Hyperspectral Narrowband Data Propel Gigantic Leap in the Earth Remote Sensing

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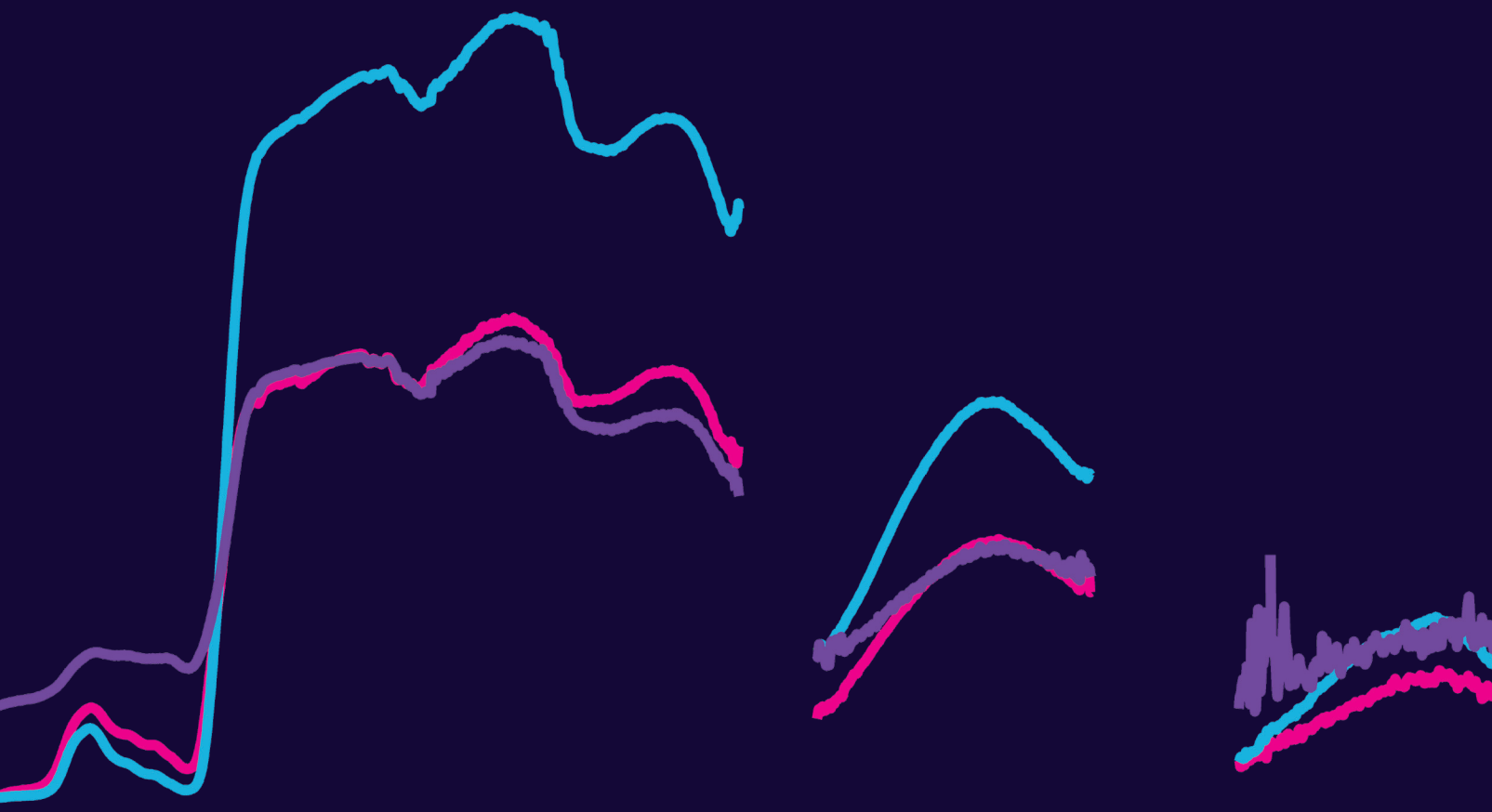

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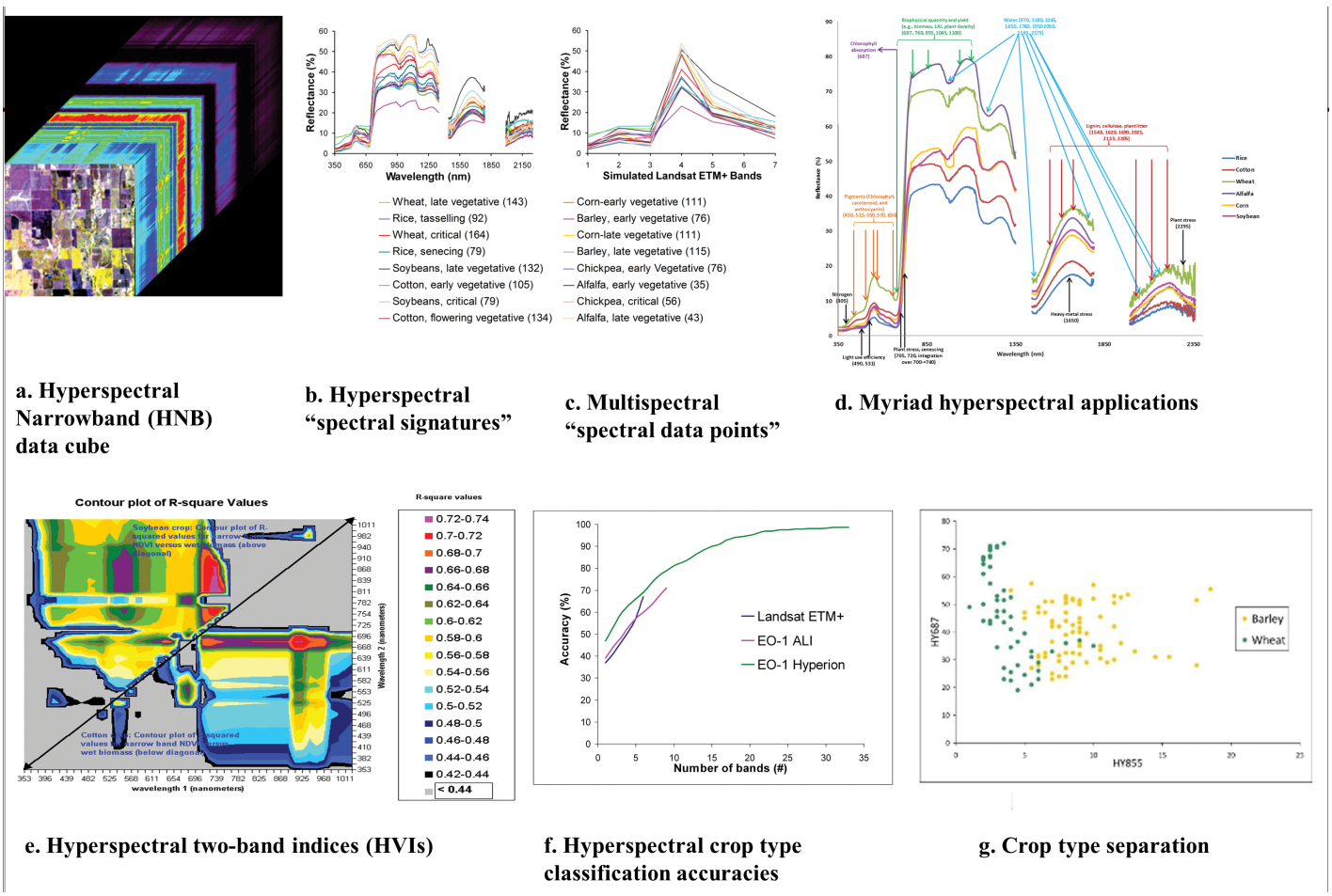
Hyperspectral narrowbands (HNBs) capture data as nearly continuous "spectral signatures" rather than a "few spectral data points" along the electromagnetic spectrum as with multispectral broadbands (MBBs). Almost all of satellite remote sensing of the Earth in the twentieth century was conducted using MBB data from sensors such as the Landsat-series, Advanced Very High-Resolution Radiometer (AVHRR), SPOT (Système Pour l'Observation de la Terre), and the Indian Remote Sensing (IRS) satellites. These systems typically provide 4 to 9 broad spectral wavebands spread from 400 to 2500 nm, often with one or two additional bands in the thermal range. Significant advances in the study of the Earth have been made based on these data [Thenkabail et al., 2018a,b,c,d; Thenkabail et al., 2015a,b,c]. Possibilities of great advances that can be made using HNB data over MBB data are well established based on studies conducted using hyperspectral sensors such as the hand-held spectroradiometers, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), and spaceborne Earth Observing -1 (EO-1) Hyperion [Thenkabail 2018a,b,c,d]. The twenty-first century is already seeing the dawn of hyperspectral imaging data from sensors such as the German Aerospace Center's (DLR's) DESIS (DLR Earth Sensing Imaging Spectrometer) onboard the MUSES (Multi-User System for Earth Sensing) platform on the International Space Station (ISS), the polar-orbiting Italian Space Agency's (ASI) PRISMA (PRecursore IperSpettrale della Missione Applicativa), and many other upcoming sensors such as the NASA Surface Biology and Geology (SBG) [Thenkabail et al., 2018a,b,c,d]. These satellites acquire data in hundreds of narrow spectral bands of 1 to 10 nm width, typically between 400 to 2500 nm; also future planned missions will be extending HNBs to the thermal (9,000 to 14,000 nm) electromagnetic spectrum. This expansion creates a quantum leap in new data, new information, and myriad possible new applications in the study of the Earth in addition to great advances in existing applications.

Given the above, the objective of this article is to provide insights on the gigantic leap in our understanding, modeling, mapping, and monitoring of the Earth that can be made using HNB relative to MBB by focusing on agricultural and vegetation applications. We will address this in four aspects:



a. Hyperspectral Narrowband (HNB) data cube

b. Hyperspectral "spectral signatures"

c. Multispectral "spectral data points"

d. Myriad hyperspectral applications

e. Hyperspectral two-band indices (HVIs)

f. Hyperspectral crop type classification accuracies

g. Crop type separation

Figure 1. Hyperspectral narrowband (HNB) data advances. This figure shows many advances of hyperspectral data. Hyperspectral data come in 100s of narrowbands as seen in the data cube (Fig. 1a). It is possible to extract, for example, agricultural crops' spectral signatures using HNBs (Fig. 1b) as opposed to a few data points along the spectrum as in multispectral broadbands (MBBs; Fig. 1c). A multitude of applications are possible using HNBs as illustrated in Fig. 1d. HNBs are used to compute thousands of two-band hyperspectral vegetation indices (HVIs) (Fig. 1e). The Fig. 1e top diagonal provides soybean biomass models and bottom diagonal provides cotton biomass models. Accuracies in crop type classification can be improved by as much as 30% compared to MBBs (Fig. 1f). HNBs offer greater possibilities of separating crop types by selecting unique wavebands along the spectrum (Fig. 1g). [Figure revised and adopted from several research papers of Thenkabail et al. [Thenkabail et al., 2018a,b,c,d].

1. Comparison between HNB and MBB data;
2. Spectral libraries of agricultural crops;
3. HNB data analysis in general; and
4. HNB analysis using machine learning (ML) and cloud computing.

Hyperspectral Narrowband (HNB) versus Multispectral Broadband (MBB) Data

Over the last 50 years, great advances in Earth observation (EO) and Earth studies were achieved, primarily using MBBs, as documented in the three volume Remote Sensing Handbook [Thenkabail et al., 2015a,b,c]. Nevertheless, HNBs allow for a gigantic leap in information-gathering of the planet Earth [Thenkabail et al., 2018a,b,c,d; Aneece and Thenkabail, 2018; Marshall and Thenkabail, 2015; Mariotto et al., 2013; Middleton et al., 2009; Aneece and Thenkabail, 2019]. Hyperspectral data come in hundreds or thousands of narrowbands (Figure 1a, 1b), each with 1-10 nm bandwidth, continuously along the spectrum (e.g., 400 to 2500 nm; 8000 to 14500 nm). They offer numerous possibilities for targeted applications such as species composition, vegetation or crop type separation, light-use efficiency estimation, and net primary productivity assessment. The quantum leap with HNB data compared to MBB can be visualized by comparing Figure 1b with 1c. HNBs (Figure 1d) along with HNB-derived two-band and multi-band HVIs (Figure 1e) are used to model, map, and monitor plant biophysical properties (e.g., LAI, biomass, yield, density), biochemical properties (e.g, anthocyanins, carotenoids, chlorophyll), plant health properties (e.g., disease and stress assessments, insect infestation, drought), structural properties (e.g., planophile versus erectophile), nutrient content (e.g., nitrogen), and moisture content (e.g., leaf moisture) studies and so on [Aneece and Thenkabail, 2018; Marshall and Thenkabail, 2015; Mariotto et al., 2013; Middleton et al., 2009; Aneece and Thenkabail, 2019].

The possibilities and advances are innumerable [Thenkabail et al., 2018a,b,c,d], (Figure 1). For example, using about 20 to 30 HNBs the classification accuracies of many agricultural crops or land cover/land use (LCLU) classes can be increased by about 30% relative to 6 to 11 MBBs of sensors such as Landsat Enhanced Thematic Mapper (ETM+) and Advanced Land Imager (ALI) (Figure 1f). HNBs also offer many distinct possibilities of separating crop types by choosing unique wavebands found in distinct portions of the spectrum (Figure 1g). They help derive thousands of hyperspectral vegetation indices (HVIs) to model vegetation quantities such as its biophysical and biochemical quantities (Figure 1e).

Spectral Libraries: Global Hyperspectral Imaging Spectral-Libraries of Agricultural Crops (GHISA)

Hyperspectral data can advance myriad applications for the Earth if there are adequate high-quality reference training and validation data [Aneece and Thenkabail, 2019]. Ideally, well-organized spectral libraries of features, such as minerals, soils, and vegetation are web-enabled and made available for rapid modeling, mapping, and monitoring a wide array of characteristics. A good example is a test of concept Global Hyperspectral Imaging Spectral-Libraries of Agricultural Crops (GHISA) [Aneece and Thenkabail, 2019] developed for each agroecological zones (e.g., AEZs; Fig. 2a; see Thenkabail et al., 2021 for different AEZs) or even sub-AEZs when crop characteristics vary widely even within AEZs. A comprehensive GHISA needs to take into consideration a wide array of crop characteristics such as crop types, crop growth stages, cultivars, biophysical, biochemical, and plant structure and health parameters, management practices (e.g., tillage, drainage), inputs (e.g., nitrogen, fertilizers), and drought conditions. The spectral libraries can be developed using data from any type of satellite sensors such as a hyperspectral sensor (Fig. 2b, top row) or Landsat multispectral ones (Fig. 2b, bottom row). These spectral libraries are then deciphered using qualitative or quantitative spectral matching techniques (SMTs) (Fig. 2c) [Thenkabail et al., 2007]. These libraries [Aneece and Thenkabail, 2019] are further

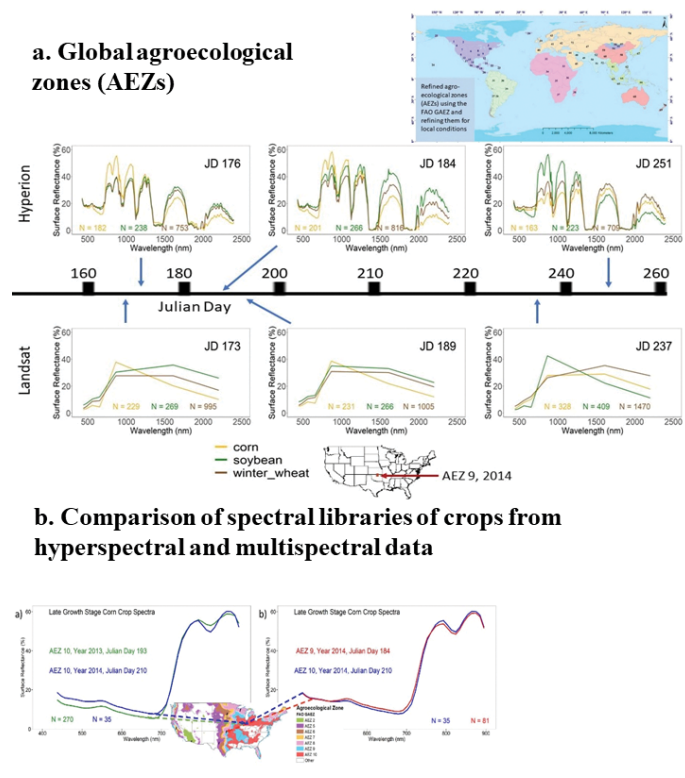


Figure 2. Global hyperspectral Imaging Spectral-libraries of Agricultural Crops (GHISA). The reference training and validation spectral libraries of agricultural crops are developed for each agroecological zone (AEZ) (Fig. 2a; different AEZs are described in [Thenkabail et al., 2014]) based on precise knowledge of the ground data from which spectral libraries are derived using any satellite sensor data. These spectral libraries are illustrated for three crops (corn, soybeans, and winter wheat) for one AEZ in USA using Hyperion hyperspectral data (Fig. 2b top row) and Landsat multispectral data (Fig. 2b bottom row) which can then be used in a wide array of analyses (e.g., spectral matching, Figure 2c).

fed into training and validation machine learning algorithms (MLAs) to model, map, and monitor agricultural features such as cropland extent in global, regional, national, and farm scales [Thenkabail et al., 2021]. Once these libraries are in place, the products can be repeatedly and accurately produced year after year to develop a multitude of agricultural cropland products.

Broad Philosophies of Hyperspectral Data Analysis

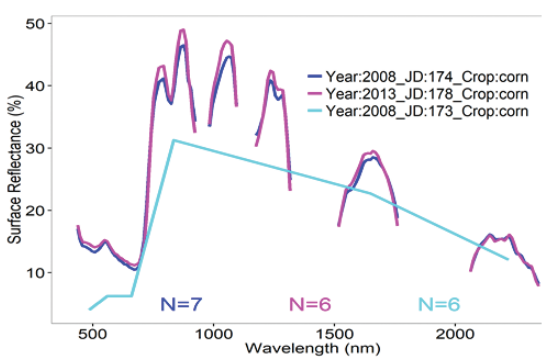
Hyperspectral data bring their own challenges, such as massive data volumes, data redundancy, Hughes phenomenon or curse of data dimensionality, complexities of data analysis, and need for highly trained experts [Thenkabail et al., 2018a,b,c,d]. Further, unlike the MBB data HNB data from different sources still need a mature Application Programming Interface (API). These challenges were largely addressed over the last two decades by an international community of experts and recent advances in machine learning, artificial intelligence, and cloud computing. Overall, there are three broad philosophies regarding hyperspectral data analysis [Thenkabail et al., 2018a,b,c,d] (Figure 3):

A. Full spectral Analysis (FSA);
B. Optimal hyperspectral narrowband analysis (OHNBs); and
C. Transformations and normalizations such as Hyperspectral vegetation indices (HVIs)

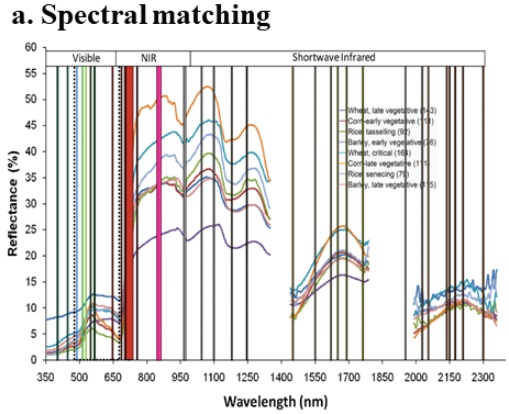
There are many other approaches of hyperspectral data analysis [Thenkabail et al., 2018a,b,c,d; Thenkabail et al., 2015a,b,c], which fall into one or more of the three philosophies listed above.

In the FSA all HNBs, as continuous-spectrum spectral signatures, are used in the analysis (Fig. 3a, 2c). FSA includes methods such as partial least squares regression (PLSR), wavelet analysis, continuum removal, spectral angle mapper (SAM), area under the spectra (integral), artificial neural networks (ANN's), and SMTs (Fig. 3a, 2d) [Thenkabail et al., 2018a,b,c,d; Thenkabail et al., 2015a,b,c; Aneece and Thenkabail, 2018; Marshall and Thenkabail, 2015; Mariotto et al., 2013; Middleton et al., 2009; Aneece and Thenkabail, 2019; Thenkabail et al., 2007].

FSA, for example, would involve creating an ideal spectral databank/libraries [Aneece and Thenkabail, 2019; Thenkabail et al., 2007; Thenkabail et al., 2021] of individual agricultural crops in each AEZ or sub-AEZ throughout the growing season with clear understanding and characterization of crop variables such as crop types, cultivar types, crop growth stages, crop growing conditions (e.g., irrigated or rainfed), and their biophysical, biochemical, structural, and plant health characteristics. A robust databank will involve crops grown during drought, normal, and wet years. Then the HNB data acquired over every growing season and every year will be matched with the ideal spectral databank using various SMT methods to develop models and maps of various



a. Spectral matching



c. Optimal HNBs on spectral profile

b. Optimal HNBs and features

A. Blue bands (Three columns below: band number, waveband center in nanometer or nm, and application type)
   1. 375 fPAR, leaf water
   2. 466 Chlorophyll
   3. 490 Senescing browning, ripening
B. Green bands
   4. 515 Nitrogen
   5. 520 Pigment, biomass changes
   6. 525 Vegetation vigor, pigment, nitrogen
   7. 550 Chlorophyll
   8. 575 Vegetation vigor, pigment, and nitrogen
C. Red bands
   9. 675 Chlorophyll absorption maxima
   10. 682 Biophysical quantities and yield
D. Red-edge bands
   11. 700 Stress and chlorophyll
   12. 720 Stress and chlorophyll
   13. 740 Nitrogen accumulation
E. Near-infrared (NIR) bands
   14. 845 Biophysical quantities and yield
   15. 915 Moisture, biomass, and protein
   16. 975 Moisture and biomass
F. Far NIR (FNIR) bands
   17. 845 Biophysical quantities
   18. 1215 Moisture and biomass
   19. 1245 Water sensitivity
G. Short-wave infrared (SWIR) band
   20. 1316 Nitrogen
   21. 1445 Vegetation classification and discrimination
   22. 1518 Moisture and biomass
   23. 1725 Lignin, biomass, starch, moisture
   24. 2035 Moisture and biomass
   25. 2173 Protein, nitrogen
   26. 2260 Moisture and biomass
   27. 2295 Stress
   28. 2359 Cellulose, protein, nitrogen

Figure 3. Two of the three broad philosophies in hyperspectral data analysis: Full spectral analysis (FSA) (Figure 3a) through methods like spectral matching techniques (SMTs) (Fig. 3a, also see Fig. 2c); Optimal hyperspectral narrowbands (OHNBs) (Fig. 3b, 3c).

Table 1. Some key two-band hyperspectral vegetation indices (HVIs). The HNB bands in the indices show band centers. The bandwidth is typically 5 nm (optimal) to 10 nm (maximum) for each band except the 531 nm, which has 1 nm bandwidth [Thenkabail 2018a,b,c,d].

Crop Characteristics	Crop Variable	Two-band Hyperspectral Vegetation Index (HVI)
Biophysical quantities	Biomass, LAI, Plant height, Grain yield	(855 – 682) / (855 + 682)
Biochemical quantities	Carotenoids, Anthocyanin, Nitrogen, Chlorophyll	(550 – 515) / (550 + 515)
Plant health	Stress Conditions	(855 – 720) / (855 + 720)
Plant water	Moisture, Water content of plants	(855 – 970) / (855 + 970)
Net and gross primary productivity	Light-use efficiency	(570 – 531) / (570 + 531)
Biopolymer	Lignin, Cellulose	(2205 – 2025) / (2205 + 2025)

features of interest. Rational selection of optimal hyperspectral narrowbands (OHNBs) is an alternative approach to FSA required at times to [Thenkabail et al., 2018a,b,c,d; Thenkabail et al., 2015a,b,c]: A. avoid very large data volumes, B. overcome redundant data, and C. avoid issues of Hughes phenomenon. A third and very common approach that targets the complexity in FSA is the utilization of HVIs. The HVIs target wavelengths/bands which correspond with specific crop variables, referred to as OHNBs, to best quantify, model and map specific species of crops and natural vegetation. Table 1 shows a few selected two-band HVIs. For detailed descriptions of HVIs, one may refer to [Thenkabail et al., 2018a,b,c,d]. While there are some leading OHNBs, HVIs overcome the complexity of hyperplane data to study plant biophysical and biochemical quantities [Cohen and Alchanatis in Thenkabail et al., 2018c]. These approaches pose a different kind of challenge, i.e. investing time and effort in identifying the specific optimal set of bands or VIs for the specific property in a specific zone. Instead, it might be more useful to share the ground truth data collected through global spectral libraries like GHISA [Aneece and Thenkabail, 2019] and to use the FSA approach.

Machine Learning for Petabyte Scale Big Data on the Cloud

The massive volumes of hyperspectral data call for new methods and approaches in analyzing them to gather information. This challenge requires a gigantic leap or paradigm shift in how hyperspectral data are analyzed involving four steps (Figure 4):

Analysis ready data cubes—The first step is acquiring data from multiple satellites (Fig. 4.1) and creating analysis ready data cubes (Fig. 4.2) that are in at least surface reflectance products that are harmonized and normalized seamlessly over any area of the Earth and stacked as data cubes [Thenkabail et al., 2021]. Already large volumes of Hyperion data are ingested into Google Earth Engine (GEE)* cloud.

Reference data hubs—Reference training and validation data for machine learning [Thenkabail et al., 2021] are acquired either from ground-based surveys or from sub-meter to 5 meters very high-resolution imagery (VHRI), or through national and other reliable sources. These data are properly catalogued and made accessible on the Web for easy access to anyone.

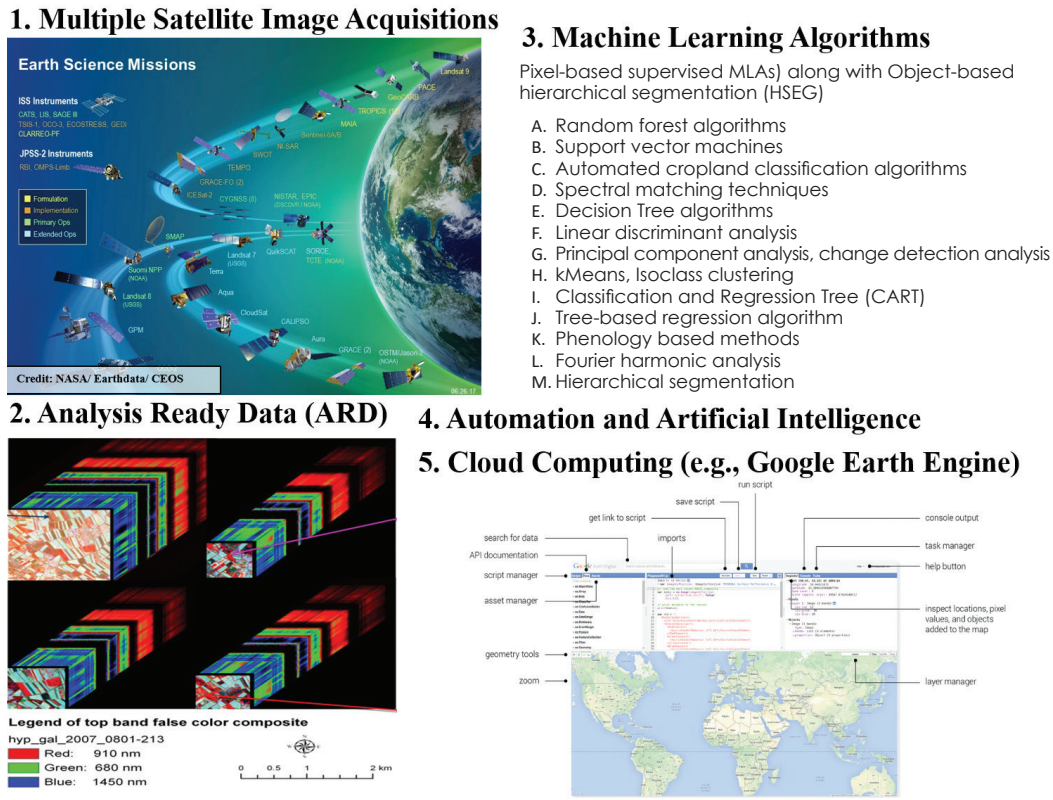


Figure 4. A gigantic leap paradigm shift in analyzing satellite sensor big data on the cloud using machine learning, deep learning, and artificial intelligence. The process is described in detail in [Thenkabail et al., 2021].

* Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Machine learning, deep learning, and Artificial Intelligence (AI)—Selecting machine learning and deep learning algorithms (Fig. 4.3) such as the supervised pixel-based and unsupervised clustering algorithms over multi-dimensional space, object-oriented classifiers, and neural networks is the next step [Thenkabail et al., 2021]. AI is powered by neural networks [Paoletti et al., 2015] such as the: 1. Convolution neural networks (CNNs) for image recognition, image labeling by utilizing features extracted from data rather than reference independent sources, 2. Recurrent neural networks (RNNs) such as signal processing allowing previous outputs to be used as input and thus handling temporal data dependencies better than CNNs, 3. Multi-layer perceptron involving reference sample selection, training the model and classification of images, and 4. Transformers building relationships between pixels and images.

Cloud computing—The above process can be automated by training algorithms on cloud computing platforms such as Google Earth Engine (GEE) [Thenkabail et al., 2021], Amazon Web Services (AWS), Microsoft Azure, or other local and institutional clouds.

A detailed paradigm-shift approach to satellite sensor data based big data analytics is demonstrated by [Thenkabail et al., 2021] in global cropland extent mapping using Landsat, Sentinel, and other data. The same approach can be adopted here for hyperspectral data. However, the key to success in modeling, mapping, and monitoring with machine learning and artificial intelligence techniques with expert knowledge using hyperspectral data will be the generation of rich and systematic spectral libraries of agricultural crops as discussed in Section 2.0 above. There will be a need to define a standardization and to develop a simple protocol for end-users around the globe to share their reference training and validation data that will be further used by the ML/AI methods.

Summary

Hyperspectral imaging spectroscopy or hyperspectral remote sensing will play a significant role in the twenty-first century remote sensing science. The new technology offers many advances by providing "spectral signatures" as opposed to a "few data points along the spectrum". First, this paper highlights the major advances offered by hyperspectral narrowband data. Second, the importance of building a powerful Global Hyperspectral Imaging Spectral-Libraries of Agricultural Crops (GHISA) to enable highly accurate models, maps, and monitoring tools of a wide array of biophysical, biochemical, plant health and plant structure parameters was discussed. Third, the three major philosophies of hyperspectral data analysis were described and established as full spectral analysis (FSA), optimal hyperspectral narrowbands (OHNBs) and use of transformations or normalizations such as hyperspectral vegetation indices (HVIs). FSA is preferred; however, both OHNBs and HVIs have their own utility and value in a multitude of applications. For example, strengths of OHNBs and HVIs when avoiding data redundancy, storage issues, and in overcoming Hughes phenomenon (or "curse of high dimensionality of data"). Fourth, the requirement of a machine learning, deep learning, and artificial intelligence (ML/DL/AI) methods on the cloud-platform to best utilize the full power of petabyte-scale hyperspectral big data to propel a quantum-leap in myriad science applications was proposed and discussed. In all this, easily accessible web-enabled analysis ready hyperspectral data through cloud-enabled processing and APIs is a must.

References

Thenkabail, P.S., Lyon, G.J., and Huete, A. 2018a. *Fundamentals, Sensor Systems, Spectral Libraries, and Data Mining for Vegetation*. CRC Press Boca Raton, Florida. 449 p.

Thenkabail, P.S., Lyon, G.J., and Huete, A. 2018b. *Hyperspectral Indices and Image Classifications for Agriculture and Vegetation*. CRC Press Boca Raton, Florida. 296 p.

Thenkabail, P.S., Lyon, G.J., and Huete, A. 2018c. *Biophysical and Biochemical Characterization and Plant Species Studies*. CRC Press Boca Raton, Florida. 348 p.

Thenkabail, P.S., Lyon, G.J., and Huete, A. 2018d. *Advanced Applications in Remote Sensing of Agricultural Crops and Natural Vegetation*. CRC Press Boca Raton, Florida. 386 p.

Thenkabail, P.S. 2015a. *Remotely Sensed Data Characterization, Classification, and Accuracies*. CRC Press Boca Raton, Florida. 678 p.

Thenkabail, P.S. 2015b. *Land Resources Monitoring, Modeling, and Mapping with Remote Sensing*. CRC Press Boca Raton, Florida. 849 p.

Thenkabail, P.S. 2015c. *Remote Sensing of Water Resources, Disasters, and Urban Studies*. CRC Press Boca Raton, Florida. 673 p.

Aneece, I. and P. Thenkabail. 2018. Accuracies Achieved in Classifying Five Leading World Crop Types and their Growth Stages Using Optimal Earth Observing-1 Hyperion Hyperspectral Narrowbands on Google Earth Engine. *Remote Sensing*. 2018, 10, 2027. https://doi.org/10.3390/rs10122027 IP-097093.

Marshall M. T. and P. Thenkabail. 2015. Developing in situ Non-Destructive Estimates of Crop Biomass to Address Issues of Scale in Remote Sensing. *Remote Sensing*. 2015; 7(1):808-835. doi:10.3390/rs70100808. IP-060652.

Mariotto, I., Thenkabail, P.S., Huete, H., Slonecker, T., Platonov, A., 2013. Hyperspectral versus Multispectral Crop- Biophysical Modeling and Type Discrimination for the HyspIRI Mission. *Remote Sensing of Environment*. 139:291-305. IP-049224.

Middleton, E.M., Cheng, Y.B., Hilker, T., Black, T.A., Krishnan, P., Coops, N.C., & Huemmrich, K.F. 2009. Linking foliage spectral responses to canopy-level ecosystem photosynthetic light-use efficiency at a Douglas-fir forest in Canada. *Canadian Journal of Remote Sensing*, 35(2), 166-188.

Aneece, I. and P. Thenkabail. 2019. Global Hyperspectral Imaging Spectral-library of Agricultural crops (GHISA) for the Conterminous United States (CONUS). Algorithm Theoretical Basis Document (ATBD). NASA Land Processes Distributed Active Archive Center (LP DAAC). IP-110217.

https://lpdaac.usgs.gov/news/release-global-hyperspectral-imaging-spectral-library-agricultural-crops-conterminous-united-states/

https://lpdaac.usgs.gov/products/ghisaconusv001/

Thenkabail, P.S., GangadharaRao, P., Biggs, T., Krishna, M., and Turral, H., 2007. Spectral Matching Techniques to Determine Historical Land use/Land cover (LULC) and Irrigated Areas using Time-series AVHRR Pathfinder Datasets in the Krishna River Basin, India. *Photogrammetric Engineering and Remote Sensing*. 73(9): 1029-1040.

Thenkabail, P.S., Teluguntla, P., Xiong, J., Oliphant, A., Congalton, R., Ozdogan, M., Gumma, M.K., Tilton, J., Giri, C., Milesi, C., Phalke, A., Massey, M., Yadav, K., Milesi, C., Sankey, T., Zhong, Y., Aneece, Y., Foley, D. 2021. Global Cropland Extent Product at 30m (GCEP30) derived using Landsat Satellite Time-series Data for the Year 2015 through Multiple Machine Learning Algorithms on Google Earth Engine (GEE) Cloud. Research Paper #, United States Geological Survey (USGS). In press. IP-119164.

Paoletti, M.E., Haut, J.M., Plaza, J., and Plaza, A. 2019. Deep learning classifiers for hyperspectral imaging: A review Author links open overlay panel. I*SPRS Journal of Photogrammetry and Remote Sensing*. 158: 279-317.

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