Data in Brief 55 (2024) 110649

Contents lists available at ScienceDirect

Data in Brief

journal homepage: www.elsevier.com/locate/dib

Data Article

Ultra-high-resolution hyperspectral imagery datasets for precision agriculture applications

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ARTICLE INFO

Article history:
Received 29 May 2024
Accepted 11 June 2024
Available online 18 June 2024

Dataset link:
cabbage_hyperspectral_dataset (Original data)
Dataset link:
Eggplant_Hyperspectral_Dataset (Original data)
Dataset link:
Cabbage_Eggplant_combined_Hyperspectral_dataset' (Original data)

Keywords:
Precision agriculture
Hyperspectral imaging
Crop detection
Vegetable crops
Machine learning

ABSTRACT

Technology infusion in agriculture has been progressing steadily, touching upon various spheres of agriculture such as crop identification, soil classification, yield prediction, disease detection, and weed-crop discrimination. On-demand crop type detection, often realized as crop mapping, is a primary requirement in agriculture. Alongside the topographic LiDAR and thermal imaging, hyperspectral remote sensing is a versatile technique for mapping and predicting various parameters of interest in agriculture. The ongoing developments in the methods and algorithms of remote sensing data analyses for crop mapping require the availability of curated, high-resolution hyperspectral datasets, varied by crop type, nutrient supply (nitrogen level), and ground truth data. Aimed at enabling the development and validation of approaches for crop mapping at the plant level, we present a high-resolution ground-based hyperspectral imaging dataset acquired over fields of two vegetable crops (cabbage, eggplant). These crops were grown on experimental plots of the University of Agricultural Sciences, Bengaluru, India, maintaining three different nitrogen levels (high, medium, and low). The datasets contain hyperspectral imagery of the vegetable crops grown under two configurations: (i) imagery, which contains only a single crop type in a scene, and (ii) imagery, which con-

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https://doi.org/10.1016/j.dib.2024.110649

tains both crops in a single scene. In both configurations, each crop has plots representing three different nitrogen levels. Ultra-high spatial resolution hyperspectral imaging data were acquired in 400 to 900 nm with an effective spectral resolution of 3 nm and spatial resolution of 3 mm using a ground-based push-broom hyperspectral imaging system (Headwall Photonics, USA). Ground truth data were also presented. The datasets are valuable for developing and validating various methods and algorithms for precision agriculture applications, such as machine learning methods for crop mapping at plants and estimating crop growth responses to different nitrogen levels.

Specifications Table

Subject	
Specific subject area	Precision Agriculture and Terrestrial Hyperspectral Remote Sensing
Data format	Raw and processed data in .hdr format readable by most image processing software packages
Type of data	Ultra-high resolution hyperspectral imagery (raster) with associated ground truth presented in '.hdr', files
Data collection	Hyperspectral data was collected using a push-broom terrestrial hyperspectral imaging (THI) spectroradiometer (Make: Headwall Photonics; model: A-series; USA) in the 400–900 nm range of the electromagnetic spectrum. The images were acquired by mounting the THI on a tripod platform that can be adjusted to maintain scene-sensor geometry. The THI measures reflected radiation. The data recorded in integer counts of reflected radiation intensity were further processed and calibrated to yield the standard surface reflectance product. The reference reflectance measurements acquired over a reference panel coated with Barium Sulphate were also acquired simultaneously with the imagery acquisition for further usage in the calibration process.
Data source location	Location: Gandhi Krishi Vigyana Kendra, University of Agricultural Sciences, Bengaluru, India. Geographical latitude and longitude: 13° 5′15.43″N 77°33′59.93″E
Data accessibility	Repository name: Mendeley Data Cabbage: 10.17632/whgnf4s4bp.1 Eggplant: 10.17632/t4rysh9rxf.1 Cabbage and Eggplant: 10.17632/cww6zkdcmb.1 Cabbage data URL: https://data.mendeley.com/datasets/whgnf4s4bp/1 Eggplant data URL: https://data.mendeley.com/datasets/t4rysh9rxf/1 Cabbage and Eggplant data URL: https://data.mendeley.com/datasets/cww6zkdcmb/1
Related research article	None

1. Value of the Data

- Calibrated ultra-high resolution proximal hyperspectral images are valuable datasets for scientists working in precision agriculture.
- The presented datasets can serve as reference datasets for researchers and practitioners working on computer vision and machine learning-based approaches for automatic crop type detection.

- The datasets calibrated and referenced for crop nutrient status enable scientists and startup companies to develop transferable pattern recognition approaches for computer-based crop nutrient suggestion models.
- In a first-of-its-kind, the presented ultra-high resolution calibrated hyperspectral imaging datasets help assess farm-level spectral imaging modelling for plant-sensitive crop nutrient prescription models.
- Pixel, object, and spectral indices-based methods used in crop detection and mapping applications using spectral modelling and knowledge transfer remote sensing study are some of the arenas found handy by the datasets.

2. Background

Benefiting from the rapid advances in computing and analysis methods, the hyperspectral imaging technique has been widely used for various applications in agriculture [1–3]. Various aspects of crop sensing- detection, identification, and biophysical characteristics have been studied predominantly using airborne and satellite-based hyperspectral imaging [2–8]. Because of the nature of these space-based platforms, the sensitivity and resolution of the datasets are suitable to address the gross features of crops, considering the farm as the measurement unit [5]. The fast-evolving proximal and drone-based hyperspectral imaging cameras allow sensing and modelling crops at a finer scale – within the field and plant level at the finest level of resolution. Adding up and advancing the reference datasets available for public access [2–4], the datasets presented in this work are aimed to be benchmark datasets available for developing and implementing models and methods for crop detection and nutrient characterization.

3. Data Description

The calibrated hyperspectral datasets acquired, both in radiance and reflectance mode, pertain to two widely consumed vegetable crops, cabbage (scientific name: *Brassica oleracea* var. *capitata*; cultivar: Pusa Mukta) and eggplant (scientific name: *Solanum melongena*; cultivar: Surya). The terrestrial hyperspectral images were acquired over the experimental research plots such that there is a full-frame imagery for each crop separately and both the crops combined. Accordingly, the data are organized by creating independent folders for the crops considered as "Cabbage_Crop.rar," "Eggplant_Crop.rar," and "Cabbage_Eggplant_Crops.rar". Each compressed file belongs to cabbage, eggplant, and its combined cabbage and eggplant, respectively. On extracting the *"XXXX_Crop.rar"* file, there are three files in each folder. The files "xxxx_Radiance_Data.hdr", "xxxx_Reflectance_Data.hdr", and "xxxx_N2_Concentration_GT.hdr", belong to radiance, reflectance, and its ground truth data. The detailed folders and file names are organized in Fig. 1, and ground class information is mentioned in Table 1.

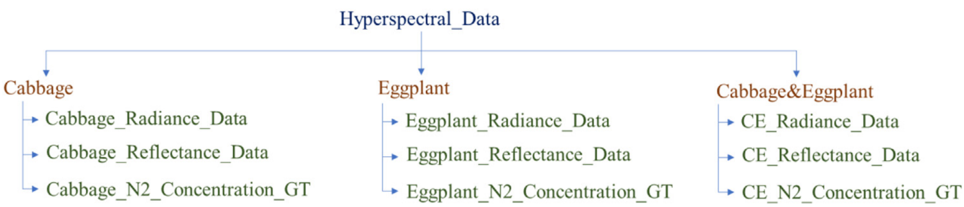

Fig. 1. Folder organized structure of radiance, reflectance, and ground truth data.

Table 1
Ground truth class information for different Nitrogen (N_2) level.

Cabbage (dataset: Cabbage)		Cabbage and Eggplant (dataset: Cabbage and Eggplant)	
Nitrogen Level	**Class No.**	**Nitrogen Level**	**Class No.**
Low	1	Cabbage_Low	1
Medium	2	Cabbage_Medium	2
High	3	Cabbage_High	3
		Eggplant_Low	4
Eggplant (dataset: Eggplant)		Eggplant_Medium	5
Nitrogen Level	**Class No.**	Eggplant_High	6
Low	1		
Medium	2		
High	3		

4. Experimental Design, Materials and Methods

4.1. Experimental design

As part of a larger research perspective of developing remote sensing-based methods for sub-farm crop discrimination and nutrient status estimation, a crop-growing experimental layout was designed and implemented on the research farms of the University of Agricultural Sciences, Bengaluru, India, from February to June 2022 [9]. The experimental plots were irrigated through a drip irrigation system. The crop growing experimental design contained plots of size 12 $m \times$ 18 m, each of which was subdivided into three subplots of 6m $\times$ 12 m. For each plot, there were four replications. The sub-plots were supplied with three different levels of mineral N fertiliser, designated as low, medium, and high, based on the regional standards of fertilisation recommendations. The rate of N fertiliser for the different treatment levels was estimated based on rows. Accordingly, urea was applied for the ‘medium N’ at the rate of 46 kg N ha^{-1} for tomato, 60 kg N ha^{-1} for cabbage, and 50 kg N ha^{-1} for eggplant. In reference to this, the ‘high N’ and ‘low N’ referred to 50 % more and 50 % less, respectively. Apart from nitrogen, a blanket application of phosphorus (P) and potassium (K) was applied at the rate of 41.5 kg ha-1 and 16.6 kg ha-1, respectively, for cabbage and eggplant at the time of sowing.

4.2. Data acquisition

The terrestrial hyperspectral imager (Model: A – Series; Manufacturer: Headwall Photonics, USA) was used to acquire data in the visible and near-infrared (400 - 1000 nm) regions. The instrument is a push broom sensor, which is mounted on the controlled rotating stage. The specification of the speed of rotation was calculated based on the sun illumination intensity measured using a reflectance reference panel of Barium Sulphate (white reference plate).

4.3. Data pre-processing method

The hyperspectral imagery files contain the recorded spectral radiance using a terrestrial spectral imaging radiometer. The raw integer counts were converted into the surface reflectance by normalizing the reference reflectance computed from the reference panel. Local spectral noise in the data was removed by applying the Savitzy-Golay filter (Fig. 2).

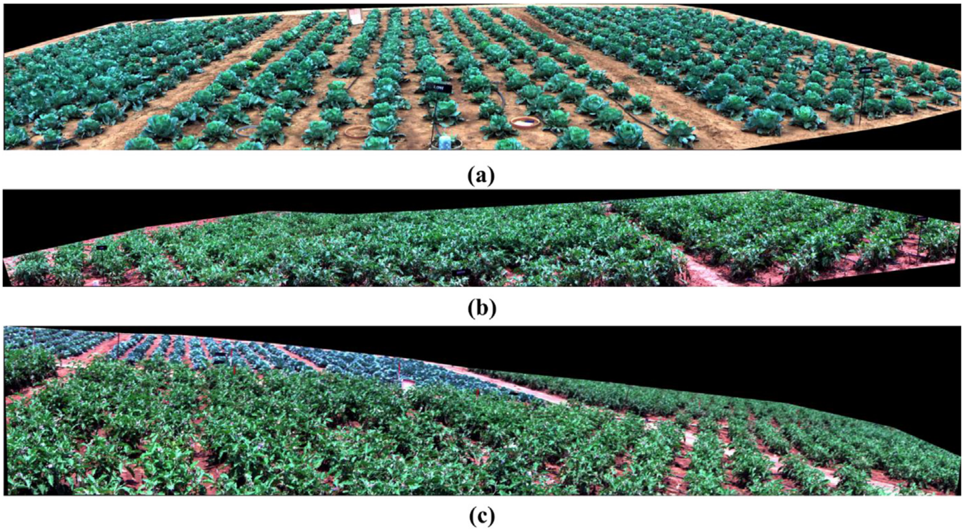

Fig. 2. example true colour compositions of data sets: visualizations of datasets of the crops; (a) cabbage, (b) eggplant, and (c) cabbage and eggplant combined.

Limitations

While the imagery was acquired following suggested measurement protocols and environmental settings, solar glint is persistent in ultra-high-resolution imagery. This phenomenon, common to any high-resolution reflectance-based spectral imaging (including RGB multispectral sensors) from proximal or drone platforms, is due to the optical-geometry-incurred radiometric distortion and needs to be corrected, preferably before using datasets with methods of a transferable modelling nature.

Ethics Statement

No animal or human subjects are used in the experimental setup. The data is not collected from any social media platform.

CRediT Author Statement

Conceptualization, Methodology: Rama Rao Nidamanuri, Usha Rani Nelakuditi; Resources: Rama Rao Nidamanuri; Data preparation: M. Vamshi Krishna; Data calibration: Manohar Kumar C. V. S. S; Writing - Original Draft: M. Vamshi Krishna; Review & Editing: Usha Rani Nelakuditi, Rama Rao Nidamanuri

Data Availability

cabbage_hyperspectral_dataset (Original data) (Mendeley Data).
Eggplant_Hyperspectral_Dataset (Original data) (Mendeley Data).
Cabbage_Eggplant_combined_Hyperspectral_dataset' (Original data) (Mendeley Data).

Acknowledgements

This research data acquisition was undertaken as part of ongoing activities to develop reference datasets for artificial intelligence applications in precision agriculture. The instrument support received from the Department of Science and Technology, Government of India during the initiation of this work is gratefully acknowledged.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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