI is a ratio of difference between the red (R) and near infrared (NIR) intensities to their sum (i.e., **(NIR - R) / (NIR + R)**) **and** ranges from -1 to +1 (Rouse et al., 1973). Water takes values closer to -1, green vegetation takes values close to +1 (Tong et al., 2019), and values close to 0 indicate urbanized area and lack of vegetation (Galvão et al., 2011). In many scenarios, values below 0.1 correspond to bodies of water and bare ground (Kim et al., 2017; Xu et al., 2017), while higher values are indicators of high photosynthetic activity linked to scrub land, temperate forest, rain forest and agricultural fields containing growing crops (Moura et al., 2012). Given the ability of NDVI to quantify vegetation greenness and density, it provides a useful tool for measuring plant health and productivity over time (Baniya et al., 2018; Xu et al., 2017; Tian et al., 2015; Tian et al., 2015), photosynthetic activity (Wingate et al., 2019; Gillespie et al., 2018), plant phenology (Bai et al., 2019; Novillo et al., 2019; Y. Liu et al., 2015), trophic interactions (Luan et al., 2018), biomass (Galvão et al., 2011), and the global carbon cycle (Novillo et al., 2019). Given the relatively fine spatial resolution of 30 m and moderately high temporal resolution of 16 days of Landsat imagery (Xu et al., 2017), the generated NDVI have the potential to answer many questions that require high spatial and temporal details in the index.

Traditionally, accessing the Landsat data that requires a reliable source with easy-to-interact API, and deriving the NDVI over a large space and for a long time period is a computationally intensive task. Both of these complexities are addressed by Google Earth Engine (GEE), which is a cloud-computing platform (Prasai et.al, 2021; Gorelick et al., 2017; Thapa & Prasai, 2022). GEE utilizes Google's computational infrastructure and open access remote sensing datasets (Coleman et al., 2020; Mutanga & Kumar, 2019). The GEE platform enables users and researchers to easily and quickly access freely available public data archives which can be used to develop global and large-scale remote sensing applications (Xia et al., 2019; Midekisa et al., 2017). Historically, such analyses required that researchers find the appropriate source of remote sensing data, download and store them locally and run the computation algorithms in their local machine (Coleman et al., 2020). Analyses were limited by local storage, processing power, and the time required to download very large datasets (Prasai et al.,2021). With GEE, data from various sources are immediately available for analysis without having to download locally (Gorelick et al., 2017). GEE also provides free powerful Graphics Processing Unit (GPU) that can analyze raster data faster than local computers (Coleman et al., 2020). GEE has the features of an automatic parallel processing and

fast computational platform to effectively deal with the challenges of big data processing (Coleman et al., 2020; Martin et al., 2019; Gorelick et al., 2017). In addition, users can study and explore their own dataset in the GEE platform (Coleman et al., 2020; Shaharum et al., 2020; Xia et al., 2019). GEE has been used in a number of research projects related to vegetation mapping and monitoring (Xia et al., 2019) , land cover mapping (Hamunyela et al., 2020), crops mapping (Thieme et al., 2020) , disaster management (Midekisa et al., 2017), earth sciences related research, and several similar studies (Xia et al., 2019). We used GEE python API to assess NDVI trends for the years 1988–2020 in Chitwan National Park (CNP), Nepal. The objectives of this study were to (1) assess the vegetation dynamics in CNP from 1988–2020 and (2) evaluate the utility of GEE Python API in deriving NDVI information. In this study, we studied annual and seasonal NDVI changes in CNP from 1988–2020 to identify its annual and seasonal variation. Although numerous studies on vegetation dynamics have been conducted in this region (Dai et al.,2020; Baniya et al., 2018; Krakaeur et al., 2017), only limited studies have used remote sensing approach and none has used GEE, one of the newest methodological approaches.

2. Materials And Methods

2.1 Study Area

Our study area was focused on Chitwan National Park, Nepal (Figure1). CNP is located between 27°18’ to 27°41’ N latitude and 83°41’ to 83°49’ E longitude (Thapa & Kelly, 2017) in south-central Nepal. CNP includes a core park area of 952.63 km^2 and a buffer zone (750 km^2) surrounding the core park (Kafley et al., 2019). Elevation ranges between 100 m in lowland terai and 815 m in the Churia hills. Highest and lowest recorded temperature in Chitwan National Park are 27 and 14°C, respectively, with mean annual temperatures of 21°C (Miami & Dongol, 2018). Precipitation averages approximately 2500 mm/year. The park includes diverse ecological systems ranging from early successional communities on alluvial floodplains along the Narayani, Rapti and few watersheds to the climax forests in the foothills and on the slopes of the Churia Range (Plains & Park, 2019). Most of CNP is covered with forest (around 70%) that are composed predominantly of deciduous and semi-deciduous trees (Prasai, 2021). Remaining areas are occupied by various land cover types such as agriculture and settlement (15%), grassland (around 8%), and riverbank and exposed surfaces (around 7%) (Plains & Park, 2019). CNP also includes plant communities representative of the terai-duar savanna and grassland ecoregion, which is listed among the 200 globally important areas of biodiversity in the world because of its rich diversity of large mammals (Wikramanayake et al., 2001).

2.2 Data extraction and preparation

We used GEE database to extract Landsat image collections. We used Landsat 5, 7 and 8 to calculate NDVI for the years 1988– 2020. We used Landsat collection 2 tier 1 products. These products have been atmospherically corrected to use for the analyses (Gorelick et al., 2017).We merged the Landsat collections and matched their bands before calculating NDVI. We used the image collections that have

less than 20 % cloud cover in our study. We clipped the Landsat data to our study area using the boundary file of CNP uploaded in our GEE private database.

2.2.1.Data cleaning and processing

We performed exploratory data analyses and plotted the seasonal and overall NDVI using matplotlib in Python (Figure 2). We recorded non-parametric distribution and non-stationary behavior of our dataset (Figures 3) and chose Thiel Sen regressor which is appropriate in non-parametric datasets to study the trends (Buitinck *et al.,* 2013).

We developed a Python function to calculate NDVI for the entire time frame and to automate the calculation process (Figure 2). Then we developed another Python function to calculate the average value of pixels of the study area and calculated a single daily NDVI value for the years 1988–2020. We used the mean as the reducer function for this function. The average value of NDVI can be used to study the vegetation productivity change in any place (Krakaeur et al., 2017). When the NDVI values are averaged on a regional scale, cloud contamination and small-scale actual changes are expected to balanced out (Dai et al. 2020). We calculated missing values of NDVI data using linear interpolation technique. Then we constructed a dataframe for our NDVI values with the corresponding dates and group those datasets in different seasons using pandas package in Python. We grouped and filtered the daily NDVI records into 5 datasets (4 seasons + 1 overall NDVI). We classified seasons as winter (December–February), pre-monsoon (March–May), monsoon (June–September) and post-monsoon (October–November) based on temperature and precipitation patterns in Nepal ((Baniya et al., 2018).

2.3 Data analyses

2.3.1 Thiel Sen estimator

We used a Thiel Sen regressor in GEE Python API to estimate the time series trend. Temporal changes in vegetation indices can be quantified using the Thiel Sen regression models, either by aggregating NDVI/pixel value of a day to a single annual value or by incorporating a seasonality parameter (Xu et al., 2017). Thiel Sen Estimator is insensitive to outliers and is more appropriate in cases of non-parametric datasets (Figure 4) than simple linear regression models (Buitinck *et al.*, 2013). It is also known by the name Sen's slope estimator, slope selection, or single median method. It is a common non-parametric technique for estimating a linear trend (Buitinck *et al.*, 2013). We calculated regression coefficients and p-values using Theil Sen regressor function in Python (Figure 4). We also calculated the mean and standard deviations of four distinct seasons and overall annual data using mean and standard deviation functions in Python (Figure 4).

2.3.2 Decomposition

Decomposition is a technique used to separate the series into its additive components and use each one depending on the nature of the research. We studied seasonal patterns and multi-year trends of NDVI in CNP from 1988–2020 and plotted those using matplotlib in Python (Figures 4 and Figure 5). A trend

exists if there is a persistent increase/decrease pattern over time and seasonal pattern exists when a time series is influenced by seasonal components/factors (Xu et al., 2017).

3. Results

We observed positive trends of NDVI in all seasons in CNP from 1988–2020 (Figure 4 a) before decomposition of the values into trends and seasons. These inter annual trends ranged between 0.0005 per year and 0.0007 per year. The seasonal NDVI in the duration of study exhibited the characteristic bimodal distribution (Figure 3). With an annual NDVI of 0.395, the seasonal NDVI ranged between 0.341 and 0.357 (Fig 3).

We then decomposed the series into the trend and seasonal components. Seasonal component reflects to the normal component of the time series that occur every year to the same extent.

We also recorded seasonal behavior in the NDVI during the studied time frame (Figures 4 and Figure 5). Trend component shows the long term progression in the time series data and seasonal component describes if there is a seasonal pattern (normal component that occur every year to the same extent) in time series data (Xu et al., 2017).

4. Discussion

We observed a positive trend of NDVI in CNP for the period 1988–2020 (Figure 4 a). This trend holds for the complete time series of NDVI as well as for its seasonal values. A positive NDVI trend can result from an improved ecosystem conditions (Stapp et al., 2016; Sarma et al., 2015). Recent ecological restoration programs (https://bansanchar.com/wp-content/uploads/2019/01/State-of-Nepals-Forests-DFRS_1457599484.pdf) might have enhanced green vegetation cover in CNP that explains the positive trend of NDVI. A recent study by Baniya et.al (2018) analyzing NDVI of entire country of Nepal for the period 1982–2015 found similar results with comparable annual rates of positive changes (0.0008 per year). This study shows that the ecology and ecosystem conditions are better in the country.

The positive trend of NDVI may be attributed to increasing forest cover in the country. For example, in 1987–1998, forest covered 39.6% of the total area (Stapp et al., 2016). In 2010-2014, the forest cover in Nepal was reported as 40.36% of total national surface. A growing body of literature has indicated that community-based forest management has been effective in controlling forest degradation in Nepal at least in the last 25 years (Adhikari et al., 2021; Thapa et al., 2020; Baniya et al., 2018; Stapp et al., 2016). Stapp et al. (2016) showed that people's participation in community forestry program in CNP directly strengthened the forest conservation. During the mid-20th century, the lowland forests of southern Nepal were rapidly cleared to promote timber harvest, agricultural expansion, and malaria eradication (Stapp et al., 2016). Furthermore, increased migration, due to development in infrastructures in Terai during the 20th century resulted in development of commercial forestry, expansion of agriculture, and settlements which in turn led to forest clearing (Baniya et al., 2018; Stapp et al., 2016).

Implementation of the National Parks and Wildlife Conservation Act of 1973, the Forest Act of 1993 and the Forest Rules and Regulations of 1995 to establish regulations for government managed forests, protected forests, private and leasehold forests, and community forests further supported restoration of degraded forest in the country (Baniya et al., 2018; Stapp et al., 2016). These acts also helped in restoring and stabilizing degraded floodplain in CNP after the massive Rapti River floods in 1993 (Stapp et al., 2016).

This is the first study to derive and analyze vegetation index of Nepal using GEE Python API and its vast remote sensing data library. GEE Python API has supported planetary scale analyses and offered a technique to monitor the Earth's physical surface at high and temporal resolution (Mutanga & Kumar, 2019; Venkatappa et al., 2019). The innovative processing workflow used in our study with a focus on the unification of different data formats provide a foundation to turn similar future projects into community-based platforms for radar data processing, analysis and conversion (Liu et al., 2015).

GEE Python API can be useful in conducting research related to population mapping (Gorelick et al., 2017; Hamunyela et al., 2020; Xia et al., 2019), water resource mapping (Gorelick et al., 2017), forest mapping (Hamunyela et al., 2020), and cropland mapping (Thieme et al., 2020), among others. Researchers having some prior programming language experience, particularly in parallel processing, should be able to use GEE Python API with little help. There are abundant online resources, tutorials and instructions for those willing to learn the skills to work on this platform (Coleman et al., 2020). Google also offers GEE workshops suitable for those with various coding and remote sensing experiences.

5. Conclusion

In this study, we presented a method to study NDVI annual and seasonal trends using GEE Python API. We observed a positive annual and seasonal trend in NDVI in CNP, Nepal during a 32-year period. Our main objective was to demonstrate that GEE Python API could be rapidly used to perform a time-series analysis of NDVI trends. We therefore completed all remote sensing analyses (e.g., image retrieval, image analysis, classification and report generation) using GEE Python API. This cloud-based processor proved to be a powerful and efficient tool. Thus, we believe that the open-source nature of GEE Python API and its library of remote sensing data could impact remote sensing projects throughout the world (Prasai et. al, 2021).

Declarations

Author Contributions: Conceptualization, Ritika Prasai; methodology, Ritika Prasai; data cleaning, Ritika Prasai; writing—original draft preparation, Ritika Prasai; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: Thanks to Dr. Qiusheng Wu for his online resource materials.

References

Adhikari, D., Prasai, R., Lamichhane, S., Gautam, D., Sharma, S., & Acharya, S. (2021). Climate Change Impacts and Adaptation Strategies in Trans-Himalaya Region of Nepal. *Journal of Forest and Livelihood*, *20*, 1.

Bai, Y., Yang, Y., & Jiang, H. (2019). Intercomparison of AVHRR GIMMS3g, terra MODIS, and SPOT-VGT NDVI products over the Mongolian Plateau. *Remote Sensing*, *11*(17). https://doi.org/10.3390/rs11172030

Baniya, B., Tang, Q., Huang, Z., Sun, S., & Techato, K. anan. (2018). Spatial and temporal variation of NDVI in response to climate change and the implication for carbon dynamics in Nepal. *Forests*, *9*(6). https://doi.org/10.3390/f9060329

Coleman, R. W., Stavros, N., Yadav, V., & Parazoo, N. (2020). A simplified framework for high-resolution urban vegetation classification with optical imagery in the Los Angeles Megacity. *Remote Sensing*, *12*(15). https://doi.org/10.3390/RS12152399

Connell, J. H., & Orias, E. (1964). The Ecological Regulation of Species Diversity. *The American Naturalist*, *98*(903), 399–414. https://doi.org/10.1086/282335

Dai, J., Roberts, D. A., Stow, D. A., An, L., & Zhao, Q. (2020). Green Vegetation Cover Has Steadily Increased since Establishment of Community Forests in Western Chitwan, Nepal. *Remote Sensing*, *12*(24), 4071. doi:10.3390/rs12244071

Galvão, L. S., dos Santos, J. R., Roberts, D. A., Breunig, F. M., Toomey, M., & de Moura, Y. M. (2011). On intra-annual EVI variability in the dry season of tropical forest: A case study with MODIS and hyperspectral data. *Remote Sensing of Environment*, *115*(9), 2350–2359. https://doi.org/10.1016/j.rse.2011.04.035

Gillespie, T. W., Ostermann-Kelm, S., Dong, C., Willis, K. S., Okin, G. S., & MacDonald, G. M. (2018). Monitoring changes of NDVI in protected areas of southern California. *Ecological Indicators*, *88*, 485–494. https://doi.org/10.1016/j.ecolind.2018.01.031

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hamunyela, E., Rosca, S., Mirt, A., Engle, E., Herold, M., Gieseke, F., & Verbesselt, J. (2020). Implementation of BFASTmonitor Algorithm on Google Earth Engine to support large-area and sub-annual change

monitoring using Earth Observation Data. *Remote Sensing*, *12*(18), 2953. https://doi.org/10.3390/rs12182953

Inman, V. L., & Lyons, M. B. (2020). Automated inundation mapping over large areas using Landsat data and google earth engine. *Remote Sensing*, *12*(8). https://doi.org/10.3390/RS12081348

Kafley, H., Lamichhane, B. R., Maharjan, R., Khadka, M., Bhattarai, N., & Gompper, M. E. (2019). Tiger and leopard co-occurrence: intraguild interactions in response to human and livestock disturbance. *Basic and Applied Ecology*, *40*(November), 78–89. https://doi.org/10.1016/j.baae.2019.07.007

Kafley, H., Lamichhane, B. R., Maharjan, R., Thapaliya, B., Bhattarai, N., Khadka, M., & Gompper, M. E. (2019). Estimating prey abundance and distribution from camera trap data using binomial mixture models. *European Journal of Wildlife Research*, *65*(5), 0–14. https://doi.org/10.1007/s10344-019-1308-0

Kim, Y., Park, N. W., & Lee, K. Do. (2017). Self-learning based land-cover classification using sequential class patterns from past land-cover maps. *Remote Sensing*, *9*(9). https://doi.org/10.3390/rs9090921

Krakauer, N., Lakhankar, T., & Anadón, J. (2017). Mapping and Attributing Normalized Difference Vegetation Index Trends for Nepal. *Remote Sensing*, *9*(10), 986. doi:10.3390/rs9100986

Liu, X., Zhu, X., Li, S., Liu, Y., & Pan, Y. (2015). Changes in growing season vegetation and their associated driving forces in China during 2001-2012. *Remote Sensing*, *7*(11), 15517–15535. https://doi.org/10.3390/rs71115517

Liu, Y., Li, Y., Li, S., & Motesharrei, S. (2015). Spatial and temporal patterns of global NDVI trends: Correlations with climate and human factors. *Remote Sensing*, *7*(10), 13233–13250. https://doi.org/10.3390/rs71013233

Luan, J., Liu, D., Zhang, L., Huang, Q., Feng, J., Lin, M., & Li, G. (2018). Analysis of the spatial-temporal change of the vegetation index in the upper reach of Han River Basin in 2000–2016. *Proceedings of the International Association of Hydrological Sciences*, *379*, 287–292. https://doi.org/10.5194/piahs-379-287-2018

Marino, J. A., Peacor, S. D., Bunnell, D. B., Vanderploeg, H. A., Pothoven, S. A., Elgin, A. K., Bence, J. R., Jiao, J., & Ionides, E. L. (2019). Evaluating consumptive and nonconsumptive predator effects on prey density using field time-series data. *Ecology*, *100*(3), 1–14. https://doi.org/10.1002/ecy.2583

Martin, E. H., Jensen, R. R., Hardin, P. J., Kisingo, A. W., Shoo, R. A., & Eustace, A. (2019). Assessing changes in Tanzania's Kwakuchinja Wildlife Corridor using multitemporal satellite imagery and open source tools. *Applied Geography*, *110*. https://doi.org/10.1016/j.apgeog.2019.102051

Midekisa, A., Holl, F., Savory, D. J., Andrade-Pacheco, R., Gething, P. W., Bennett, A., & Sturrock, H. J. W. (2017). Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud

computing. *PLoS ONE*, *12*(9). https://doi.org/10.1371/journal.pone.0184926

Mlenga, D. H., & Jordaan, A. J. (2020). Integrated drought monitoring framework for Eswatini applying standardised precipitation index and normalised difference vegetation index. *Jàmbá Journal of Disaster Risk Studies*, *12*(1). https://doi.org/10.4102/jamba.v12i1.749

Moffiet, T., Mengersen, K., King, R., Witte, C., & Armston, J. (2006). Modelling of foliage projected cover using Landsat-7 spectral imagery: Spectral indices for greenness and brightness. Transmuted family of distributions-development of View project Socio-spatial statistics View project Modelling of foliage projected cover using Landsat-7 spectral imagery: Spectral indices for greenness and brightness. Conference Paper modelling of foliage projected cover using landsat-7 spectral imagery: spectral indices for greenness and brightness. 20–24. https://doi.org/10.13140/2.1.4855.0726

Moura, Y. M., Galvão, L. S., dos Santos, J. R., Roberts, D. A., & Breunig, F. M. (2012). Use of MISR/Terra data to study intra- and inter-annual EVI variations in the dry season of tropical forest. *Remote Sensing of Environment*, *127*, 260–270. https://doi.org/10.1016/j.rse.2012.09.013

Mutanga, O., & Kumar, L. (2019). Google earth engine applications. In *Remote Sensing* (Vol. 11, Issue 5). MDPI AG. https://doi.org/10.3390/rs11050591

Novillo, C. J., Arrogante-Funes, P., & Romero-Calcerrada, R. (2019). Recent NDVI trends in mainland Spain: Land-cover and phytoclimatic-type implications. *ISPRS International Journal of Geo-Information*, *8*(1). https://doi.org/10.3390/ijgi8010043

Plains, F., & Park, N. (2019). Comparative Study in Habitat Suitability Analysis of Wild Water buffalo (Bubalus arnee) in Two Flood Plains of Chitwan National Park (CNP), Nepal. *International Journal of Research Studies in Zoology*, *5*(3). https://doi.org/10.20431/2454-941x.0503001

Prasai, R. (2022). Earth engine application to retrieve long-term terrestrial and aquatic time series of satellite reflectance data. *International Journal of Multidisciplinary Research and Growth Evaluation*, 165–171. https://doi.org/10.54660/anfo.2022.3.3.11

Prasai, R. (2021). *Distribution of bengal tiger (0RW1S34RfeSDcfkexd09rT2panthera tigris1RW1S34RfeSDcfkexd09rT2) and their main prey species in chitwan national park, nepal* (Order No. 28544104). Available from ProQuest Dissertations & Theses Global. (2555987929). Retrieved from https://zeus.tarleton.edu/login?url=https://www.proquest.com/dissertations-theses/distribution-bengal-tiger-em-panthera-tigris/docview/2555987929/se-2?accountid=7078

Prasai, R., Kafley, H., Upadhaya, S., Thapa, S., Shrestha, P., Dudley, A., & Timilsina, Y. P. (2021). Population status and distribution of the Critically Endangered Bengal Florican Houbaropsis bengalensis in the

grassland of Koshi Tappu Wildlife Reserve, Nepal. *Journal of Threatened Taxa*, *13*(9), 19293–19301. https://doi.org/10.11609/jott.6503.13.9.19293-19301

Prasai, R., Schwertner, T. W., Mainali, K., Mathewson, H., Kafley, H., Thapa, S., Adhikari, D., Medley, P., & Drake, J. (2021). Application of Google earth engine python API and NAIP imagery for land use and land cover classification: A case study in Florida, USA. *Ecological Informatics*, *66*, 101474. https://doi.org/10.1016/j.ecoinf.2021.101474

Rouse, J. W., R. H. Haas, J. A. Schell, and D.W. Deering. (1973). Monitoring vegetation systems in the great plains with ERTS. *Third NASA ERTS Symposium*, NASA SP-351 I, Washington, D.C., USA, 1973, 309–317

Sarma, K., Kumar, A., Krishna, M., Medhi, M., & Tripathi, O. P. (2015). Predicting Suitable Habitats for the Vulnerable Eastern Hoolock Gibbon, Hoolock leuconedys, in India Using the MaxEnt Model. *Folia Primatologica*, *86*(4), 387–397. https://doi.org/10.1159/000381952

Thapa, N., & Prasai, R. (2022). Impacts of Floods in Land Use Land Cover Change:- a Case Study of Indrawati and Melamchi River, Melamchi, and Indrawati Municipality, Nepal. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4104357

Thapa, S., Prasai, R., & Pahadi, R. (2020). Does gender-based leadership affect good governance in community forest management ? A case study from Bhaktapur district. *Banko Janakari*, *30*(2), 59–70. https://doi.org/10.3126/banko.v30i2.33479

Figures

Figure 1

Map of Chitwan National Park, Nepal showing broad land cover and administrative boundaries

Figure 2

Data cleaning and processing in the Jupyter notebook (Source code: https://github.com/RitikaPrasai/Temporal-Variation-of-NDVI-using-GEE-Python-API/blob/main/NDVI%20plots%20in%20time%20series%20in%20python%202020.ipynb)

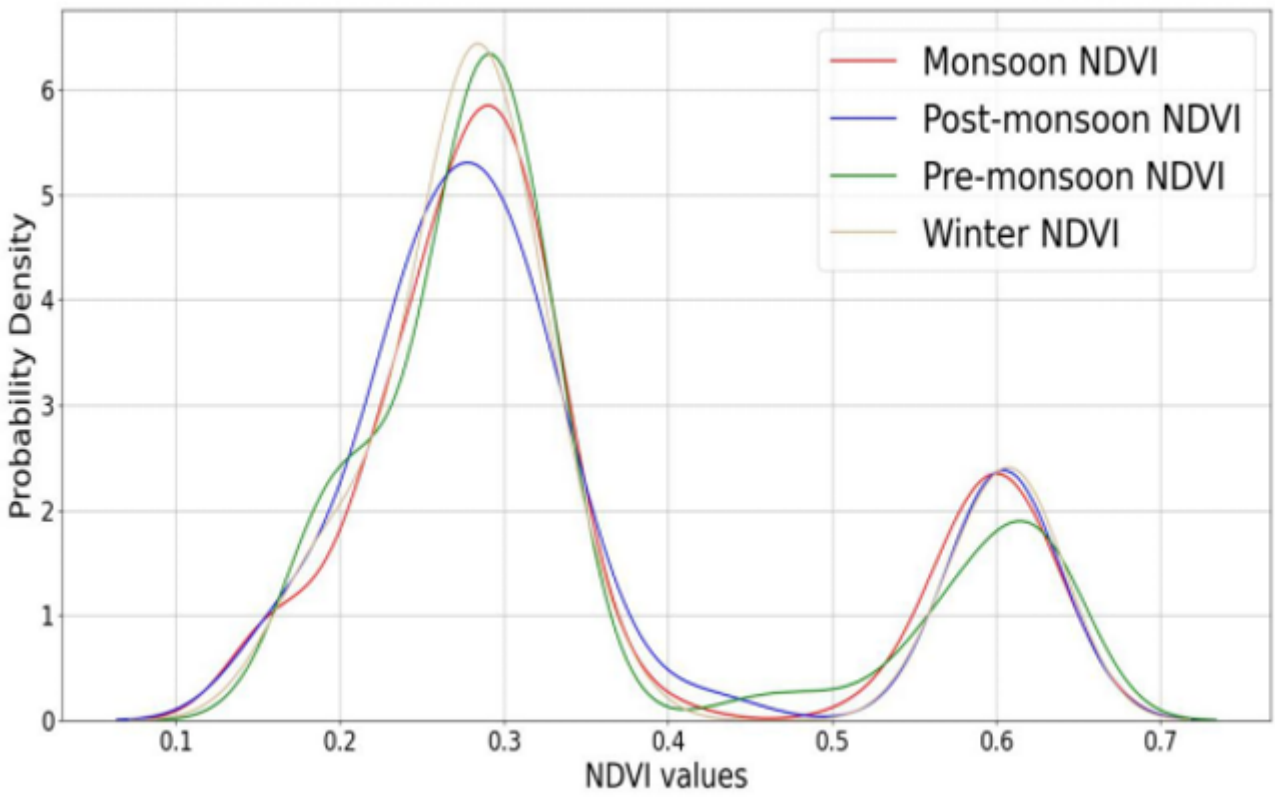

Figure 3

Probability density of Normalized Difference Vegetation Index (NDVI) of four different seasons in Chitwan National Park, Nepal, 1988–2020

Figure 4

Temporal variation of Normalized Difference Vegetation Index (NDVI) trends: (a) Annual, (b) Winter, (c) Pre-monsoon, (d) Post-monsoon, and (e) Monsoon

Figure 5

Time series Normalized Difference Vegetation Index (NDVI) decomposition in Chitwan National Park, Nepal, 1988–2020