# Precision Agriculture: A Web-GIS Framework for Health and Stress Assessment Using Multi-Source Remote Sensing Data

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**Abstract**

Climate change has an immense impact on many fields, especially in the agricultural sector the reduction in crop yield, pre-maturation of crops, and water scarcity that may lead to drought, and scarcity of food in India. Agriculture plays a significant role in India where approximately 60% of the population works in the agricultural sector, contributing 20.2% to India's Gross Domestic Product (GDP). India has one of the largest populations 1.2 billion in the whole world (Census 2011), Precision Agriculture (PA) techniques with the utilization of Unmanned Ariel Vehicles (UAV), equipped with multi-sensor along with satellite imagery providing more spectral and temporal resolution. The primary objective of this research is to create a model within the Google Earth Engine (GEE) framework, a WebGIS platform that enables its users to access analyses and visualize geospatial data for a wide range of applications. This model will enable researchers to calculate several indices for crop health and stress assessment mentioned in this research in their respective Areas of Interest (AOI) whether using either a UAV or satellite dataset. These indices help in evaluating water stress, disease detection, biomass and nitrogen estimation, and soil moisture estimation in crops, various tools and techniques will be employed for data processing, comparing, and analysis to acquire the optimal precision, additionally, ground truthing measures were also utilized to validate the accuracy of the outcomes. This research will help in supporting PA practices and promoting sustainable development in the agricultural sector.

## 1. Introduction

This specific study focuses on the village of Haridwar district of Uttarakhand India, Haridwar is known for its cultural prosperity, pilgrimage, and agriculture, agriculture plays a pivotal role in the economy of Haridwar, with major crops including rice, wheat, and pulses, where wheat and rice contributes 35% of Gross Cropped Area (GCA)(Tuteja, 2013). With technological transformation over the past century, many initiatives for instance Green Revolution, have revolutionized the face of agriculture(Patel, 2013). PA is a crucial element of Sustainable development(Berry et al., 2003). Expansion in agricultural areas, developing nations might still face challenges in achieving food security due to inadequate source management (Calzadilla et al., 2013). Food security is an integral part of sustainable development (Charles et al., 2014). With the latest advancements in the agricultural sector, technologies such as remote sensing (RS) serve a crucial role within the agricultural sector by providing information for decision-making (Atzberger, 2013). RS and Geographic Information System (GIS) can help us in pest and disease detection without using destructive approaches for collecting data (Al-Ghanmi & Al-Jabri, 2019). Satellites work as a backbone for earth observation, continuously evolving and advancing over the past few decades, but still lack in "temporal and spectral resolution", that's where (UAV) drones provide solutions to these drawbacks and their potential in PA (McCabe et al., 2016). Many developed countries have now implemented the use of UAV, Photogrammetry, and RS for PA (Colomina & Molina, 2014). UAVs also come with certain disadvantages such as limited payload capacity, flight duration, and cost (Velusamy et al., 2022). Multispectral and thermal imagery possess great significance in agricultural applications (Raeva et al., 2019). Thermal imagery may have a few advantages over optical RS in agricultural monitoring but also brings a few drawbacks like atmospheric attenuation, camera calibrations, and complex soil and plant interactions are some of the reasons for limited use in the agricultural sector(Khanal et al., 2017). We can also calibrate satellite data from low-cost UAV multispectral data to increase spatial resolution and accuracy. (Pandey & Jain, 2019). By calculating certain indices like SAVI and OSAVI, Biomass and disease detection is possible by using multispectral data(Khan et al., 2020), Furthermore, we can also calculate biomass (Schaefer & Lamb, 2016) and water stress (Ballester et al., 2018) using NDVI, likewise, disease detection can be done using GNDVI (Pourazar et al., 2019). Water content in vegetation can be detected by calculating NDWI (Gao et al., 2015), chlorophyll and nitrogen content can be calculated using CI (Taskos et al., 2015) The research aims to collect processes and analyze the data across different levels, with the objective of the optimal combination of software and hardware for PA based on the availability of the resources. Creating a model on GEE which help future researchers and researchers calculate these indices at their respective AOI either having satellite or UAV multispectral data, and validate accuracy and reliability through a rigorous validation process including ground truthing the data and cross-referencing the outcomes.

## 2. Study Area

The study area chosen for this study is a village named ‘Khanjarpur’ which falls in the Haridwar district of Uttarakhand (Fig 1), India. The geographical centroid of this village is 29.8665° N, 77.9060° E with an elevation of 268 meters above mean sea level falls in the subtropical region in the world with an annual average temperature of 28.17℃ | 82.706 ℉ and an average rainfall of 98.16 mm | 3.86 inches annually. Wheat and sugarcane are the dominant crops that are grown here there is also a river named as Solani River which flows near the village and is the main source of irrigation, with a total population of 6,435. Most of the people who live in this village engaged in primary activities as cultivators and labour activity, and some engaged in business and other secondary activities, (Census 2011). The study area is divided into a total of 61 parcels differentiating wheat from sugarcane as shown in (Fig 2).

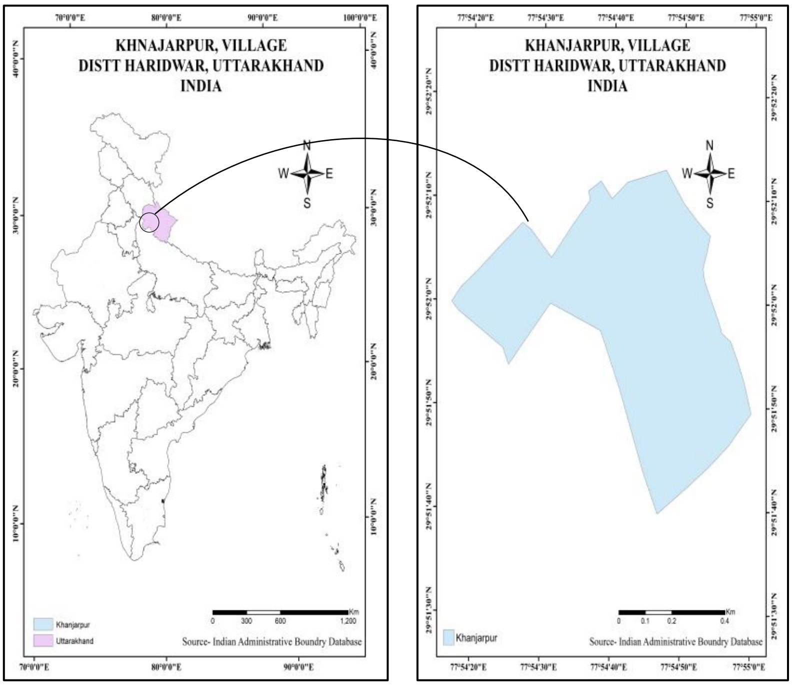


Fig 1 Study Area Khanjarpur village

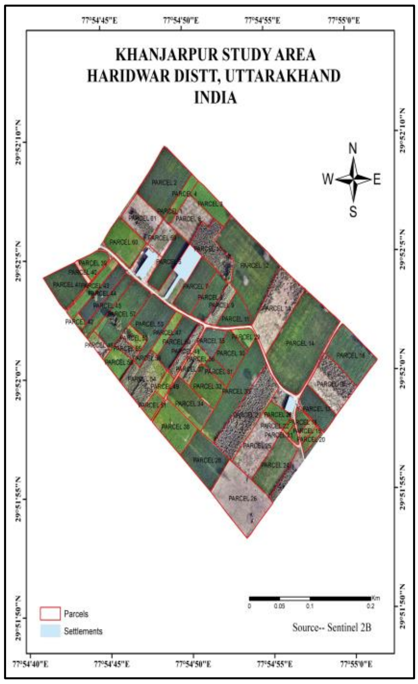


Fig 2 Study area Parcels

### 2.1 Data Acquisition and Instrumentation

The data used in this study is sourced from two remote sensing platforms, the satellites that were used are Sentinel 2B and Landsat 8, and at different resolutions and spectral band combinations, the UAVs used for acquiring the data are a ‘self-assembled UAVs in geomatics lab of civil the engineering department of IIT Roorkee named Rhaegal KJ(Fig3), equipped with ‘Micasense’ multispectral camera with 5 bands(Fig 5) and RGB UAV that is DJI Mavic 3E(Fig 4) both the UAVs operate with RTK (Real Time Kinematics) precession providing a high level of accuracy while capturing the data, as shown in (Table1).

Table 1 UAV Specification

| Sr.no | Name | Type | Speed | Camera | Endurance | GNSS |
|---|---|---|---|---|---|---|
| 1 | DJIMavic 3E | Quadcopter | 6-8 m/s | RGB | 45 mins | GPS+Galileo+BeiDou+GLONASS(DJI website) |
| 2 | Rhaegal KJ | Quadcopter | 6-8 m/s | Multispectral | 18-29 mins | RTK multiband (L1, L2, L5) |

Fig 3 Rhaegal KJ

Fig 4 DJI Mavic 3E


Fig 5 Micasense Rededege M

### 3. Methodology

This study conducted comprehensive research to investigate the optimal combination of software and hardware to create a model on GEE for promoting PA practices. Beginning with selecting the AOI, by harnessing data from UAV with multispectral sensor, and satellite images of Sentinel 2B, and Landsat 8 OLI. Data processing is conducted on ArcGIS and GEE, by using machine learning algorithms a model is created on GEE to calculate all the indices used in this study, this model enables to retrieval of data from either Sentinel 2B or Landsat 8 OLI, can also set a specific date and AOI for data acquisition and can select the maximum cloud cover percentage for the better-quality dataset, and a swap tool is also embedded in the model so it will be easy to see the difference or change detection in their respective AOI. The validation of the model is done by comparing the same indices calculated on ArcGIS and GEE and also validating them by having multiple ground surveys within the area of Interest. The methodology steps are also explained in the flow chart presented in Fig 8.

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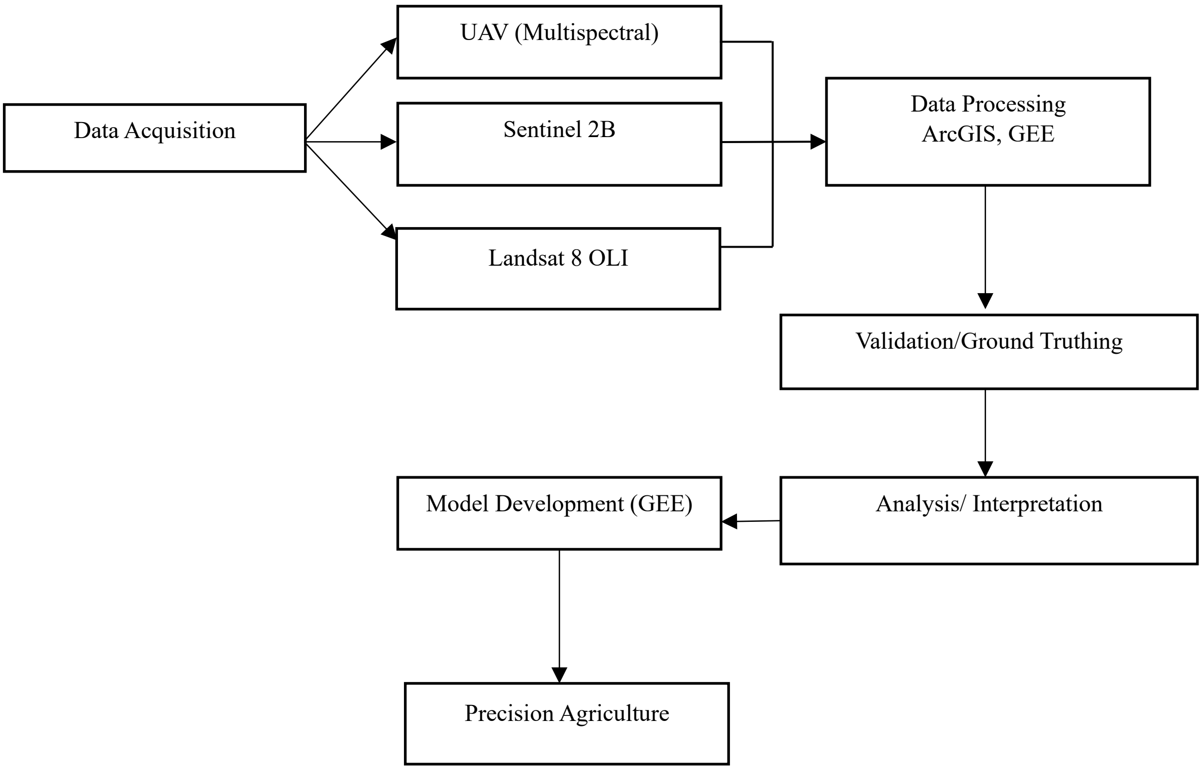


Fig 6 Methodology

## 4. Indices and Results

For this study, a total of five indices were performed by using multispectral images of the AOI both on satellite and UAV data, including the Normalized Difference Vegetation Index (NDVI) shown in equation no.1

$$\text{NDVI} = \frac{NIR-Red}{NIR+Red} \quad (1)$$

The range of NDVI lies between [ -1; +1] values < 0 near -1 depicting non-vegetated, buildups, bare soil, or water bodies. Values close to zero depict stressed or sparse vegetation and values close to +1 show dense vegetation, such as crops or forests.

The second index that is applied in this study is the Green Normalised Difference Index (GNDVI) this index is similar to NDVI but rather than using the Red band it uses the Green band and NIR band, as depicted in equation no. 2

$$\text{GNDVI} = \frac{NIR-GreeN}{NIR+Green} \quad (2)$$

The values of GNDVI range from [-1; +1] values < 0 near -1depicting non-vegetated, buildups, bare soil, or water bodies. Values close to 0 depict stressed or sparse vegetation or crops under stress and values close to +1 show dense vegetation, such as crops or forests.

The third index applied in this study is the Normalized Difference Water Index (NDWI)which also used Green and NIR bands, as shown in equation no.3

$$\text{NDWI}= \frac{Green-NIR}{Green+NIR} \quad (3)$$

The values of NDWI lie between [-1; +1] values < 0 close to -1 indicating nonwater features, soil, vegetation, or buildups, values near 0 depicting sparse vegetation, soil with high water content, values near +1 showing large water bodies rivers, and dams, ponds.

The next index is the Soil Adjusted Vegetation Index, which includes NIR and Red and also there is a constant (L) = which is the soil condition Index (0.5) value is generally used. (Huete, 1988), as depicted in the equation no.4

$$\text{SAVI} = \frac{NIR-Red}{NIR+Red+L} \times (1 + L) \quad (4)$$

The values lie between [-1; +1] with values <0 near -1 indicating a non-vegetated area or dessert region. Values near 0 depict sparse vegetation, and values near +1 indicate a high level of vegetation density or forest.

The fifth index that is applied in this study is the Chlorophyll index which includes Red and RedEdge bands, as shown in equation no.5

$$\text{CI} = \frac{NIR}{RedEdge} - 1 \quad (5)$$

The value of CI lies between [-1; +1] with values < 0 -1 showing minimal or absence of chlorophyll content can be found in deserts, or bare land, values near 0 depict a low amount of chlorophyll present in the vegetation could be sparse or unhealthy vegetation, values near +1 shows a high level of chlorophyll concentration which includes dense vegetation, forest.

## 4. Conclusion

In conclusion to this study, by calculation of a total of five different indices on the model developed on GEE, based on the analysis of all the indices, provides evident information about the wheat parcels number 2, 5, and 7(Fig2) exhibit robust health indications of the wheat crop within the AOI showing a high concentration of Biomass, no water stress and no disease detection with good vegetation water content and high nitrogen and Chlorophyll concentration with dense vegetation indices values ranging from (+0.6; +0.87). Additionally, it was observed that there was a critical water stress pattern emerged in the northeastern part of wheat parcel number 8 (Fig 2) with an NDWI value between (-0.47; +0.12). On 1 February 2024, Khanjarpur received a heavy hail storm. Subsequently, data was collected again on 3 February, this meteorological event helped alleviate the issue of water stress in parcel number 8 but also damaged crops due to the intense amount of hailstorm accompanying winds, despite there is regrowth observed in the damaged wheat crop within a few weeks which was verified by performing the field survey in different parcels, but there is still minimal loss detected in wheat parcel number 34, 44, 53, 57, 58 (Fig 2), which may affect the total yield of the wheat parcels, sugar cane crop in parcels number 61, 10, 55, 54, 48, 10, 9, 27, 16, 13, (Fig 2) have minimal damages from a hailstorm due to their rigid structure, however, due to sparse vegetation of sugarcane it is difficult to get the actual indices value of the crop due to soil reflectance captured by UAV multispectral camera, which may influence the outcomes. The conclusion to this study is wheat parcels number 2, 5, and 7(Fig 2) will have the best yield comparatively to the other parcels within the AOI, the remaining wheat parcels also show good indices reflectance but comparatively lesser than parcel number 2, 5, 7(Fig 2) and wheat parcels number 34, 44, 53, 57, and 58(Fig 2) will have less yield due to crop destruction, the limitation while working on a small area like khanjarpur village, satellite with less spectral resolution may not able to provide the high accuracy data, which may influence the outcomes of the results. The indices calculated through this model will help in making an informed decision, such as optimizing irrigation schedules, disease, and water stress detection, and managing fertilization practices, this practice may help in improving crop yield and can help in improving sustainable practices in the agricultural domain.

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