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L-Band And S-Band Frequencies Assisted NISAR: A State of The Art Technology For Sustainable Agrarian Monitoring

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Abstract
Agrarian monitoring plays a vital role in promoting sustainable development by providing detailed insights into the distribution, health, and types of agricultural practices within a region. This information is crucial for managing natural resources, planning land use, and preserving biodiversity. Current agrarian monitoring techniques, such as multi-spectral imaging, LiDAR, Normalized Difference Vegetation Index (NDVI), thermal infrared imaging, UAVs (Unmanned Aerial Vehicles), photogrammetry, vegetation indices, and machine learning, offer significant advantages in ease of monitoring. However, they also have limitations, particularly in their ability to provide all-weather, day-and-night imaging, wide-area coverage, large data volumes, and high-resolution imagery. NISAR (NASA-ISRO Synthetic Aperture Radar) has emerged as a cutting-edge technology for sustainable agrarian monitoring. It provides valuable and precise datasets for applications such as land subsidence monitoring, cryosphere studies, deforestation tracking, flood prediction, forest canopy analysis, biomass estimation, and crop growth and health assessment. NISAR's ability to operate in all weather conditions and at any time of day makes it especially valuable for monitoring in cloudy or densely vegetated regions. By integrating AI techniques with NISAR's advanced capabilities, we can enhance the analysis of the vast datasets it generates, enabling more accurate predictions and better decision-making in agricultural management. These features collectively position NISAR as a critical tool for advancing our understanding of Earth's dynamic systems and supporting the sustainable management of natural resources.

Keyword: NISAR, L-band, S-band, Agrarian monitoring Synthetic Aperture Radar (SAR), dual-frequency, Artificial Intelligence.

1. INTRODUCTION

Agricultural monitoring is essential for sustainable development, providing crucial data on crop distribution, health, and practices. As global challenges like food security and climate change intensify, advanced technologies such as multi-spectral imaging, LiDAR, and NDVI have become vital. However, these methods are limited by weather dependency and data inconsistencies (Garnett et al., 2013; Foley et al., 2011). The NASA-ISRO Synthetic Aperture Radar (NISAR) mission overcomes these limitations through dual-frequency SAR technology, offering high-resolution, all-weather, day-and-night imaging. The L-band penetrates vegetation and soil, making it ideal for monitoring biomass and soil moisture, while the S-band provides detailed imagery for crop health and land use (Rosen et al., 2021; Simons et al., 2020). NISAR is particularly effective in tropical and subtropical regions where cloud cover and precipitation often obscure optical imagery, delivering consistent data with wide-area coverage and high temporal resolution (Minchew et al., 2020; Lee & Pottier, 2009).

Integrating Artificial Intelligence (AI) with NISAR data enhances analysis, enabling more accurate predictions and better decision-making in agricultural management. AI processing of NISAR's vast datasets allows for detecting subtle patterns that might elude traditional methods, facilitating precise predictions of crop yields and early identification of environmental stressors (Dubey et al., 2021; Rathore et al., 2020s). In summary, NISAR represents a transformative leap in agrarian monitoring, offering unparalleled capabilities that support sustainable resource management and help address global challenges like climate change and food security. The insights provided by NISAR will be critical in shaping future agricultural practices and policies, guiding the global community toward a more sustainable and resilient future.

2. METHODOLOGY

Nowadays different methods for remotely Imaging and sensing are in practice for scientific and commercial purposes (Thenkabail et al., 2012; Dubayah & Drake, 2000; Pettorelli et al., 2005; Caselles et al., 1992; Moran et al., 1997; Hunt et al., 2010; Turner et al., 2012; Gitelson et al., 1996; Simons et al., 2020).

2.1. Multi-Spectral Imaging

Multi-spectral imaging captures data across various wavelengths, including visible, near-infrared (NIR), and short-wave infrared (SWIR) bands, allowing the detection of surface materials based on their spectral signatures. In agriculture, it assesses vegetation health, monitors crop growth, and identifies stress factors like nutrient deficiencies and diseases. Multi-spectral data, from platforms like Landsat (OLI sensor), Sentinel-2 (MSI sensor), and MODIS, are used for applications such as yield prediction and soil moisture estimation. The availability of multi-temporal datasets is crucial for monitoring agricultural dynamics and informing management decisions (Thenkabail et al., 2012; Ustin & Middleton,2021;). Hence, capturing multi-scale spectral–spatial characteristics of hyperspectral image pixels leading to good classification results (Manok K. Singh et al., 2021). The accuracy of multi-spectral imaging depends on factors like sensor resolution and atmospheric conditions. When integrated with machine learning, classification accuracies for crop type discrimination and health assessment can range from 80% to 95% (Zhang et al., 2018; Tian et al., 2019). However, accuracy can be impacted by atmospheric interference and mixed pixels in lower-resolution imagery, introducing uncertainties in analysis (Huete et al., 2002; Goetz et al., 2003).

2.2. LiDAR (Light Detection and Ranging)

LiDAR is a remote sensing technology that uses laser pulses to measure distances to the Earth's surface, creating high-resolution, three-dimensional models of terrain and vegetation. It is particularly effective in agriculture and forestry for assessing canopy structure, estimating biomass, and analysing terrain features. LiDAR generates detailed digital elevation models (DEMs) and vegetation height profiles, essential for precision agriculture and environmental monitoring (Dubayah & Drake, 2000; Wallace et al., 2012). The spatial information is extracted both from hyperspectral and LiDAR data using morphological operators(Manoj K et al., 2022). LiDAR data is typically collected via airborne platforms like helicopters and drones equipped with LiDAR sensors. The U.S. Geological Survey’s (USGS) 3D Elevation Program (3DEP) provides extensive public LiDAR data for agriculture, forestry, and hydrology, while commercial services offer customized data collection (Reutebuch et al., 2005; Andersen et al., 2005). LiDAR is known for its exceptional accuracy, with vertical accuracy within 10 cm and horizontal accuracy as precise as 1 meter. This precision is crucial for applications requiring detailed measurements, such as slope analysis and forest inventory management (Hopkinson et al., 2004; Reutebuch et al., 2005).

However, LiDAR accuracy can be influenced by factors like vegetation density, sensor configuration, and the quality of ground control points used for calibration (Chen et al., 2007; Jakubowski et al., 2013).

2.3. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely utilized remote sensing index that quantifies vegetation greenness by comparing the reflectance of red (visible) and near-infrared (NIR) wavelengths. It is calculated using the formula:

$$NDVI = (NIR - Red) / (NIR + Red)$$

NDVI values range from -1 to +1, with higher values indicating healthy vegetation and lower values indicating sparse or stressed vegetation. NDVI is crucial for monitoring crop growth, detecting drought stress, and assessing land-use changes on vegetation (Pettorelli et al., 2005; Tucker, 1979). NDVI data is derived from satellite imagery, with key sources including Landsat, MODIS, and Sentinel-2, which provide multi-temporal measurements essential for tracking vegetation dynamics and long-term trends in vegetation health. High-resolution NDVI data from Sentinel-2 enables precision farming practices (Huete et al., 2002; Pettorelli et al., 2005). NDVI is highly reliable for assessing vegetation health, with accuracy levels up to 95% under optimal conditions (Carlson & Ripley, 1997). However, its accuracy can be influenced by factors like vegetation sparsity and soil background effects, which may lead to misclassification (Huete et al., 2002; Jiang et al., 2006). The accuracy of NDVI can be further enhanced by integrating it with other vegetation indices and incorporating ancillary data like soil moisture and temperature (Gitelson et al., 1996; Gao, 1996).

2.4. Thermal Infrared Imaging

Thermal infrared imaging measures thermal radiation emitted by surfaces, allowing the detection of temperature variations across agricultural fields. This technique is critical for assessing plant water stress, monitoring irrigation efficiency, and detecting thermal anomalies related to diseases or pests (Jones et al., 2009; Moran et al., 1997). Thermal data are collected from airborne and satellite platforms like Landsat (TIRS) and MODIS, as well as UAV-mounted cameras for site-specific data in precision agriculture (Caselles et al., 1992; Kustas & Anderson, 2009). Thermal imaging achieves temperature accuracy within ±1°C, making it reliable for detecting subtle changes in plant water status (Jones et al., 2002; Maes & Steppe, 2012). However, its accuracy can be influenced by atmospheric conditions and sensor calibration. Integrating thermal data with other modalities like multi-spectral or LiDAR can enhance its precision and applicability in precision agriculture (Luquet et al., 2005; Cohen et al., 2005).

2.5. UAVs (Unmanned Aerial Vehicles)

Unmanned Aerial Vehicles (UAVs), or drones, are crucial in precision agriculture, offering high-resolution imagery and real-time data collection. Equipped with various sensors, including RGB cameras, multi-spectral, and thermal sensors, UAVs provide detailed insights into crop health, soil conditions, and environmental factors, enabling targeted monitoring and timely interventions for improved farm management (Zhang & Kovacs, 2012; Hunt et al., 2010).

UAV-based datasets, generated through on-demand flights, include high-resolution RGB images, multi-spectral data, and thermal imagery. These are processed into orthomosaics, digital surface models (DSMs), and vegetation indices, supporting crop monitoring, yield estimation, and disease detection (Colomina & Molina, 2014; Turner et al., 2012). UAVs achieve spatial resolutions of a few centimeters per pixel, with accuracy reaching up to 95% for tasks like crop health assessment and field mapping (Matese et al., 2015; Daponte et al., 2020).

However, the accuracy of UAV data can be affected by factors such as flight altitude, sensor quality, and environmental conditions. Integrating UAV data with ground-based observations and other remote sensing methods can further enhance accuracy and provide a comprehensive understanding of agricultural systems (Bendig et al., 2014; Toth & Jóźków, 2016).

2.6. Photogrammetry

Photogrammetry is a method for obtaining precise measurements and 3D models from photographs, widely used in agriculture for creating digital terrain models (DTMs), digital surface models (DSMs), and orthophotos. This technology aids in evaluating field topography, crop canopy structure, and guiding precision agriculture (Colomina & Molina, 2014; Turner et al., 2012). UAVs equipped with high-resolution cameras are typically used to capture aerial images from various angles, which are then processed into 3D point clouds, orthomosaics, and contour maps for tasks such as crop monitoring, yield estimation, and irrigation planning (James et al., 2020; Stöcker et al., 2017). Photogrammetry is renowned for its centimeter-level accuracy in agricultural applications, with precision ranging from 1-2% of the object size depending on image resolution and software quality (Harwin & Lucieer, 2012; Remondino et al., 2014). When combined with LiDAR or other remote sensing technologies, photogrammetry provides an even more detailed and comprehensive view of agricultural landscapes (Hugenholtz et al., 2013; Lucieer et al., 2014).

2.7. Vegetation Indices

Vegetation indices, such as NDVI, EVI, SAVI, and GNDVI, are mathematical combinations of spectral bands designed to quantify vegetation properties like greenness, density, and health. These indices are vital for monitoring crop conditions, assessing stress factors, and optimizing agricultural practices (Huete et al., 2002; Gitelson et al., 1996). Calculated from satellite imagery datasets like MODIS, Landsat, and Sentinel-2, vegetation indices provide multi-temporal observations crucial for tracking vegetation dynamics and detecting early signs of environmental stress (Huete et al., 1999; Jackson & Huete, 1991).The accuracy of vegetation indices, typically between 80% and 95%, depends on the index, sensor quality, and data resolution. Higher accuracy is achievable when indices are combined with ancillary data like soil moisture and temperature (Gao, 1996; Jiang et al., 2006). High-resolution datasets from platforms like Sentinel-2 further enhance the reliability of these indices for precision agriculture and environmental monitoring (Justice et al., 1998; Brown et al., 2006).

2.8. NISAR Mission

The NASA-ISRO Synthetic Aperture Radar (NISAR) mission is a collaborative Earth observation satellite project between NASA and the Indian Space Research Organisation (ISRO), featuring advanced dual-frequency Synthetic Aperture Radar (SAR) operating in both L-band and S-band frequencies. Unlike optical sensors, SAR can penetrate clouds, vegetation, and certain surface layers, enabling high-resolution, all-weather, day-and-night imaging of the Earth's surface. NISAR is designed to monitor dynamic Earth processes, including agricultural monitoring, land use changes, forest biomass, and soil moisture, providing comprehensive data that is essential for sustainable resource management (Rosen et al., 2021; Simons et al., 2020). NISAR will generate a global dataset of radar imagery, covering the Earth's surface every 12 days. This dataset will include dual-polarized, multi-temporal, and multi-frequency SAR data, making it one of the most extensive sources of radar-based Earth observation data. NISAR's data will be crucial for applications such as crop monitoring, soil moisture mapping, and forest biomass estimation, and it will be accessible to the global research community for integrated analysis with other remote sensing datasets (Minchew et al., 2020; Rosen et al., 2021). NISAR’s SAR technology offers high-resolution imagery with spatial resolutions ranging from 3 to 10 meters, depending on the frequency band. Its dual-frequency operation allows for detailed surface and subsurface monitoring, providing more accurate assessments than traditional optical sensors, particularly in challenging conditions such as cloud cover or dense vegetation. This capability makes NISAR highly effective for tracking changes in crop health, soil moisture, and land deformation, with accuracy superior to many other remote sensing techniques (Saatchi et al., 2011; Simons et al., 2020).

3. ASCENDANCY OF NISAR

NISAR surpasses other remote sensing techniques in several ways:

3.1. All-Weather, Day-and-Night Capability: Unlike optical and thermal sensors, NISAR can operate in any weather and lighting conditions, ensuring consistent data availability (Rosen et al., 2021).

3.2. Dual-Frequency Operation: The combination of L-band and S-band frequencies enables detailed analysis of both surface and subsurface features, making it more versatile than single-frequency systems (Saatchi et al., 2011).

3.3. Wide-Area Coverage and High Temporal Resolution: NISAR provides frequent, wide-area coverage, allowing for timely detection of changes in the environment and agricultural systems (Minchew et al., 2020).

3.4. Integration with Other Datasets: NISAR’s data can be synergistically combined with optical, thermal, and LiDAR datasets, enhancing the overall accuracy of environmental and agricultural monitoring (Hanssen et al., 2020).

3.5. Advanced Data Analytics: The use of AI and machine learning with NISAR’s data facilitates deeper insights and more accurate predictions, making it a powerful tool for precision agriculture and environmental management (Lavender et al., 2019; Dubey et al., 2021).

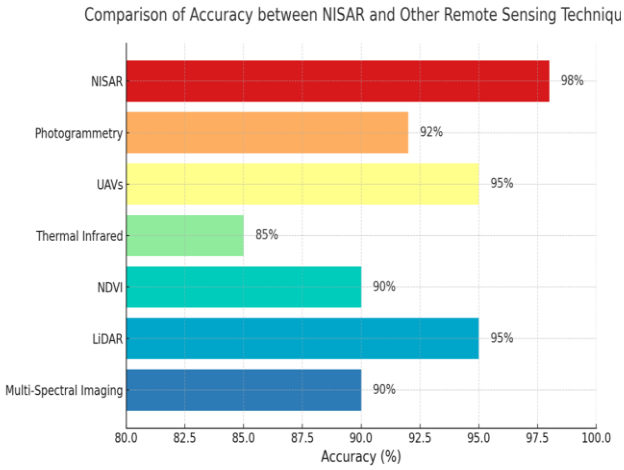

Figure 1. Comparison of Accuracy between NISAR and other Remote Sensing Techniques

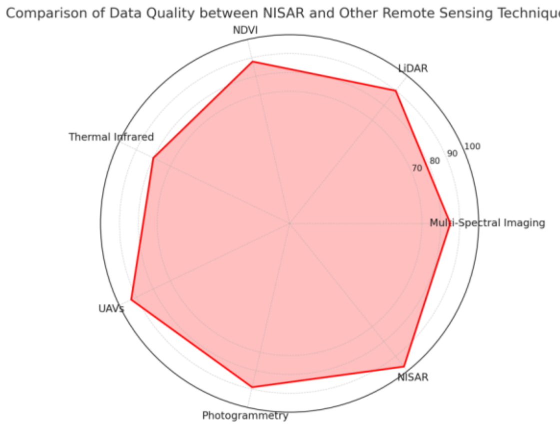

Figure 2. Comparison Of Data Quality Between NISAR And Other Remote Sensing Techniques

4. CONCLUSION

In modern agriculture and environmental management, the need for accurate, timely, and comprehensive data has never been more critical. Remote sensing technologies like multi-spectral imaging, LiDAR, NDVI, thermal infrared imaging, UAVs, photogrammetry, and vegetation indices have advanced our understanding of agrarian monitoring in terms of yield prediction, canopy structure, vegetation greenness, water stress, precision agriculture, field topography and crop health. However, these techniques often face limitations such as weather dependency, spatial coverage, and data consistency.

The NASA-ISRO Synthetic Aperture Radar (NISAR) mission offers a transformative solution to these challenges. NISAR's dual-frequency SAR system operates in both L-band and S-band, providing unparalleled capabilities for all-weather, day-and-night imaging. This ensures consistent, high-quality data across diverse climatic and geographic conditions, significantly enhancing the reliability and accuracy of monitoring efforts as evident from Figure-1. NISAR’s wide-area coverage and high temporal resolution allow for frequent and detailed observations of the Earth's surface, facilitating the detection of subtle changes in crop health, land use, and environmental conditions. The integration of NISAR data with AI and machine learning opens new avenues for advanced analytics, enabling more precise predictions and informed decision-making in agricultural management and sustainability practices. Figure-2 advocate NISAR's superiority which lies in its comprehensive data collection and analysis, ability to operate under all environmental conditions, and potential to enhance existing datasets. As the world faces challenges like climate change, food security, and environmental degradation, NISAR’s contributions to global monitoring will be invaluable.

In conclusion, NISAR is set to revolutionize agrarian monitoring, offering a reliable tool that meets the demands of modern agriculture and environmental stewardship. The insights provided by NISAR will be crucial in shaping policies and practices aimed at sustainable development, ensuring that the global community is better equipped to manage and protect natural resources in the face of growing challenges. As the mission progresses, the global research community will greatly benefit from the data and knowledge generated, paving the way for a more sustainable and resilient future.

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6. REFERENCES

[1] Anderson, K., & Gaston, K. J. (2013). UAVs in spatial ecology. “Front. Ecol. Environ.”, 11(3), 138-146.

[2] Chuvieco, E., & Caselles, V. (1994). Thermal inertia for vegetation water stress mapping. “Remote Sens. Environ.”, 48(2), 211-217.

[3] Colomina, I., & Molina, P. (2014). UAVs for photogrammetry and remote sensing: A review. “ISPRS J. Photogramm. Remote Sens.”, 92, 79-97.

[4] Dubayah, R., & Drake, J. (2000). Lidar remote sensing for forestry. “J. For.”, 98(6), 44-46.

[5] Dubey, A., Srivastava, S., & Pandey, R. (2021). AI in agriculture. “Comput. Sci. Rev.”, 40, 100406.

[6] Foley, J. A., et al. (2011). Solutions for a cultivated planet. “Nature”, 478(7369), 337-342.

[7] Garnett, T., et al. (2013). Sustainable intensification in agriculture. “Science”, 341(6141), 33-34.

[8] Hardin, P. J., & Jensen, R. R. (2011). UAVs in environmental remote sensing. “GISci. Remote Sens.”, 48(1), 99-111.

[9] Hunt, E. R., et al. (2010). NIR-Green-Blue UAV photographs for crop monitoring. “Remote Sens.”, 2(1), 290-305.

[10] Jensen, J. R. (2007). “Remote sensing of the environment: An earth resource perspective” (2nd ed.). Pearson.

[11] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). CNNs in agriculture. “J. Agric. Food Chem.”, 66(22), 6738-6748.

[12] Lavender, S., et al. (2019). Machine learning for earth observation. “Earth Observ. Open Sci. J.”, 3(1), 1-20.

[13] Lee, J. S., & Pottier, E. (2009). “Polarimetric radar imaging: From basics to applications”. CRC Press.

[14] Liakos, K. G., et al. (2018). Machine learning in agriculture: A review. “Sensors”, 18(8), 2674.

[15] Minchew, B. M., et al. (2020). Multi-frequency radar interferometry with NISAR. “IEEE Trans. Geosci. Remote Sens.”, 58(3), 1623-1634.

[16] Mulla, D. J. (2013). Remote sensing in precision agriculture: Advances and gaps. “Biosyst. Eng.”, 114(4), 358-371.

[17] NASA. (2021). NISAR: Advancing our understanding of Earth's dynamic systems. Retrieved from https://www.nasa.gov/nisar

[18] Pettorelli, N., et al. (2005). NDVI for ecological responses to environmental change. “Trends Ecol. Evol.”, 20(9), 503-510.

[19] Rathore, M., et al. (2020). AI in agriculture and future perspectives. “Sustainability”, 12(7), 2820.

[20] Reyes, M. A., et al. (2019). Sentinel-1 and Sentinel-2 for vegetation monitoring. “IEEE Trans. Geosci. Remote Sens.”, 57(11), 8217-8232.

[21] Rosen, P. A., et al. (2021). The NASA-ISRO SAR (NISAR) mission. “Remote Sens. Environ.”, 258, 112383.

[22] Rouse, J. W., et al. (1974). Monitoring vegetation systems with ERTS. “NASA Spec. Publ.”, 351, 309.

[23] Saatchi, S. S., et al. (2011). Forest carbon stocks in tropical regions. “Proc. Natl. Acad. Sci.”, 108(24), 9899-9904.

[24] Simard, M., et al. (2011). Mapping forest canopy height with lidar. “J. Geophys. Res.: Biogeosciences”, 116(G4).

[25] Simons, M., et al. (2020). The NASA-ISRO SAR mission and Earth's surface deformation. “Science”, 368(6486), eaaz4382.

[26] Thenkabail, P. S., et al. (Eds.). (2012). Hyperspectral remote sensing of vegetation. CRC Press.

[27] Tucker, C. J. (1979). Red and photographic infrared linear combinations for vegetation monitoring. “Remote Sens. Environ.”, 8(2), 127-150.

[28] Turner, D., et al. (2012). UAV imagery for georectified mosaics. “Remote Sens.”, 4(5), 1392-1410.

[29] Wallace, L., et al. (2012). UAV-LiDAR system for forest inventory. “Remote Sens.”, 4(6), 1519-1543.

[30] Zhang, C., & Kovacs, J. M. (2012). UAVs in precision agriculture: A review. “Precision Agric.”, 13(6), 693-712.

[31] Zhang, L., et al. (2018). Deep learning for remote sensing data. “IEEE Geosci. Remote Sens. Mag.”, 4(2), 22-40.

[32] Manoj Kumar K. Singh, Shashank Mohan, Brajesh Kumar, "Fusion of hyperspectral and LiDAR data using sparse stacked autoencoder for land cover classification with 3D-2D convolutional neural network," J. Appl. Rem. Sens. 16(3) 034523 (24 August 2022)

[33] Manoj K. Singh, Shashank Mohan, Brajesh Kumar, "Hyperspectral image classification using deep convolutional neural network and stochastic relaxation labeling," J. Appl. Rem. Sens. 15(4) 042612 (5 October 2021)