International Journal of Multidisciplinary Research and Growth Evaluation.

Earth engine application to retrieve long-term terrestrial and aquatic time series of satellite reflectance data

Ritika Prasai
Department of Biology, Baylor University, Waco, Texas, USA

* Corresponding Author: **Ritika Prasai**

Article Info

ISSN (online): 2582-7138
Volume: 03
Issue: 03
May-June 2022
Received: 09-04-2022;
Accepted: 24-04-2022
Page No: 165-171
DOI:
https://doi.org/10.54660/anfo.2022.3.3.11

Abstract
Google earth engine is an open source cloud based computing platform that is designed to process large scale datasets. Owing to its capacity and features, it can be useful to wide range of applications-the most prominent being vegetation mapping and monitoring, earth sciences related studies and many others. We have developed a web tool based on google earth engine to encourage and assist the researchers from non-programming background to use google earth engine. This application is freely available and can be accessed at https://mapcoordinates.info/. In the current version, this application has some interesting features like data filter, generates time series plots, time series records and metadata in .csv format. Users can download the time series records of any location, select the satellite sensor, choose the model, filter the cloud cover, scale factor. This application also visualizes the time slider feature for the location selected on the map.

Keywords: Google earth engine; database; open source; Python; web-based application; timeseries

1. Introduction

Google earth engine is an open source cloud based computing platform that is designed to process large scale datasets (Prasai et al., 2021, Inman & Lyons, 2020, Gorelick et al., 2017, Midekisa et al., 2017). Users do not require the latest computers or software to work on big data (Phan et al., 2020, Thieme et al., 2020). Owing to its capacity and features, it can be useful to wide range of applications-the most prominent being vegetation mapping and monitoring (Venkatappa et al., 2019, Wang et al., 2015), disaster management (Xia et al., 2019), earth sciences related studies and many others (Prasai et al., 2021). We have developed a web tool based on google earth engine to encourage and assist the researchers from non-programming background to use google earth engine. This application is freely accessible and available at https://mapcoordinates.info/. This tool extracts the datasets from the google earth engine database. It uses Python API to interact with google earth engine database. In the current version, this application has some interesting features like data filter, generates time series plots, time series records and metadata in .csv format. Users can download the time series records of any location, select the satellite sensor, choose the algorithm to process the datasets, filter the cloud cover, scale factor. This application also visualizes the time slider feature for the location selected on the map.

2. Data and Methods

2.1. Conceptual Framework

https://mapcoordinates.info/ has a web-client as the front-end and GEE as computing back-ends. The front end is the graphical user interface (GUI) web client where the users can specify the algorithms, date range, filter the datasets and send requests to run the analyses (Figure 1). We used Ipywidgets a python based library, HTML and CSS to design GUI/front end of this application. Since all storages and computing operations are made on the cloud (GEE), the web-client can be accessed from any browser supporting device such as mobile, laptop or desktop computing devices.

However, the framework is developed mainly with PC environments in mind and thus it is not optimized for mobile applications. The back end uses GEE to access satellite data, conduct the analyses and use Google's cloud computing capabilities. We used Python API to interact with GEE backend. Current version of this tool has 3 algorithms (NDVI/NDCI), 2 BDA, Turbidity Index). We can select the location using polygon icon present on the left corner of the tool. It provides time slider to detect the changes on the map. Users can filter the datasets based on scale, clouds cover, dates. They get the time series datasets and metadata in .csv format and plots after passing request through submit button present on the GUI.

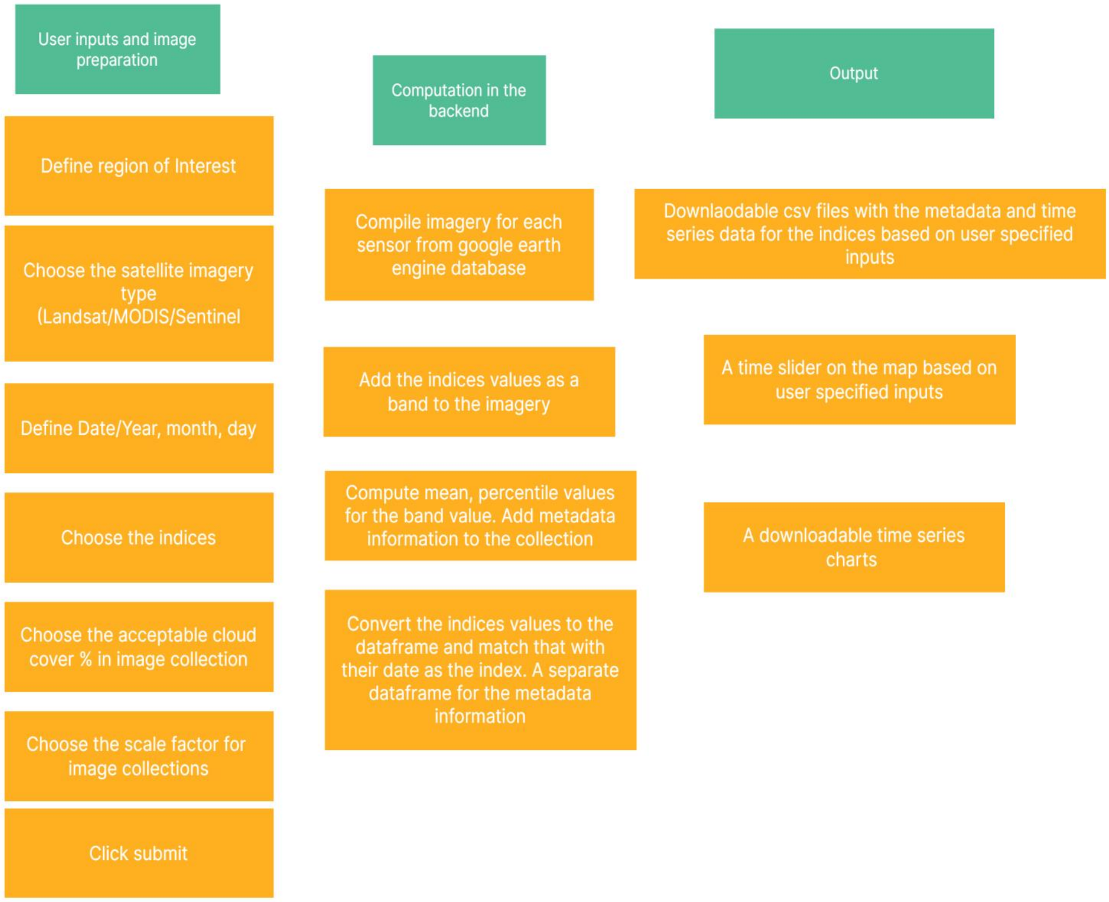
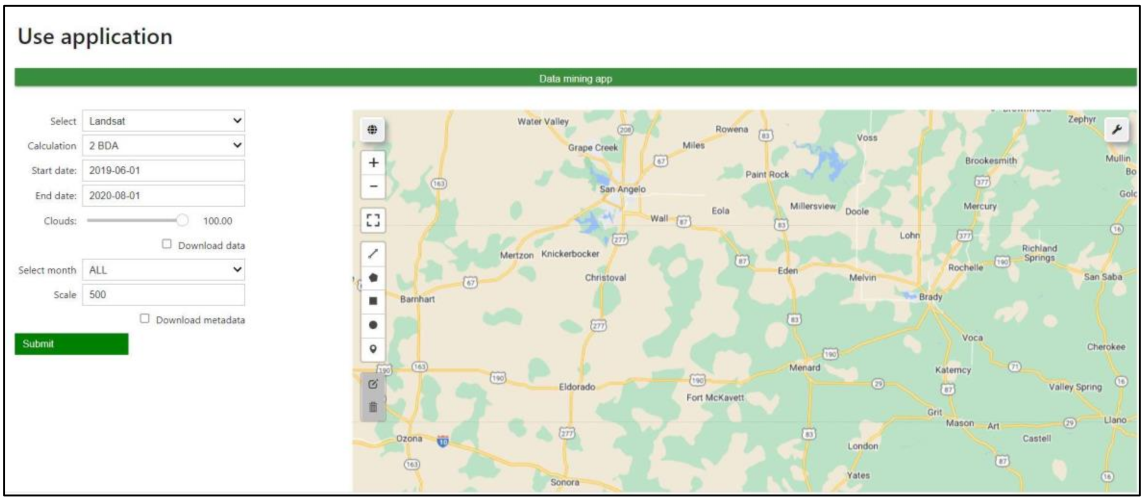
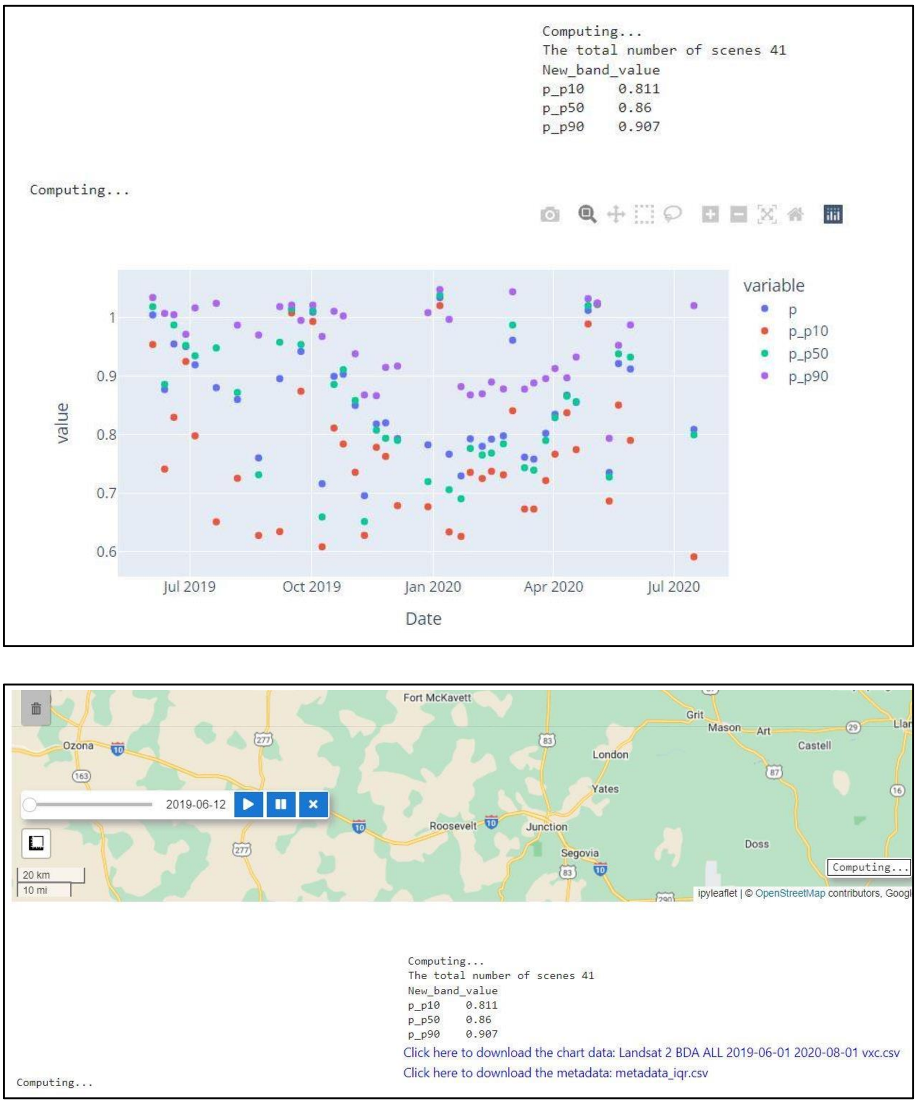


Fig 1: Flow chart describing the overall application design





Source: Video link: https://www.youtube.com/watch?v=jgkYn6oyucY

Fig 2: GUI of the application

2.2. Data

We have included three satellite imagery in the current version: Landsat (1984-current), Sentinel (2015-current) and MODIS (2000-current). We used these datasets from the google earth engine database.

2.2.1. Landsat Datasets

We used Landsat collection 2 tier 1 products available in google earth engine database. These collections include the improved dataset collections over collection 1 which supports recent developments in data processing and algorithm development (Gorelick et al., 2017). These collections have been corrected using the Landsat Ecosystem Disturbance Adaptive Processing System and Land Surface Reflectance Code software. USGS resampled these collections to a spatial resolution of 30 m using cubic convolution. These collections have been then filtered and images of higher quality have been stored in Tier1.

2.2.1.1. Landsat 8 products

We have included atmospherically corrected surface reflectance datasets from the collection 2 tier 1 collections. These products are derived/produced by the Landsat 8 OLI/TIRS sensors (Gorelick et al., 2017). These collections include 5 visible and near infrared bands and 2 short wave bands. We have not included thermal band in this collection. These collections are created with the Land Surface Reflectance code (LaSRC) (Gorelick et al., 2017). More information about this product can be found at (https://developers.google.com/earthengine/datasets/catalog/LANDSAT_LE08_C02_T1_L2.

2.2.1.2. Landsat 7 products

We included atmospherically corrected surface reflectance datasets from the collection 2 tier 1 collections. These datasets contain 4 visible and near-infrared bands and 2 short wave infrared bands which are orthorectified to get surface reflectance, one thermal infrared (TIR) band which is processed to orthorectified surface temperature (Gorelick et al., 2017). There is also intermediate bands used in the calculation of the ST products as well as QA bands. These products are created with the Landsat Ecosystem Disturbance Adaptive Processing Systems (LEDAPS) algorithm (version 3.4.0) (Gorelick et al., 2017). More information about the datasets can be found at (https://developers.google.com/earthengine/datasets/catalog/LANDSAT_LE07_C02_T1_L2)

2.2.1.3. Landsat 5 products

We have included surface reflectance and land surface temperature datasets that are atmospherically corrected and derived from the Landsat TM sensor. These datasets contains 4 visible and near-infrared (VNIR) bands and 2 short-wave infrared (SWIR) bands which are processed to obtain orthorectified surface reflectance, and one thermal infrared (TIR) band processed to orthorectified surface temperature (Gorelick et al., 2017). They also contain intermediate bands used in calculation of the ST products, as well as QA bands (Gorelick et al., 2017). These datasets are created with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (version 3.4.0). More information about these datasets can be obtained from the link: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C02_T1_L2

2.2.1.4. Merging Landsat Products

We used merge algorithm to merge the Landsat products. We matched the bands in Landsat 8 with Landsat 7 and Landsat 5 before merging the datasets. We did not include the thermal band from Landsat 8 products while merging the datasets.

2.2.2. MODIS datasets

We have included the datasets that provides an estimate of the surface reflectance of Terra MODIS bands. They have 7 bands and 500m resolution. The datasets is atmospherically corrected for gasses, aerosols and Rayleigh scattering (Gorelick et al., 2017). There are also quality layer and 4 observation bands included (Gorelick et al., 2017). The value for each pixel is selected from all the acquisitions within the 8-day composite on the basis of high observation coverage, low view angle, the absence of clouds or cloud shadow and aerosol loading. More information of the datasets can be found from the link: https://developers.google.com/earthengine/datasets/catalog/MODIS_006_MOD09A1

2.2.3. Sentinel dataset

This dataset consist high resolution, multi-spectral imaging mission supporting Copernicus Land monitoring. This dataset contains 12 UINT 16 spectral bands representing SR. They were downloaded from scihub and computed by running sen2cor. We used cloud filter to filter out the clouds from the datasets (Gorelick et al., 2017). These datasets are ready to use for monitoring vegetation, soil, water cover as well as observation of inland waterways and coastal areas. More information about the datasets can be found at: https://developers.google.com/earthengine/datasets/catalog/COPERNICUS_S2_SR#description

2.3. Tools and techniques

We used both existing as well as newly developed scripts to retrieve data, compute and visualize. For example, time slider, plots display on the map are existing source codes we used and we developed source codes to design GUI, algorithms and time series computation and download functionality using GEE Python API. Table 1 shows our method of algorithms development based on dataset/satellite imagery type.

```
#algorithms for the calculation for Landsat
#functions to calculate algorithms
def addNdci(img):
    ndci=img.normalizedDifference(['red', 'nir']).rename(name);
    return img.addBands(ndci)

def NDTI(img):
    ndti=img.normalizedDifference(['green', 'red']).rename(name)
    return img.addBands(ndti)


#2BDA algorithm
def bda(img):
    BDA=img.select('nir').divide(img.select('red')).rename(name)
    return img.addBands(BDA)

#3BDA algorithm
def tbda(img):
    BDA=img.select('green').subtract(img.select('red')).divide(img.select('red')).rename(name)
    return img.addBands(BDA)
```

```
#algorithms for the calculation for MODIS
#functions to calculate algorithms
def addNdciM(img):
    ndci=img.normalizedDifference(['sur_refl_b02', 'sur_refl_b01']).rename(name);
    return img.addBands(ndci)

def NDTIM(img):
    ndti=img.normalizedDifference(['sur_refl_b04','sur_refl_b03'  ]).rename(name);
    return img.addBands(ndti)

#2BDA algorithm
def bdaM(img):
    BDA=img.select('sur_refl_b02').divide(img.select('sur_refl_b01')).rename(name)
    return img.addBands(BDA)

#3BDA algorithm
def tbdaM(img):
    BDA=img.select('sur_refl_b04').subtract(img.select('sur_refl_b01')).divide(img.select('sur_refl_b04')).rename(name)
    return img.addBands(BDA)
```

```
#algorithms for the calculation for sentinel
def NDCIs(img):
    ndci=img.normalizedDifference(['B8', 'B4']).rename(name);
    return img.addBands(ndci)

def NDTIs(img):
    ndti=img.normalizedDifference(['B4', 'B3']).rename(name);
    return img.addBands(ndti)

#2BDA algorithm
def bdas(img):
    BDA=img.select('B8').divide(img.select('B4')).rename(name)
    return img.addBands(BDA)

#3BDA algorithm
def tbdas(img):
    BDA=img.select('B3').subtract(img.select('B4')).divide(img.select('B3')).rename(name)
    return img.addBands(BDA)
```

Fig 3: Sample codes used to develop algorithms from the satellite reflectance data

2.3.1. Algorithms used

We used normalized difference vegetation index (NDVI), 2BDA, 3 BDA and Turbidity Index (TI) algorithms in our web-based tool. NDVI is the ratio of red and near infrared bands and used in wide range of research related to assess vegetation health (Gandhi et al., 2015; Prasai, 2021). NDVI is widely used in studying land use land cover (Somayajula et al., 2021), habit suitability (Prasai et al., 2021), species conservation (Nieto et al., 2015), floods and risk mapping (Gabban et al., 2006) related research projects. Normalized difference chlorophyll index (NDCI) is also the ratio of red and near infrared bands and used to quantify the chlorophyll pigments in inland water bodies (S. Mishra & Mishra, 2012) 2BDA and 3BDA algorithms are also used to extract chlorophyll concentration in inland water bodies (Buma & Lee, 2020). TI is one of the water quality parameters and gives information about the clarity of the water (Zheng & DiGiacomo, 2020).

Table 1: Algorithms used in the web-based tool

Sensor Image	Index	Band combination
Landsat	NDVI/NDCI	(Near Infrared-Red)/(Near Infrared + Red)
	2BDA	Near Infrared/Red
	3 BDA	(Green-Red)/(Green + Red)
	TI	(Green-Red)/Red
MODIS	NDVI/NDCI	(Sur_refl_b02- Sur_refl_b01)/ (Sur_refl_b02 + Sur_refl_b01)
	2 BDA	Sur_refl_b02/Sur_refl_b0
	3 BDA	(Sur_refl_b04- Sur_refl_b03)/ (Sur_refl_b04
	TI	(Sur_refl_b04- Sur_refl_b03)/ (Sur_refl_b04 + Sur_refl_b03)
Sentinel	NDVI/NDCI	(B8-B4)/(B8 + B4)
	2 BDA	B8/B4
	3 BDA	(B3-B4)/(B3)
	TI	(B4-B3)/(B4 + B3)

References

1. Augusto-Silva P, Ogashawara I, Barbosa C, de Carvalho L, Jorge D, Fornari C, *et al*. Analysis of MERIS Reflectance Algorithms for Estimating Chlorophyll-a Concentration in a Brazilian Reservoir. Remote Sensing. 2014; 6(12):11689-11707. https://doi.org/10.3390/rs61211689
2. Bai Y, Yang Y, Jiang H. Inter comparison of AVHRR GIMMS3g, terra MODIS, and SPOT-VGT NDVI products over the Mongolian Plateau. Remote Sensing, 2019, 11(17). https://doi.org/10.3390/rs11172030
3. Buma WG, Lee SI. Evaluation of Sentinel-2 and Landsat 8 Images for Estimating Chlorophyll-a Concentrations in Lake Chad, Africa. Remote Sensing. 2020; 12(15):2437. https://doi.org/10.3390/rs12152437.
4. Gabban A, San-Miguel-Ayanz J, Viegas DX. On the suitability of the use of normalized difference vegetation index for forest fire risk assessment. International Journal of Remote Sensing. 2006; 27(22):5095-5102. https://doi.org/10.1080/01431160500185656.
5. Gandhi GM, Parthiban S, Thummalu N, Christy A. Ndvi: Vegetation Change Detection Using Remote Sensing and Gis-A Case Study of Vellore District. Procedia Computer Science. 2015; 57:1199-1210. https://doi.org/10.1016/j.procs.2015.07.415.
6. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment. 2017; 202:18-27. https://doi.org/10.1016/j.rse.2017.06.031
7. Hamunyela E, Rosca S, Mirt A, Engle E, Herold M, Gieseke F, Verbesselt J. Implementation of BFAST monitor Algorithm on Google Earth Engine to support large-area and sub-annual change monitoring using Earth Observation Data. Remote Sensing. 2020; 12(18):2953. https://doi.org/10.3390/rs12182953.
8. Inman VL, Lyons MB. Automated inundation mapping over large areas using Landsat data and google earth engine. Remote Sensing, 2020, 12(8). https://doi.org/10.3390/RS12081348
9. Johansen R, Beck R, Nowosad J, Nietch C, Xu M, Shu S, Yang B, *et al*. Evaluating the portability of satellite derived chlorophyll-a algorithms for temperate inland lakes using airborne hyperspectral imagery and dense surface observations. Harmful Algae. 2018; 76:35-46. https://doi.org/10.1016/j.hal.2018.05.001.
10. Kim Y, Park NW, Lee KDo. Self-learning based land-cover classification using sequential class patterns from past land-cover maps. Remote Sensing, 2017, 9(9). https://doi.org/10.3390/rs9090921.
11. Krakauer N, Lakhankar T, Anadón J. Mapping and Attributing Normalized Difference Vegetation Index Trends for Nepal. Remote Sensing. 2017; 9(10):986.

doi:10.3390/rs9100986.
12. Le C, Hu C, Cannizzaro J, English D, Muller-Karger F, Lee Z. Evaluation of chlorophyll-a remote sensing algorithms for an optically complex estuary. Remote Sensing of Environment. 2013; 129:75-89. https://doi.org/10.1016/j.rse.2012.11.001.
13. Liu X, Zhu X, Li S, Liu Y, Pan Y. Changes in growing season vegetation and their associated driving forces in China during 2001-2012. Remote Sensing. 2015; 7(11):15517-15535. https://doi.org/10.3390/rs71115517.
14. Liu Y, Li Y, Li S, Motesharrei S. Spatial and temporal patterns of global NDVI trends: Correlations with climate and human factors. Remote Sensing. 2015; 7(10):13233-13250. https://doi.org/10.3390/rs71013233.
15. Luan J, Liu D, Zhang L, Huang Q, Feng J, Lin M, *et al*. 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. 2018; 379:287-292. https://doi.org/10.5194/piahs-379-287-2018
16. Merve Kaymaz E. Estimating Chlorophyll-A Concentration using Remote Sensing Techniques. Annals of Reviews & Research, 2018, 4(2). https://doi.org/10.19080/arr.2018.04.555633
17. Midekisa A, Holl F, Savory DJ, Andrade-Pacheco R, Gething PW, Bennett A, *et al*. Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. PLOS ONE, 2017, 12(9):e0184926. https://doi.org/10.1371/journal.pone.0184926
18. Mishra S, Mishra DR. Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. Remote Sensing of Environment. 2012; 117:394-406. https://doi.org/10.1016/j.rse.2011.10.016.
19. Mishra S, Mishra DR. Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. Remote Sensing of Environment. 2012; 117:394-406. https://doi.org/10.1016/j.rse.2011.10.016
20. Mlenga DH, Jordaan AJ. Integrated drought monitoring framework for Eswatini applying standardized precipitation index and normalised difference vegetation index. Jàmbá Journal of Disaster Risk Studies, 2020, 12(1). https://doi.org/10.4102/jamba.v12i1.749.
21. Moses WJ, Gitelson AA, Berdnikov S, Saprygin V, Povazhnyi V. Operational MERIS-based NIR-red algorithms for estimating chlorophyll-a concentrations in coastal waters-The Azov Sea case study. Remote Sensing of Environment. 2012; 121:118-124. https://doi.org/10.1016/j.rse.2012.01.024
22. Moura YM, Galvão LS, dos Santos JR, Roberts DA, Breunig FM. Use of MISR/Terra data to study intra- and inter-annual EVI variations in the dry season of tropical forest. Remote Sensing of Environment. 2012; 127:260-270. https://doi.org/10.1016/j.rse.2012.09.013
23. Mutanga O, Kumar L. Google earth engine applications. In Remote Sensing, 2019, 11(5). MDPI AG. https://doi.org/10.3390/rs11050591.
24. Nieto S, Flombaum P, Garbulsky MF. Can temporal and spatial NDVI predict regional bird-species richness? Global Ecology and Conservation. 2015; 3:729-735. https://doi.org/10.1016/j.gecco.2015.03.005
25. Novillo CJ, Arrogante-Funes P, Romero-Calcerrada R. Recent NDVI trends in mainland Spain: Land-cover and phytoclimatic-type implications. *ISPRS International* Journal of Geo Information, 2019, 8(1). https://doi.org/10.3390/ijgi8010043.
26. Pedreros-Guarda M, Abarca-del-Río R, Escalona K, García I, Parra S. A Google Earth Engine Application to Retrieve Long-Term Surface Temperature for Small Lakes. Case: San Pedro Lagoons, Chile. Remote Sensing. 2021; 13(22):4544. https://doi.org/10.3390/rs13224544.
27. Phan TN, Kuch V, Lehnert LW. Land Cover Classification using Google Earth Engine and Random Forest Classifier-The Role of Image Composition. Remote Sensing. 2020; 12(15):2411. https://doi.org/10.3390/rs12152411.
28. Poddar S, Chacko N, Swain D. Estimation of Chlorophyll-a in Northern Coastal Bay of Bengal Using Landsat-8 OLI and Sentinel-2 MSI Sensors. Frontiers in Marine Science, 2019, 6. https://doi.org/10.3389/fmars.2019.00598
29. Prasai R. Distribution of Bengal Tiger (Panthera tigris) and Their Main Prey Species in Chitwan National Park, Nepal (Doctoral dissertation, Tarleton State University), 2021.
30. Prasai R, Kafley H, Upadhaya S, Thapa S, Shrestha P, Dudley A, Timilsina YP. 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. 2021; 13(9):19293-19301. https://doi.org/10.11609/jott.6503.13.9.19293-19301.
31. Prasai R, Schwertner TW, Mainali K, Mathewson H, Kafley H, Thapa S, *et al*. 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. 2021; 66:101474. https://doi.org/10.1016/j.ecoinf.2021.101474
32. Rouse JW, RH Haas, JA. Schell, DW Deering. Monitoring vegetation systems in the great plains with ERTS. Third NASA ERTS Symposium, NASA SP-351 I, Washington, DC, USA, 1973, 309-317
33. Somayajula VKA, Ghai D, Kumar S. Land Use/Land Cover Change Analysis using NDVI, PCA. 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021. https://doi.org/10.1109/iccmc51019.2021.9418025
34. Thieme A, Yadav S, Oddo PC, Fitz JM, McCartney S, King L, *et al*. Using NASA Earth observations and Google Earth Engine to map winter cover crop conservation performance in the Chesapeake Bay watershed. Remote Sensing of Environment. 2020; 248:111943. https://doi.org/10.1016/j.rse.2020.111943
35. Venkatappa Sasaki, Shrestha Tripathi, Ma. Determination of Vegetation Thresholds for Assessing Land Use and Land Use Changes in Cambodia using the Google Earth Engine Cloud-Computing Platform. Remote Sensing. 2019; 11(13):1514. https://doi.org/10.3390/rs11131514.
36. Wang H, Zhao Y, Pu R, Zhang Z. Mapping Robinia Pseudoacacia Forest Health Conditions by Using Combined Spectral, Spatial, and Textural Information Extracted from IKONOS Imagery and Random Forest

Classifier. Remote Sensing. 2015; 7(7):9020-9044. https://doi.org/10.3390/rs70709020.
37. Wang S, Li J, Zhang B, Lee Z, Spyrakos E, Feng L, *et al*. Corrigendum to ‘Changes of water clarity in large lakes and reservoirs across China observed from long-term MODIS’ [Remote Sensing of Environment 247 (2020)]. Remote Sensing of Environment. 2020; 248:111984. https://doi.org/10.1016/j.rse.2020.111984.
38. Xia H, Zhao J, Qin Y, Yang J, Cui Y, Song H, *et al*. Changes in Water Surface Area during 1989–2017 in the Huai River Basin using Landsat Data and Google Earth Engine. Remote Sensing. 2019; 11(15):1824. https://doi.org/10.3390/rs11151824.
39. Yang C, Ye H. Enhanced Chlorophyll-a in the Coastal Waters near the Eastern Guangdong during the Downwelling Favorable Wind Period. Remote Sensing. 2022; 14(5):1138. https://doi.org/10.3390/rs14051138.
40. Zhang D, Yang X, Sun X, Gong J, Liu Y. Dynamic change and quantitative analysis of Zhelin Bay based on multi-source spatial data. SPIE Proceedings, 2008. https://doi.org/10.1117/12.812742
41. Zheng G, DiGiacomo P. A simple water clarity-turbidity index for marine andinland waters: Great Lakes case study. A Simple Water Clarity-Turbidity Index for Marine Andinland Waters: Great Lakes Case Study, 2020. https://doi.org/10.1002/essoar.10503921.1.