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Satellite-Based Assessment of Crop Gross Primary Productivity and Yield Using MODIS Datasets and GEE approach: A Case Study of Maharashtra state of India

Ravi Sharma[1*], Kaywan Othman Ahmed[2], Cheikh Faye[3]

[1]Department of Civil Engineering, School of Core Engineering, Faculty of Science, Technology and Architecture (FoSTA), Manipal University Jaipur, Dehmi Kalan, Jaipur303007, India

[2] Civil Engineering Department, Tishk International University, Sulaimani, Iraq; Kaywan.osman@tiu.edu.iq

[3]Department of Geography, U.F.R. Sciences et Technologies, Laboratory of Geomatics and Environment, Assane Seck Univesity of Ziguinchor, BP 523, Ziguinchor, Dakar, Senegal; cheikh.faye@univ-zig.sn

*Corresponding author: rvmudgal@gmail.com

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Abstract

Satellite remote sensing data, combined with carbon cycle processes, has led to the development of several models for estimating vegetation productivity. There is a growing interest in accurate crop yield assessments using these methods for county observing and agricultural resiliency with food safety. The existing methods used to estimate vegetation productivity from satellite data at a global scale may not accurately account for the differences in crop growth patterns and variability within agricultural land. A recent report estimated crop yields in six administrative divisions of Maharashtra State, India, including Amravati, Aurangabad, Konkan, Nagpur, Nashik, and Pune. The study was used the satellite datasets such as MOD17A2H.006: Terra Gross Primary Productivity 8-Day Global 500m data to estimate gross primary productivity (GPP) over croplands at 500-m spatial resolution. These datasets are prepared by using the radiation-use efficiency idea and may be utilized as input data to models for calculating hydrological cycle systems and biogeochemistry of flora. Notably, there are no limitations on the utilization, commercialization, or distribution of the data and products obtained from the LP DAAC, specifically those derived from MODIS.

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The research utilized a method of estimating crop yields by multiplying crops' calculated Gross Primary Productivity (GPP) during the growing season with a standard Harvest Index (HI) at a resolution of 500 meters. This approach successfully captured the typical productivity patterns and seasonal changes in cropland, providing reassurance about the accuracy of the study's methods. The study concludes are very effective techniques and results for practical crop yield monitoring on are regional and local scales. The research findings also highlight the potential for utilizing global satellite interpretations to enhance agricultural management, inform policy decisions, and improve the food security of regions and the world. In conclusion, this study shows the potential of satellite remote sensing data for accurately estimating crop yields and informing agricultural policies at a regional level. The availability of MODIS data and products using LP DAAC facilitates further research in this area, potentially leading to improved agricultural management and food security.

Keywords: Crop yield, Gross primary productivity (GPP), MODIS, Google earth engine (GEE); Agriculture system

1. Introduction

Accurately measuring crop yield at local and worldwide scales is crucial for making informed agricultural decisions and policies. Various techniques have been created to assess crop yield for different types of crops. Agricultural surveys are reliable for estimating crop yield, but they become less effective when dealing with greater areas due to their period and an economic restriction. To overcome these limitations, remote sensing through satellite imagery has become popular for agronomic applications with crop yield observation. The efficiency of these remote sensing techniques, such as recent satellite histories like MODIS data, offer global coverage and frequent observations while being complex to photosynthetic plant cover. These records also deliver moderately long-term overlying records and consistent sampling. Old-style methods for estimating crop yield rely on experiential relations among vegetation biomass and satellite spectral vegetation indices. Gross primary productivity (GPP) measures the quantity of carbon fixed in photosynthesis by all producers in ecology. However, producers' metabolic processes (respiration) consume much of this energy. Monitoring GPP is critical in considering worldwide carbon budgets and terrestrial environment dynamics and supporting nutrition, feed, timber, and fibre creation, which are essential for human welfare and development. In the past two decades, remote sensing techniques have been utilized to derive various GPP products with dissimilar spatial and temporal characteristics (Xiao et al., 2019).

The net primary productivity is the fixed carbon amount not used by plants and is available to various consumers in the ecosystem. In a stable ecosystem, there is a balance between gross primary productivity and total consumption, resulting in no net accumulation or reduction in the total organic matter present. A different method for assessing crop produce involves using the GPP of vegetation and empirical harvest index (HI), which are exactly applied to dissimilar kinds of crops. GPP, which represents the carbon absorbed through photosynthesis, is assessed using light use efficiency (LUE) model and satellite inputs at spatial and temporal rulers appropriate for agricultural applications. The MOD17A2H.006 creation delivers constant GPP approximations with eight-day temporal reliability and 500-m spatial resolution for entire vegetated ecologies globally from 2000 onwards. While GPP measures the added quantity of carbon accumulated in vegetation biomass from photosynthesis, farming applications mainly focus on calculating approximate yield grain, usually a lesser fraction of GPP. Crop yield can be calculated by creating GPP and an empirical harvest index (HI), which varies based on crop type and environmental conditions. Google Earth Engine is a cloud-based platform for geospatial processing; it is available through Python and JavaScript Application Program Interfaces (APIs). The JavaScript API can be accessed via the Code Editor, a web-based Integrated Development Environment (IDE) where operators can write and execute scripts for geospatial analysis and processing workflows. The Code Editor offers full access to the capabilities of Earth Engine. GEE is designed for efficient geospatial data analysis at a planetary scale, and it has a large data catalog and powerful CPUs that allow for cooperative data investigation, making it an informal and fast method to procedure and analyze information. GEE is used for various applications, including mapping crop yields using satellite data, noticing worldwide surface water variation, making dynamic Landsat-based NDVI products, and mapping global forest change. The objectives of this study are to write JavaScript code for processing and analyzing open-source raster image collections, extract GPP values from MODIS 500m resolution data using the Google Earth Engine platform and calculate the yield for Maharashtra state and each of its districts.

2. Previous Literature

Reeves and colleagues (2004) broke new ground by exploring the potential and limitations of using MODIS GPP to assess wheat yield. Their innovative approach involved transforming the GPP evaluations obtained from MODIS to wheat yield and comparing the results with actual yields at the region and national stages during the 2001 and 2002 growing periods in Montana and North Dakota. Their findings, which indicated that higher stages of spatial combination commonly enhanced the relationship between estimated and observed wheat yield, were a significant step forward in the field. Despite the fact that only state-level yield estimates were reasonably accurate, with a 5% deviation from actual yield, the state-wide yield outcomes

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were promising as they were obtained without relying on surveying empirical investigations, offering a fresh chance for appropriate wheat yield evaluations in big areas. The authors identified six hands-on constraints to assessing wheat yield by MODIS GPP and proposed three recommendations for enhancing wheat yield estimates for researchers interested in recalculating regionally specific MODIS-derived GPP estimates. Water accessibility and soil properties effect agricultural production. Groundwater assessment is able to support sustainable water-resource management (Sharma, 2026), while soil infiltration affects the movement of water into the soil and its accessibility for crops. Hiranandani et al. (2017) reported infiltration rates of 0.1–4.8 cm h^{-1} in the Sher–Umar doab of the Narmada Basin. These factors offer useful framework for understanding differences in satellite-derived GPP and crop yield across Maharashtra. In their study, Soltani et al. (2004) developed a modified harvest index (HI) approach for predicting crop yield in Chickpea. They discovered that the linear increase in HI may not be reliable in diverse environments due to the variation in the amount of rise (dHI/dt) with period. They found that dHI/dt was diverse across sowing days and linked to the pre-seed and vegetative growth periods. They adjusted the impact of the possible seed development using the linear HI idea to account for temperature and scarcity impact on HI. However, the seed growth rate was incomplete due to recent biomass-making and dry matter remobilization in the vegetative structures. The modification led to better yield predictions for chickpea production regions in Iran. In 2011,

Soil moisture and soil properties affect agricultural conditions. Sharma et al. (2016) observed how repeated wetting and drying influences the swelling behaviour of expansive soils. These findings provide background on soil-moisture changes, although their direct effects on crop productivity require further investigation. Lee et al. (2011) estimated gross primary productivity (GPP) and crop yield using MODIS in the Soyang River Basin in South Korea. They utilized a high-resolution meteorological prediction model (WRF) dataset to obtain more detailed meteorological variables and DAO data on cloudy days. They also improved the remote sensing input variables for estimating GPP and net primary productivity (NPP) by reducing cloud contamination effects on the FPAR and LAI variables. Over ten years, they collected new MODIS GPP and NPP data using WRF meteorology and cloud-filled MODIS data for the Soyang River Basin. Their findings suggested that MODIS and WRF data can be used to estimate GPP, NPP, and crop yield. In 2015,

Jaafar and Ahmad (2021) conducted a study with significant practical implications, investigating the relationship between main manufacture and harvest yields in irrigated agroecosystems of Syria. They used remotely sensed data from the MODIS sensor to derive the Enhanced Vegetation Index (EVI), Net photosynthesis (net PSN), and Gross Primary Production (GPP) indices. The research aimed to define the possibility of forecasting crop yield before harvest using these indices. The researchers analyzed the relationships among summer crop yield and the remotely sensed indices. They developed simple regression

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spatially using algorithms to forecast summer crop invention, which was validated during the conflict years in Syria. The results showed a significant correlation ($p<0.05$) between summer crop yield and EVI, GPP and net PSN. The study indicated that the remotely sensed-based models efficiently forecasted summer crop yield, particularly for cotton yields and vegetables.

The increasing summer EVI-based model could predict summer stock crop yield during crisis periods with a deviation of less than 20%, where vegetables were the major yield. The findings of this study have important implications for agricultural management in semi-arid and arid regions, particularly during crises. Using satellite images and spatially-based models can help farmers and policymakers in decision-making procedures related to crop production and food security. The study also highlights the potential of satellite data in refining our understanding of crop yield dynamics in regions affected by conflict and other crises. Madugundu et al. (2016) used Landsat-8 imagery and Eddy Covariance information to estimate the GPP of irrigated maize grown in hyper-arid situations in Saudi Arabia. They employed the Vegetation Photosynthesis Model (VPM) to estimate GPPVPM using Landsat-8 reflectance data and GPPEC using meteorological data from the Eddy Covariance system for August to November 2015. Their study found that GPPEC for the entire growth period of the maize crop was 1871 g C m-2. The aggregate GPP defined by the enhanced vegetation index (GPPEVI) was higher at 1979 g C m-2, while GPP defined by the normalized difference vegetation index (GPPNDVI) was lower at 1754 g C m-2. The results showed that GPPEVI was higher than GPPEC, with an R^2 of 0.96, P = 0.0241, and an RMSE of 12.6%. Conversely, GPPNDVI was lower than GPPEC, with an R^2 of 0.93, P = 0.0384, and an RMSE of 19.7%.

Meanwhile, Mani et al. (2017) made a significant contribution to the field by using MODIS data to investigate the changes in GPP on a seasonal and inter-annual basis in a semi-arid agricultural area in central India. The study emphasized the need to estimate the carbon budget by assessing the contribution of various agro-ecosystems in the region. The authors found that the highest annual GPP was observed in 2011, followed by 2013, 2010, 2012, and 2009, with an average GPP over the five years ranging from 0 to 1.47 kg C m–2, similar to other regions in India. They also observed that the highest average GPP occurred between September 2009 and 2013. The study concluded that the Kharif season played a significant role in carbon storage by the terrestrial biosphere in the Vidarbha region, underscoring the importance of their findings. They used a crop-specific harvest index (HIGPP) to estimate crop yields and multiplied it with the projected GPP collected above the growing period.

They found that the resulting GPP and crop production estimates were consistent with the distinguishing cropland output outlines and seasonal differences, as well as the described county-level crop

manufacture data from USDA (r = 0.96, relative RMSE = 37.0%, p < 0.05), demonstrating the usefulness of their approach for estimating crop productivity and yield. He et al. (2018) conducted a study based on the fused Landsat-MODIS data to estimate local crop GPP and yield in Montana, USA. They utilized a satellite images light use efficiency (LUE) model to evaluate the GPP of seven important crop kinds, alfalfa, barley, maize, spring wheat, and winter wheat, at a high spatial resolution of 30 meters and eight-day time steps.

Marshall et al. (2018) established a new model for assessing agro-ecosystems GPP and crop harvest at a macro-scale level GPP, which can be accumulated over the growing season and utilized with a crop-particular HI to estimate crop yield. The new model, called Production Efficiency Model Optimized for Crops (PEMOC), addresses the deficiencies of other models for macro-scale applications. The PEMOC model has demonstrated best performance to the commonly used MOD17 model at field and county levels. In terms of estimating GPP in the growing period, PEMOC and MOD17 models exhibited R^2 values and root mean squared errors (RMSE) ranging from 0.71 to 0.89 (9.87 to 17.47 gCO2d−1) and 0.59 to 0.83 (6.86 to 22.20 gCO2d−1), respectively, when compared to flux tower GPP. Additionally, when evaluating crop yield anomalies for corn, soybean, and winter wheat, PEMOC produced R^2 and RMSEs of 0.70 (0.52) and 0.60 (0.61), respectively, while MOD17 demonstrated R^2 and RMSEs of 0.65 (0.57) and 0.53 (0.66), respectively. A limited sample size for rice made it necessary to compare yields directly. In this case, PEMOC and MOD17 generated R^2 and RMSEs of 0.53 (3.42 tha−1) and 0.40 (4.89 tha−1), respectively by Mostovoy (2019).

In their study, Parida and Ranjan (2019) utilized multi-temporal remote sensing images, including Landsat-8 and MODIS, to estimate wheat land and yield in India's winter period (2016-2017). They analyzed phonological parameters resulting from time-series NDVI data to recognize the phonological changes of wheat. With NDVI profiles, they created instructions for a decision tree classifier that mapped wheat acreage to approximately 3,870 hectares. Additionally, they developed a yield model based on long-term wheat information records to predict wheat production for the season. Their yield model forecasted production to be around 4,523 tons for the winter season of 2016-2017, while the mean production was 3,482. Parida and Ranjan (2019) decided that the correctness of the yield estimate depends on the exactness of the wheat acreage map generated from satellite data.

In their research, Liu et al. (2019) explored the viability of using crop metrics derivative from Terra/MODIS satellite data for yield assessment across the Canadian Prairies at Census Agriculture Region (CAR) and Rural Municipality (RM) levels in three grassland agro-climate zones. They analyzed MODIS-derived vegetation indices, GPP, and NPP about recognized yields for spring and wheat, among others. The authors employed multiple linear regressions to measure the associations between these metrics and harvest

for the years 2000 to 2016. Their findings revealed that vegetation indices during peak crop growth phases were improved predictors of harvest than GPP or NPP, with EVI2 performing better than NDVI. Using seasonal maximum EVI2, CAR-level harvest yields could be projected with a comparative root-mean-square-error (RRMSE) of 14-20% and a Nash-Sutcliffe model efficiency coefficient (NSE) of 0.53-0.70. Liu et al. (2019) concluded that their models could be applied to both spatial scales and utilized to enhance the resolution of coarse-resolution crop yields using MODIS data.

Medar et al. (2019) suggested a new method for predicting sugarcane yield in the Karnataka region of India using long-term series, climate and soil data, NDVI, and Machine Learning models. As sugarcane farming lasts around 12 months and commences at different times of the year in Karnataka, the authors divided the yield-predicting process into three phases. They first predicted soil and climate characteristics for an entire period of the crop cycle. Next, they employed Support Vector Machine Regression (SVR) models to forecast NDVI based on the soil and weather data. Finally, they used SVR to predict sugarcane crop yield based on the NDVI. The authors obtained an accuracy of 83.49% overall in forecasting sugarcane yield under different planting periods and conditions in the Karnataka region.

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Jafar and Mourad (2021) created a crop yield estimation model using Landsat Earth observations, gridded climate, and worldwide soil data accessible in Google Earth Engine (GEE). The model integrated remote sensing and evapotranspiration-based Light Use Efficiency (LUE) approach with abiotic environmental stressors to estimate crop yield at a 30 m resolution. The model was assessed using crop yield data for wheat, potato, and corn for 2015–2020. Their results showed that the modeled and predicted field-level yield differed by no more than ±16% for the studied yields in Brazil and Lebanon examines locations and by no more than ±15% in the Spain site. The model executed the finest for wheat crops in Lebanon, with low RMSE (0.6 t/ha), MAE (0.5 t/ha), MBE (−0.06 t/ha), and RE (0.83%). The authors concluded that the GYMEE model has substantial potential for evaluating global food production.

3. Materials and Methods

The GEE platform is effectively used for this study and the research work. Firstly, the study area and description of the Terra Gross Primary Productivity 8-Day Global Data of MODIS with 500 m resolution, which is used for the study area, is described. The procedure is clarified with the objectives of considering the computational workflow of GEE in estimating gross primary productivity and crop yield.

3.1 Study Area

The study area selected for this paper covers Maharashtra State, India. This state is situated in India, and its latitude and longitude between 19° 39' 47.8080'' N and 75° 18' 1.0548'' E. There are six administrative divisions in the Maharashtra State, India: Amaravati, Aurangabad, Konkan, Nagpur, Nashik and Pune. The map below shows the districts covered in these divisions (Fig.1).

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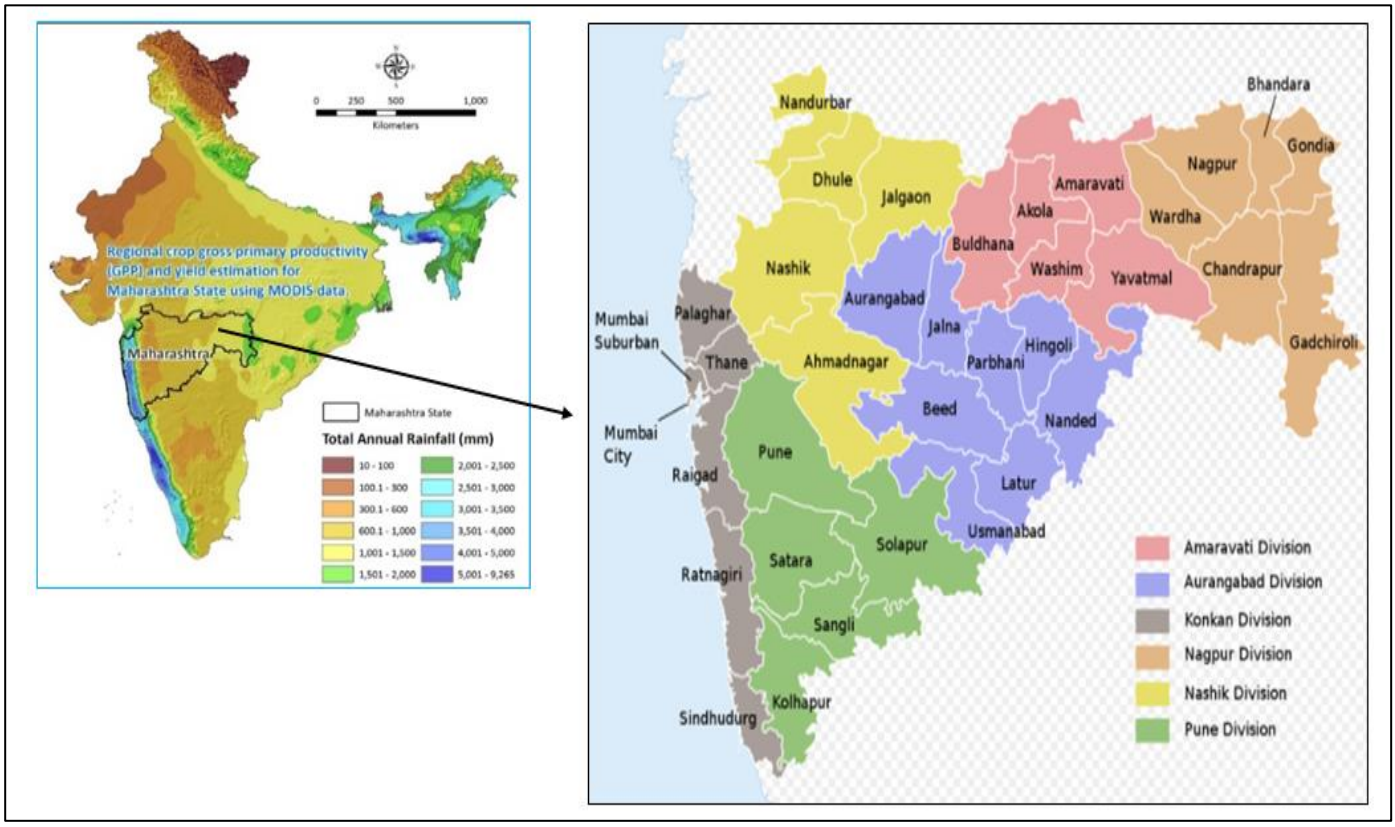


Fig.1: Different regions in Maharashtra (Source: https://en.wikipedia.org)

3.2 Data Sources and Pre-processing

a) MOD17A2H.006: Terra Gross Primary Productivity 8-Day Global 500m

The MOD17A2H V6 Gross Primary Productivity (GPP) product is a valuable dataset for understanding terrestrial energy, carbon, water cycle processes, and biogeochemistry of vegetation. The product is a composite of 8-day MODIS data with a resolution of 500m and is based on the radiation-use efficiency concept. The dataset is freely available through the LP DAAC, a NASA data center at the USGS EROS Center, and there are no restrictions on its use, sale, or redistribution. The dataset covers a long period from March 5, 2000, to June 10, 2021, making it an important resource for long-term studies. It can be accessed using the function ee.ImageCollection("MODIS/006/MOD17A2H") in the Google Earth Engine (GEE) platform (Fig.2) and Table 1.

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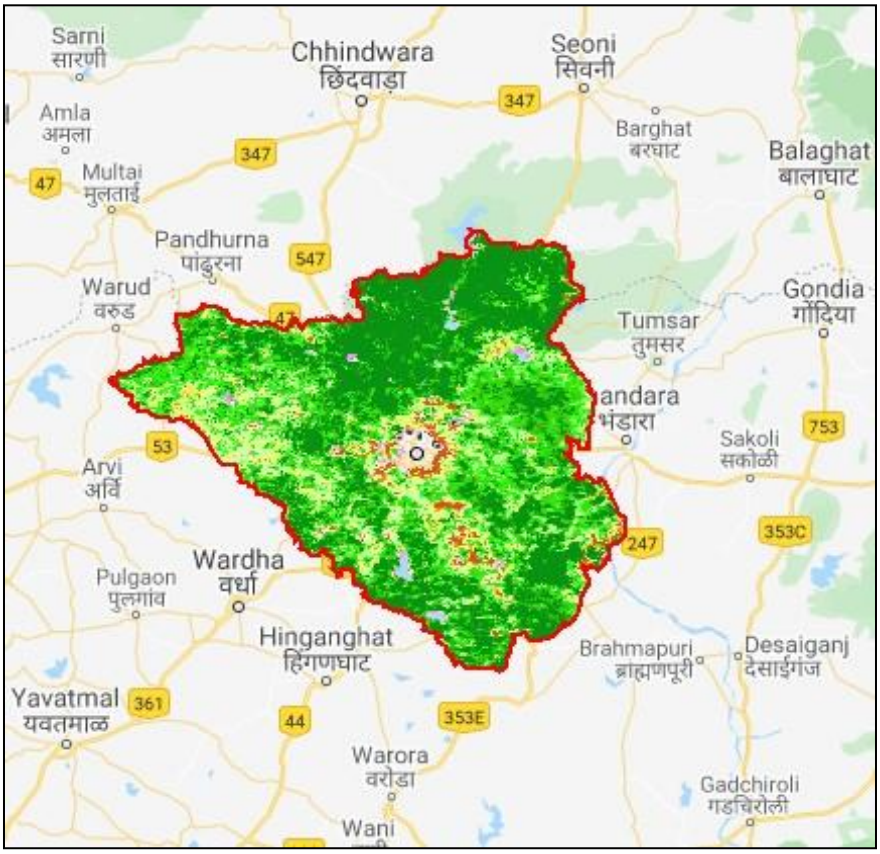


Fig. 2: MODIS dataset of Nagpur district

The table given below shows the bands used in the image collection with their description.

Table 1: Details information of Terra Gross Primary Productivity 8-Day Global 500 m MODIS Data

Name	Description	Min.	Max.	Unit	Scale
GPP	Gross primary production	0	3000	kgC/m2	0.0001

b) Copernicus Global Land Cover Layers: CGLS-LC100 collection

The Copernicus Global Land Service (CGLS) is an important part of the Land service that offers a wide range of bio-geophysical products related to the prominence and development of land surfaces across the globe. Among these products is the Dynamic Land Cover map at 100 m resolution (CGLS-LC100), which provides a worldwide land cover map with high spatial resolution. The CGLS Land Cover product offers a primary land cover scheme, with additional layers of incessant natural resource maps for simple land cover patterns. These layers offer comparative assessments for vegetation/ground cover for each land cover type,

allowing for a more detailed depiction of areas with heterogeneous land cover. This incessant classification arrangement can be useful for various applications, such as forest, crop, biodiversity and conservation, environment monitoring in Africa, climate modeling, etc. The land cover maps provided by the CGLS (v3.0.1) cover the period of 2015-2019 and have been derived from the PROBA-V 100 m time series, high-quality land cover training locations, and various ancillary datasets. The correctness of the maps has been validated to reach 80% at Level 1. The plan is to deliver annual updates from 2020 by using a Sentinel time series. As an official product of the global component of the Copernicus Land Service, this land cover dataset is fully accessible and free for all users. The resolution of the product is 100 m. The table below shows the band used in the image collection with its description (Table 2).

Table 2: Details of Copernicus Global Land Cover Data

Value	Colour value	Description
40	#F096FF	Cultivated and managed vegetation / agriculture. Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type. (Resolution: 100 m)

3.3 Google Earth Engine platform data processing:

Google Earth Engine (GEE) is a cloud-based platform designed to adapt to your needs in processing large-scale geospatial data. It offers a vast repository of remote sensing imagery and geospatial data, along with a suite of tools that are flexible for analysis and visualization. In this guide, we will walk you through the data processing workflow in the Google Earth Engine platform. To start, to define your area of interest (AOI) by specifying the geographical coordinates or selecting a boundary file. Once your AOI is set, you can tap into a wide range of satellite and environmental data from various sources, such as Landsat, Sentinel, MODIS, and other data providers, using GEE's Application Programming Interface (API). After selecting your data source, you can filter the data by date, cloud cover, or any other specific criteria. Once the data is filtered, you can preprocess it by applying various filters, such as atmospheric correction, radiometric calibration, and image fusion, to ensure data quality and consistency (Fig.3).

The next step is to perform geospatial analysis, which can be done using GEE's built-in functions and libraries. These functions can perform tasks such as image classification, object detection, time series analysis, and geospatial modeling. GEE's computing power enables you to analyze large data sets, making it an ideal platform for processing and analyzing global-scale data. You can also create custom scripts in JavaScript or Python to perform advanced analysis and modeling. These scripts can be run directly within GEE's platform and the results can be exported in various formats, including CSV, GeoTIFF, and NetCDF. Once your visualizations are completed, you can use GEE's built-in visualization tools, such as interactive maps and charts, to bring your data to life. These visualizations can be exported as static images or animations for further use and sharing.

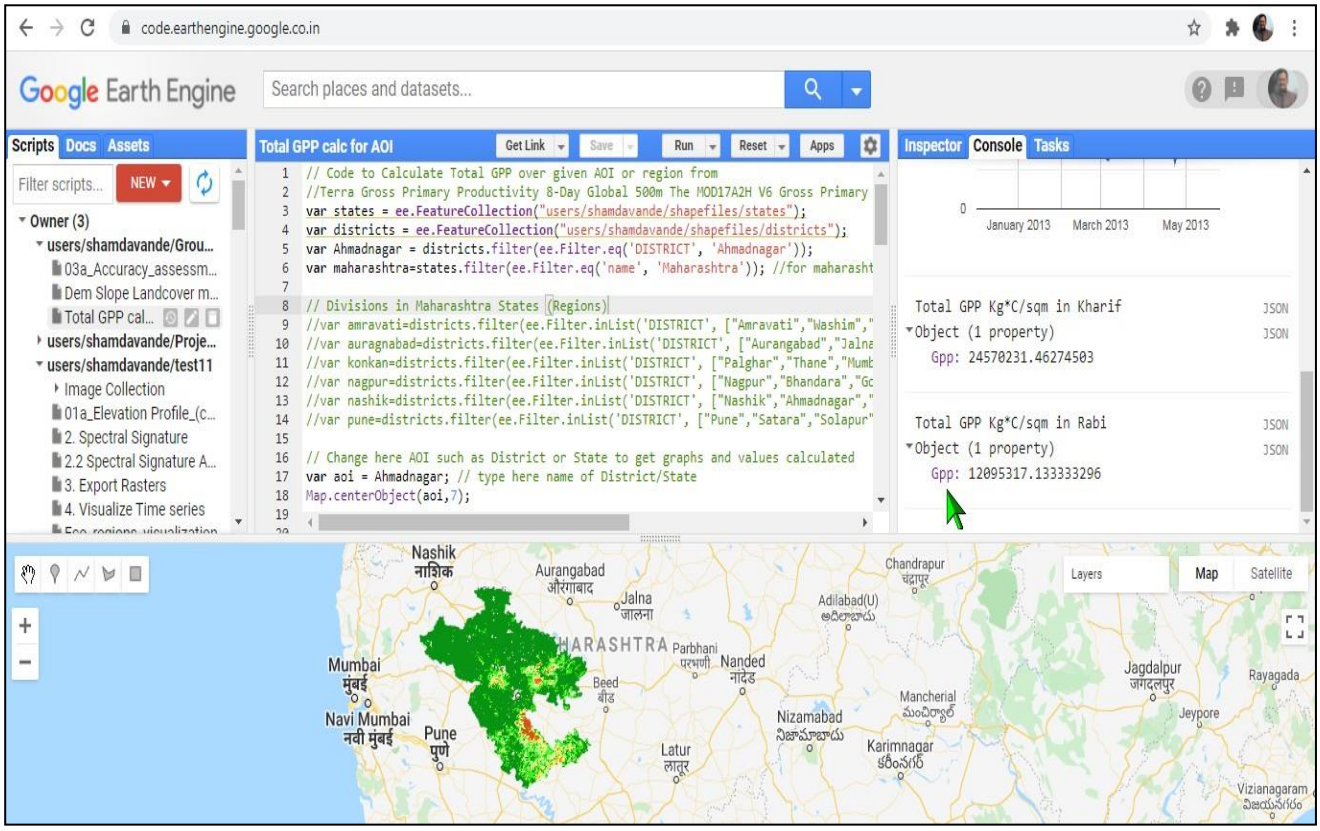


Fig. 3: Google Earth Engine Interface with code displaying outputs

The GEE platform offers a comprehensive suite of tools for accessing, processing, analyzing and visualizing large-scale geospatial data. Its cloud-based architecture and advanced computing

capabilities make it a powerful platform for researchers, scientists, and developers to perform advanced geospatial analysis and modeling. The Google EEP application, a JavaScript API, can load and visualize large satellite imagery and conduct complex geo-statistical and geospatial operations on our imagery. In this project, we are using shape files of district and state boundaries of Maharashtra State, India. These shape files are significant as they provide the spatial context for our analysis and allow us to extract the values over our areas of interest (AOIs).

Google Earth Engine is a platform that enables users to perform geospatial analysis on a vast collection of georeferenced imagery and vectors stored on Google's infrastructure. Its API provides a library of functions that can be used to process and analyze data. The public data catalogue contains numerous publicly available imagery and vector datasets, and users can also create private assets in personal folders. The Earth Engine documentation is intended for those with experience in geospatial data analysis. Fig.3 shows the Google Earth Engine interface after running the code.

3.4 Formulae used for yield estimation

$$Yield_{est} = \sum_{DOY=81}^{a} GPP_{DOY} \times 2 \times 0.9 \times HI \quad Eq.1$$

Where, Yields is the yield estimate (kgha^{-1}), a is an arbitrary growing season end point (DOY 208, 216, 225 or 233), GPP_{DOY} is daily gross primary productivity (kgCm^{-2}), two is a conversion factor from carbon to biomass, 0.9 (90%) is the annual proportion of GPP allocated to above-ground productivity. ***Harvest index*** *is defined as the pounds of grain divided by the total pounds of above ground biomass (stover plus grain). As a general rule, in a normal year (i.e., without weather extremes) the harvest index will be 0.50. The equation-1 is presented yield estimation of crop yield.*

4. Methodology

1) *Computation of the gross primary productivity and yield of certain regional crops in Maharashtra State is done using MODIS Terra GPP Global data and by masking areas outside Cultivated and managed vegetation/agriculture. Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems) available in Copernicus Global Land Cover Layers: CGLS-LC100 collection 3. This masking has supported the analytical steps to avoid noise or GPP pixel values from non-agriculture areas.*

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2) *The following are the analysis steps carried out during the current project.*

3) *Shape files of district boundaries and State boundary added to GEE Asset*

4) *Land cover class from ("COPERNICUS/Landcover/100m/Proba-V-C3/Global/2019") data available through GEE platform has been filtered for band name ('discrete_classification') which is a Cultivated and managed vegetation / agriculture areas.*

5) *Vectorised the above land cover class by using function(classes = landcoverClass.reduceToVectors) which is required to clip GPP raster image of maximum values recorded during kharif as well as rabi season.*

6) *MODIS 500m resolution image collection ("MODIS/006/MOD17A2H") has filtered with start and end dates specified for kharif as well as rabi season and "Gpp" band has been selected for further analysis.*

7) *GEE JavaScript code has been written in such way that it always clips the MODIS 500m resolution image collection to AOI specified i.e. district boundary.*

8) *Time series line chart has been generated for each season using functions:1) Chart.image.seriesByRegion(kharifSeason,aoi,ee.Reducer.max(),'Gpp';*
2)Chart.image.seriesByRegion(rabiSeason, aoi, ee.Reducer.max(),'Gpp'

9) *Image collection of maximum GPP values recorded in each date of kharif as well as rabi season is processed using image reduction function 'reduceRegion' and 'ee.Reducer.sum' within the geometry or AOI specified i.e. district boundary. On steps no.3 Vectorized landcover class has been used to clip or remove the unwanted pixels that are outside Cultivated and managed vegetation / agriculture areas.*

10) *Once all the above JavaScript processing outputs are ready, a codes are written to print the charts, sum value of GPP for each selected district (AOI), mapped the output images to display in GEE map window. Following are coding lines;*

11) *The final outputs available from code is;*

- *Time series line chart for kharif as well as rabi season.*
- *Total GPP Kg*C/sqm in Kharif season*
- *Total GPP Kg*C/sqm in Rabi season*

- *Maximum values of GPP over entire district showing distribution in Kharif season*
- *Maximum values of GPP over entire district showing distribution in Rabi season*

12) *Code is written in such way that user need to simply copy/paste district name in just 1 place in code and run the code to successfully get the values of GPP extracted for AOI/District input provided.*

5. Results and Discussions

*The Gross Primary Productivity (GPP) varies greatly among the seasons each year. The accumulation of 8 days GPP was observed to be more during the kharif season than in other seasons. This could be attributed to the monsoon rainfall during the kharif season, which leads to the uniform accumulation of GPP. The rabi season GPP was also found to be good, but it should be noted that the sown crops depend upon irrigation in this season. The GPP was much lower during the zaid season, as presented in Fig. 4 to Fig. 6. due to the scarcity of irrigated water. As a result, the rate of metabolic activities of crops is lower under limited water availability. It was observed that the 8-day GPP on 21st September 2020 increased sharply (as shown in Fig. 4) due to favourable weather conditions, such as plenty of rainfall and optimum temperature prevailing during that time, which led to carbon synthesis. It is essential to note that different land uses for each district of Maharashtra state could affect the value of GPP. This is because the different land uses have different vegetation types, distributions, and photosynthetic pathway types (As-syakur et al., 2010). The study's key findings reveal that the Aurangabad division recorded the highest total GPP of 24797 Kg*C/ha in 2020-21, constituting 21% of the entire state (Fig. 4 to 11). The study also established a strong correlation between the calculated yield and MODIS GPP values data from the Image Collection ("MODIS/006/MOD17A2H") available through Google Earth Engine (GEE). This correlation exhibits clear seasonal patterns, with the most robust correlations observed between good rainfall years and drought years in Maharashtra State. The study proposes a potential approach for establishing a relation between agriculture yield and GPP values extracted from time series satellite images of MODIS 250m and MODIS 500m datasets. Further research is needed to evaluate the effectiveness of GPP prediction models, whether based on remote sensing data or a blend of environmental factors in different ecosystems. To improve the accuracy of these models, a deeper understanding of the fundamental processes and impacts of climate variables on GPP fluctuations is essential. This knowledge can be used to enhance future GPP models.*

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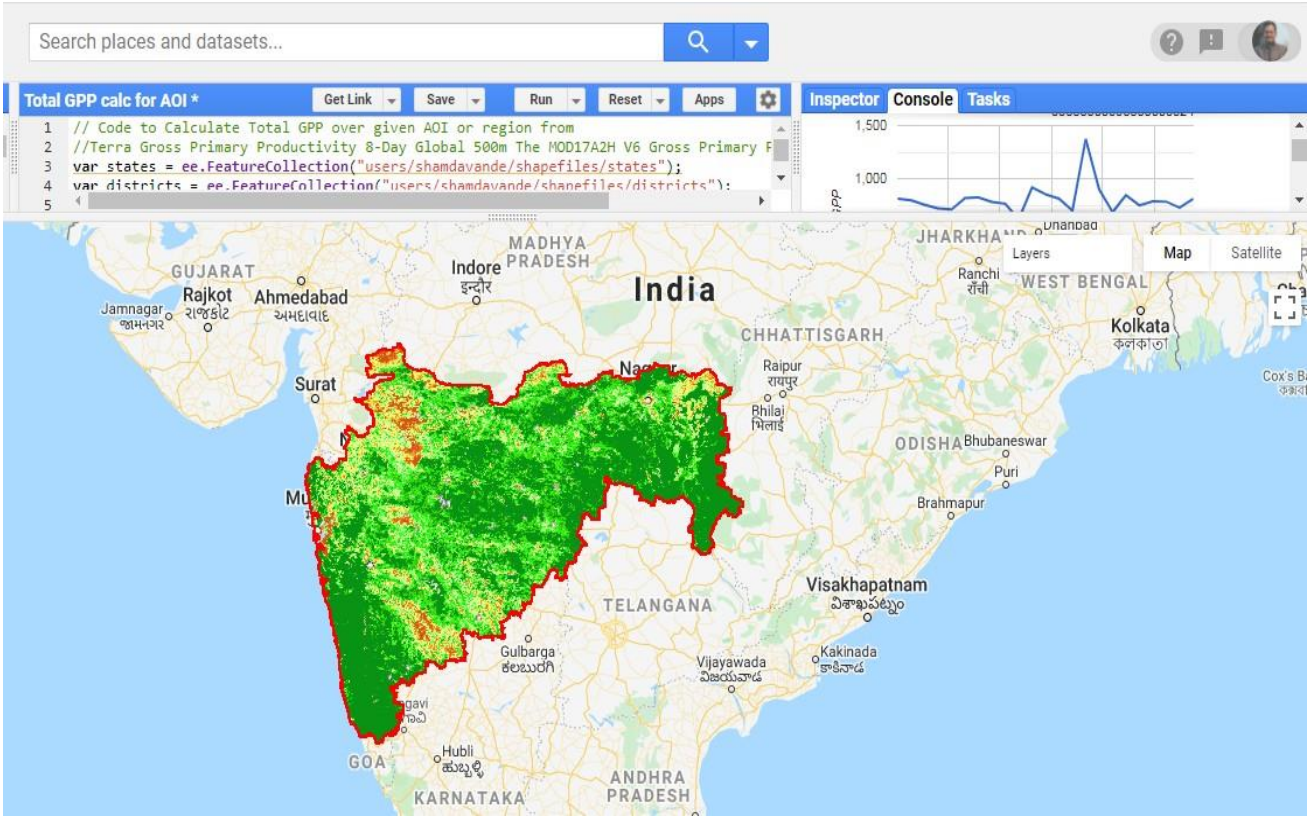


Fig. 4: GPP image collection extracted for Maharashtra State

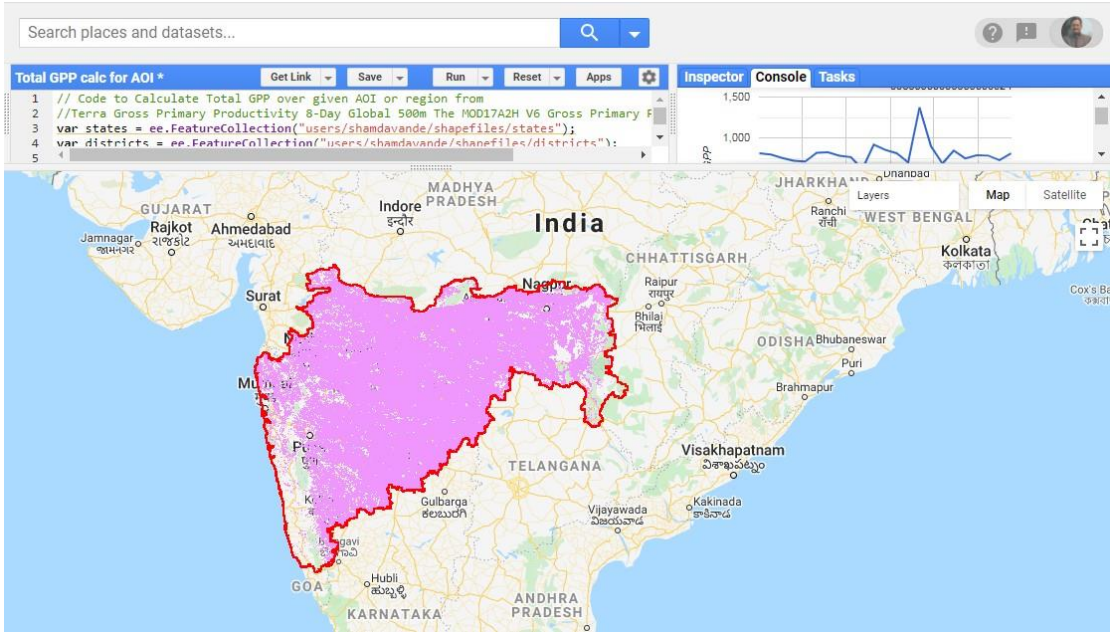


Fig. 5 Land Cover class from ("COPERNICUS/Land cover/100m/Proba-V-C3/Global/2019")

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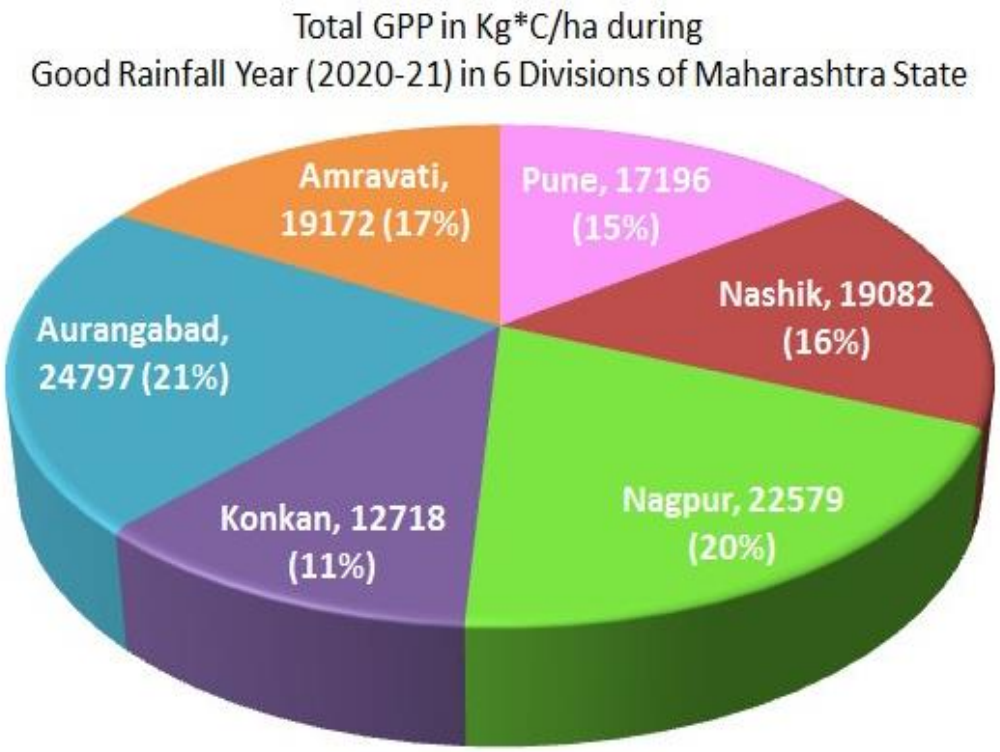


Fig. 6 Total GPP calculated for each division during good rainfall year 2020-21

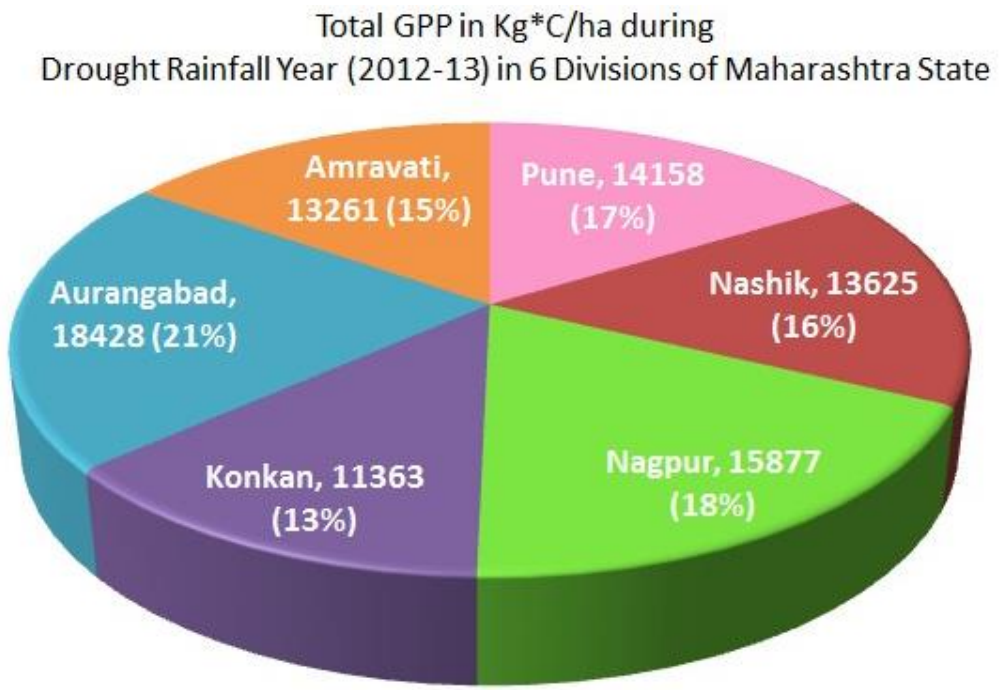


Fig. 7: Total GPP calculated for each division during drought year 2012-13

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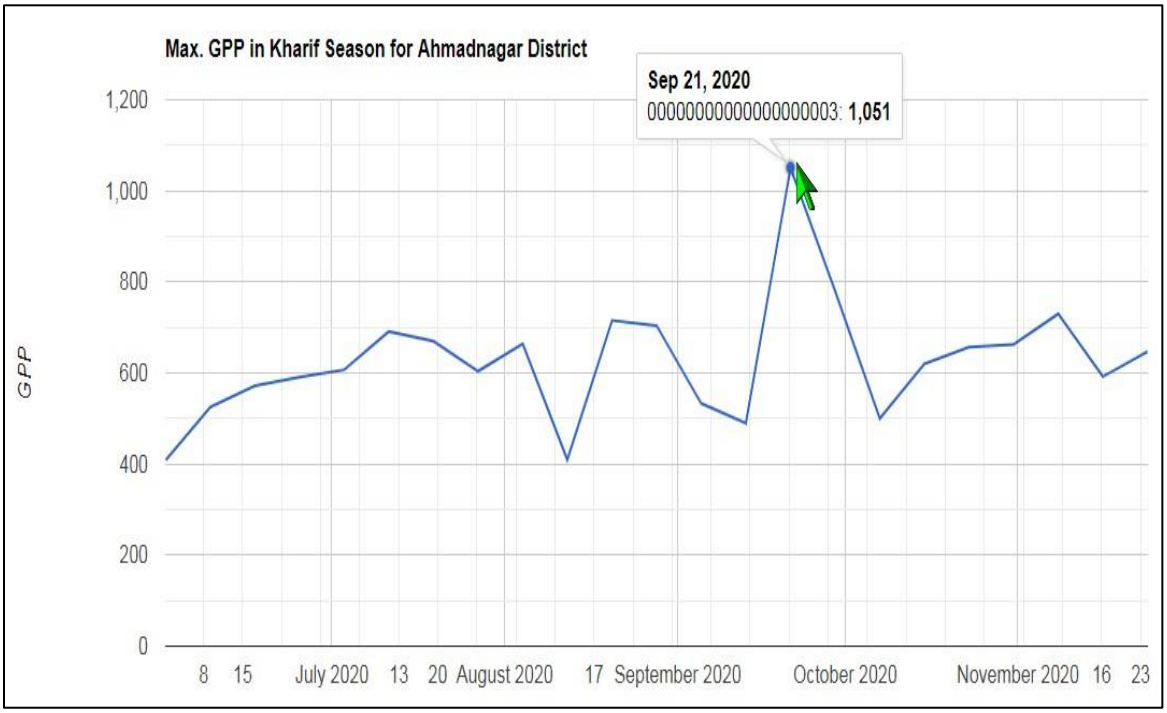


Fig.8: Max. GPP values in Kharif Season for Ahmadnagar district in good rainfall year 2020-21

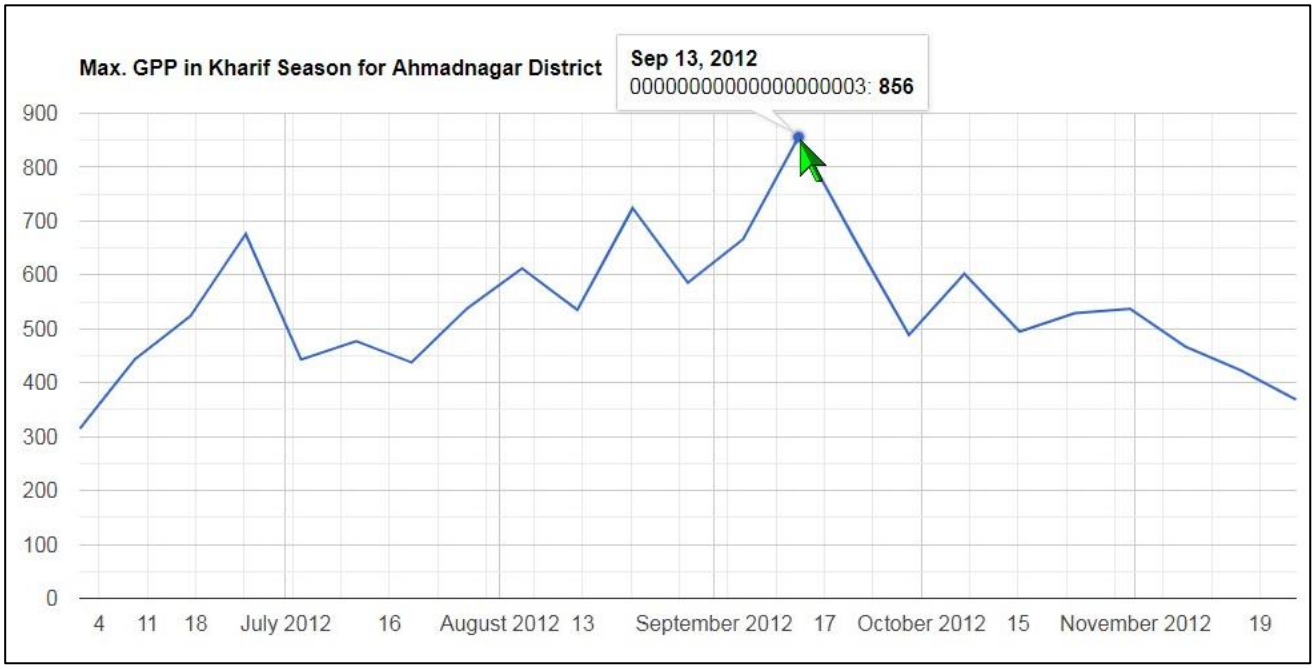


Fig. 9: Max. GPP values in Kharif Season for Ahmadnagar district in drought year 2012-13

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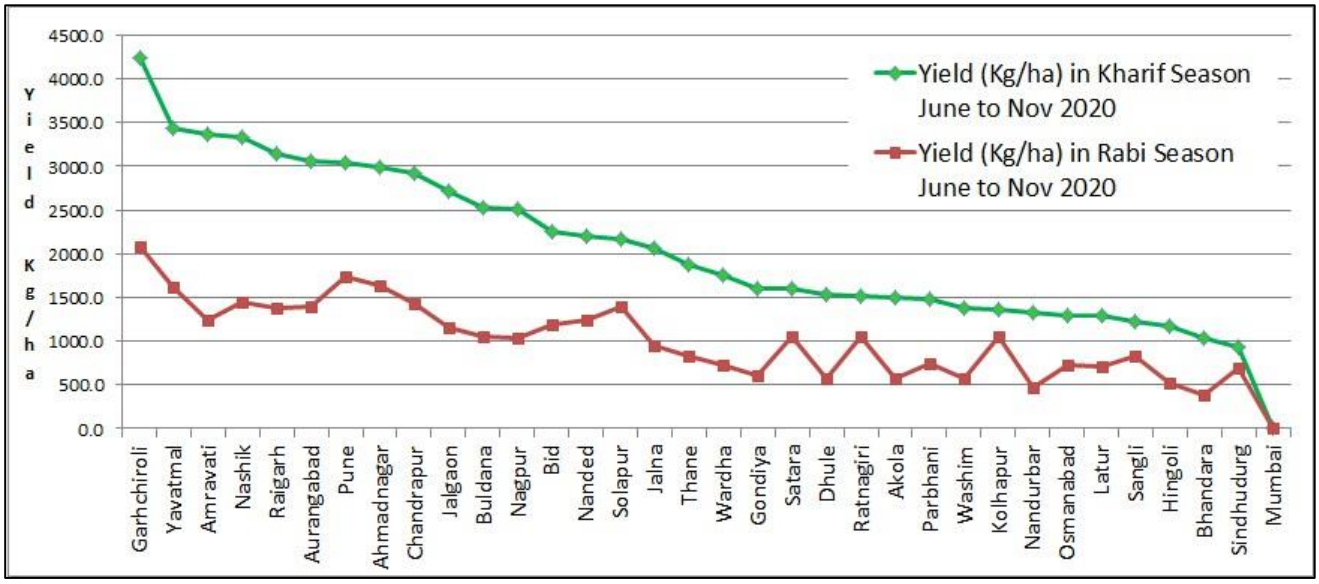


Fig. 10: Yield calculated from GPP values in good rainfall year 2020-21 for districts

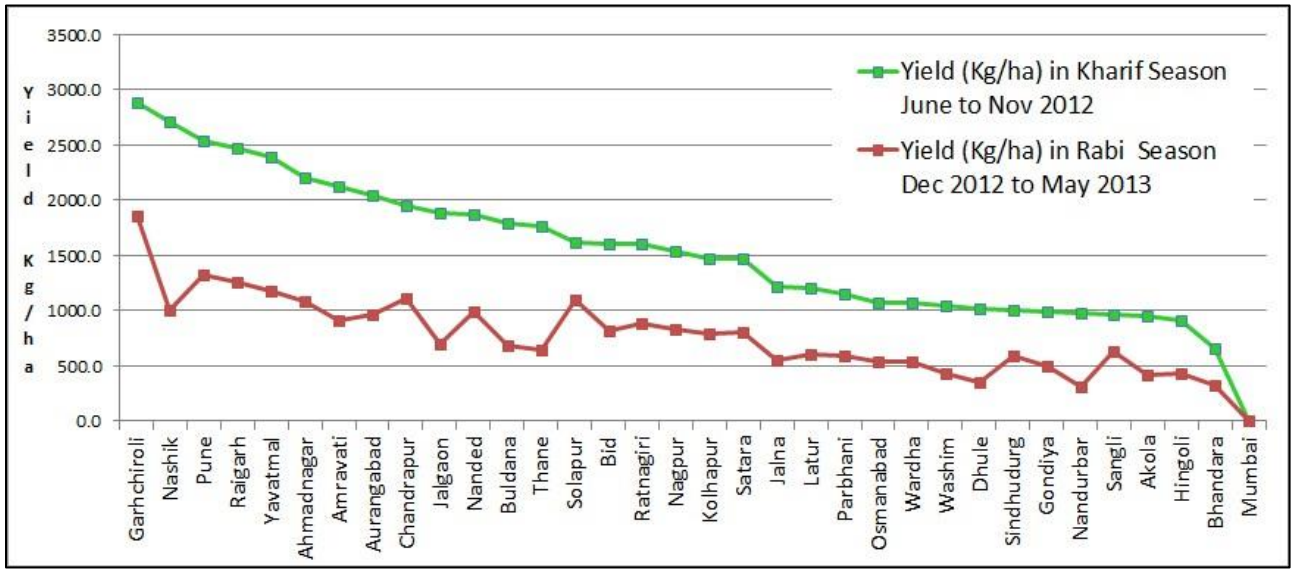


Fig. 11: Yield calculated from GPP values during drought year 2012-13 for districts

6. Conclusions

1. *This study used a MODIS satellite data-driven method to extract GPP values from 500-m resolution 8-day composite images, which were then used to calculate crop yield for two specific years in*

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Maharashtra state. These years were chosen based on their differing levels of rainfall, with one being a good rainfall year (2020-21) and the other a drought year (2012-13).

2. *The GPP values extracted for the two years revealed the effect of rainfall on agricultural productivity, with lower GPP values observed during the drought year. These results were visualized through figures 5 and 6, which depicted the GPP values for the Ahmednagar district.*

3. *The study revealed clear seasonal patterns in the correlations between the calculated crop yield and the MODIS GPP values data. These patterns were more pronounced during the good rainfall year, underscoring the potential of satellite images in establishing a relationship between agriculture yield and GPP values. The MODIS 250m and 500m datasets, in particular, show promise, offering a hopeful outlook for future agricultural research. However, the need for further research to evaluate GPP estimation models, either based on remote sensing observations or a combination of climate variables in other ecosystems, is urgent and important. To improve these models, a better understanding of the underlying mechanisms and effects of climate variables on the temporal patterns of GPP is crucial. This knowledge can then be incorporated into future models for more accurate predictions of crop yield.*

7. Importance of the Study

This study examined crop productivity in Maharashtra using MODIS-derived GPP data for two years with contrasting rainfall conditions. The lower GPP values observed during the drought year (2012–13), compared with the good rainfall year (2020–21), indicate the effect of rainfall variability on vegetation productivity. The seasonal patterns observed in Ahmednagar district also show how satellite data can be used to monitor changes in agricultural productivity. The findings may be useful for regional crop monitoring and agricultural planning, especially in areas where field observations are limited.

8. Future Research Directions

Further studies should compare MODIS-derived GPP and crop-yield estimates with actual crop-yield records to check their reliability across different crops and districts. Including rainfall, temperature, soil moisture, and irrigation data may help explain the differences in productivity between years and regions. Researchers could also examine whether higher-resolution satellite data provide more detailed information at the local scale. Machine-learning methods may offer another way to improve yield estimates and study how changes in climate affect crop production across Maharashtra.

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Data availability

The whole analysis and datasets created are presented in the article.

Ethics declarations

Clinical trial number: Not applicable.

Competing interests

The authors declare no competing interests.

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Author Contribution:

Ravi Sharma: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing, Investigation, Validation, Data Curation, Validation., **Kaywan Othman Ahmed:** Writing - Original Draft, Writing - Review & Editing, Formal analysis **Cheikh Faye**: Writing - Original Draft, Writing - Review & Editing, Validation.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. During the preparation of this work, the author(s) used CHAT-GPT Tool to improve the readability of some parts such as (checking the grammar error, spelling mistakes, long sentences, tenses, and improving the sentences) of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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