# REVIEW



# **Remote sensing enabled essential biodiversity variables for invasive alien species management: towards the development of spatial decision support system**

**K. R. L. Saranya · K. V. Satish · C. Sudhakar Reddy**

Received: 24 September 2023 / Accepted: 22 December 2023 / Published online: 4 January 2024 © The Author(s), under exclusive licence to Springer Nature Switzerland AG 2024

**Abstract** Biological invasions represent a signifcant and pervasive environmental threat, contributing substantially to global biodiversity decline. This review explores the remote sensing of invasive alien plant species within the context of integration into the Essential Biodiversity Variables framework and Spatial Decision Support System. By analyzing diverse case studies and research fndings, this work explains the signifcance, efectiveness, and challenges of using remote sensing in the management of invasive alien species. Remote sensing provides critical data for habitat mapping, population monitoring, change detection, and invasibility. Remote sensing, when employed in conjunction with feld data, ecological modelling, and spatial analyses, plays a critical role in mapping and predicting the distribution of invasive alien species. The synthesis of remote sensing and GIS technologies, along with the Essential Biodiversity Variables framework and Spatial Decision Support System, has been identifed as a robust and promising spatial approach for the monitoring, prediction, and management of invasive alien species.

**Keywords** Biodiversity · Invasion · Modelling · Remote sensing · GIS

# **Introduction**

Biological invasion is one of the direct drivers of global biodiversity decline. Biological invasions and natural disasters are similar phenomena with implicit causes, yet their occurrences remain unpredictable and uncontrollable (Ricciardi et al. [2011\)](#page-8-0). The Kunming-Montreal Global Biodiversity Framework has identifed urgent action to signifcantly decrease invasive alien species impacts on biodiversity through pathway management, prevention, and reducing introductions by at least 50% (CBD [2023\)](#page-7-0). Data pertaining to biological invasions is imperative for informing and guiding the primary facets of management processes (Van Rees et al. [2022](#page-8-1)). Conventional feld surveys are often associated with considerable time requirements, resource demands, and inherent geographic constraints. Pereira et al. [\(2013](#page-8-2)) introduced six distinct classes of Essential Biodiversity Variables (EBVs): Genetic Composition, Species Populations, Species Traits, Community Composition, Ecosystem Structure, and Ecosystem Function. The Group on Earth Observations Biodiversity Observation Network (GEO BON) has identifed alien species occurrence, alien status of a species, and the impact that a species has on biodiversity as three essential variables for invasive species management (GEO-BON [2023](#page-7-1)).

Considering the increasing proliferation and territorial expansion exhibited by invasive species, the imperative for the development and implementation of innovative solutions becomes essential. Remote

K. R. L. Saranya · K. V. Satish  $(\boxtimes)$  · C. S. Reddy Forest Biodiversity and Ecology Division, National Remote Sensing Centre, Indian Space Research Organization, Balanagar, Hyderabad, Telangana 500 037, India e-mail: dr.kvsatish@yahoo.com

sensing technologies, such as satellite imagery and aerial surveys, offer a bird's-eye view of critical habitats. The study conducted by Reddy [\(2021](#page-8-3)) presents a perspective on multiple facets of the role of remote sensing in biodiversity monitoring. Reddy et al. ([2021\)](#page-8-4) synthesized the current status of research and development in the use of remote sensing-enabled essential biodiversity variables. A review by Müllerová et al. [\(2023](#page-8-5)) highlights the value of integrating remote sensing data across scales for better insights into invasion dynamics and drivers. It recommends high-resolution satellite and UAV imagery for improved invasive species identifcation and capturing ecological processes. Monitoring invasive species using remote sensing and the Geographic Information System (GIS) involves collecting and analyzing various essential variables to track the presence, spread, and impact of invasive species on ecosystems. This review highlights the importance of continued research and innovation in the remote sensing of Earth observations for invasive species monitoring using the EBVs framework. Several EBVs play a pivotal role in providing valuable insights into the distribution, impact, and management of invasive species.

#### **Essential biodiversity variables**

#### Species populations (EBV-1)

EBV-1 is fundamental for invasive species management. It involves tracking the presence of species, identifying the extent of species infestations and their potential spread, and estimating species density, abundance, biomass and demographic characteristics of populations. Satellite remote sensing data are supporting mainly the detection of canopy-dominant plant invasions. Utilizing suitable remote sensing data and EBV-1 (Species Presence and Distribution), distribution maps of invasive species can be produced. Multispectral, hyperspectral and LiDAR data provide valuable information about the spectral and structural characteristics of vegetation, aiding in the identifcation of invasive species (Bolch et al. [2020\)](#page-6-0).

The methods and approaches for invasive plant species mapping and monitoring varied across studies. Key methods include supervised and unsupervised image classifcation, object-based image analysis, species distribution modeling, and change detection analysis. Historically, remote sensing has played a vital role in the mapping and monitoring of invasive plant species. Rouse et al. ([1975\)](#page-8-6) mapped the distribution of water hyacinth (*Eichhornia crassipes*) using aerial color infrared photographs; these maps were then utilized in herbicide application management. Dai et al. [\(2020](#page-7-2)) mapped the spatial extent of understorey *Mikania micrantha* using Landsat 8 imagery in the Chitwan National Park, Nepal, this study also developed a spectral library to understand the distribution of invasive species. Andrew and Ustin ([2008\)](#page-6-1) utilized HyMap hyperspectral data to map the distribution pattern of pepperweed (*Lepidium latifolium*) in parts of California. Kandwal et al. [\(2009](#page-7-3)) attempted to use Landsat-based vegetation indices to extract *Lantana camara* patches. Several spectral indices were analyzed for discriminating *L. camara*. The study found SAVI (Soil Adjusted Vegetation Index) and Perpendicular Vegetation Index-3 are most favourable in distinguishing populations of *L. camara*. Bradley and Mustard [\(2006](#page-7-4)) mapped and modelled the population extent of cheatgrass (*Bromus tectorum*) using Landsat MSS, TM and ETM+with the application of various landscape variables in the Great Basin in United States. The study by Kimothi et al. ([2010\)](#page-7-5) evaluated the utility of IRS LISS-IV (multi-spectral, 5.8 m), and LISS-IV plus Cartosat-1 merged data for mapping *L. camara* in a local landscape of Rajaji National Park in Uttarakhand. Kimothi and Dasari ([2010\)](#page-7-6) analyzed data from LISS III, LISS IV, Cartosat-1 and a fused image of LISS IV and Cartosat-1 to map *L. camara*. Niphadkar et al. [\(2017](#page-8-7)) compared a pixel-based and object-based classifcation method for mapping the *L. camara* in tropical mixed forests in the Biligirirangan hills, Western Ghats. Reddy et al. [\(2017](#page-8-8)) prepared the frst map of the level of alien plant invasion across vegetation types of India.

Ingole et al. [\(2018](#page-7-7)) used multispectral satellite data for mapping *Salvinia molesta* in reservoir "Tumaria", in Uttarakhand. Landsat-7 (ETM+) and Landsat-8 (OLI) for the period April 2013 to May 2015 revealed that the waterbody was free from *Salvinia molesta* until June 2013 and for the frst time appeared during September 2013. It covered 42% of the water spread area and subsequently covered 92% of the area until October 2013. Khare et al. [\(2018](#page-7-8)) assessed plant species diversity in areas afected by *L. camara* in the deciduous forests of western Himalaya using

spectral heterogeneity information. The spread of *L. camara* was precisely mapped by Pléiades -1A data, followed by comparing Pléiades -1A, RapidEye, and Landsat-8 OLI assessed plant species diversities in invaded areas. Kattenborn et al. ([2019\)](#page-7-9) have developed a spatial approach for three diferent species: *Pinus radiata, Ulex europaeus*, and *Acacia dealbata* occurring in Chile, and developed semi-automatic cover mapping (MaxEnt) and upscaling to the Sentinel scale of 20 m. Khare et al. ([2019\)](#page-7-10) aimed to test the potential of multiple very high-resolution multispectral and stereo imageries to quantify the area of *L. camara*. Arasumani et al. [\(2021](#page-6-2)) evaluated the accuracy of Sentinel-1 radar data, Sentinel-2 multispectral data, Airborne Visible-Infrared Imaging Spectrometer-Next Generation data, and three machine learning classifcation algorithms to assess invasive tree species (*Acacia* spp., *Eucalyptus* spp., and *Pinus* spp.). Results indicate that AVIRIS-NG data in combination with SVM produced the highest classifcation accuracy (98.7%). Simpson et al. ([2022\)](#page-8-9) studied water hyacinth infestation in Kuttanad, India, using Dual-Pol Sentinel-1 SAR data. Kishore et al. [\(2022](#page-7-11)) highlight the delineation of the distribution of *L. camara* and *Chromolaena odorata* in Mudumalai Tiger Reserve using very high-resolution airborne imaging spectroscopy images by evaluating the performance of a Multiple Endmember Spectral Mixture Analysis (MESMA). AVIRIS-NG-based assessment has delineated the spatial distribution of *L. camara* and *C. odorata* in Mudumalai with an overall accuracy of 87% and 84% respectively. Researchers have made signifcant strides in developing machine learning algorithms and AI models for automated detection and classifcation of invasive species from remotely sensed data. Convolutional Neural Networks (CNNs) techniques are being used to extract features and patterns from images, enabling more accurate and efficient species identifcation.

Time-series analysis of remote sensing data reveals trends in species distribution and invasion hotspot identifcation. Becker et al. [\(2013](#page-6-3)) used Landsat time series data to map the understorey cover of *Frangula alnus* and *Rhamnus cathartica*, based on an extended green season compared to the forest canopy. Izadi et al. ([2022\)](#page-7-12) mapped the dominance and distribution of the dominant invasive species *Prosopis julifora* using Landsat 8-OLI and MODIS NDVI data using time series analysis in southern Iran. The causative drivers of invasion and the fractional cover of invasive trees of genus *Prosopis* in the Afar region, Ethiopia was studied by Shiferaw et al. [\(2019](#page-8-10)) using Landsat 8 image with 17 other explanatory variables through random forest algorithm having a kappa accuracy of 0.8. Phenology-based models focus on the timing of plant life cycle events (Liu et al. [2020\)](#page-7-13), object-based image analysis (OBIA), Support vector machines analyses data providing the detailed distribution of plant invasion over an area and its impact on the landscape (Walsh et al. [2008;](#page-8-11) Gavier-Pizarro et al. [2012;](#page-7-14) Izadi et al. [2022\)](#page-7-12). Neural networks, ensemble models and ecological niche models improve robustness and predict the invasive species distribution precisely (Cord et al. [2010](#page-7-15); Gavier-Pizarro et al. [2012\)](#page-7-14). Ecological understanding and validation of the models using feld data augments the consistency of the results generated through the models.

Early detection of invasion hotspots allows for proactive management interventions to control invasions. The current research has gained advanced technology in identifying, monitoring, analysing and planning for the research problem through the application of different computational models viz., Species Distribution Models (SDMs) to predict the species based on environmental variables. These models integrate data on the presence or occurrence of species with climate or environmental variables derived from remote sensing and forecasted data to fnd out where species are likely to be distributed (Satish et al. [2023](#page-8-12)). SDMs can be efectively combined with remote sensing data to enhance the accuracy and spatial resolution of predictions. For example, West et al. [\(2016](#page-8-13)) conducted a study on predicting the presence of the invasive species Tamarisk (*Tamarix* spp.) using SDMs and remote sensing data. The authors utilized NDVI, SAVI, and tasseled cap transformations derived from an 8-month image stack of the Landsat 5 Thematic Mapper to distinguish tamarisk from native riparian vegetation. They took into account phenology to accurately identify the tamarisk. The study conducted by Ahmed et al. ([2021\)](#page-6-4) employed SDMs together with twelve distinct Sentinel 2 multispectral derived indices to map the distribution of Mesquite (*P. julifora*) in the lower Awash River basin in Ethiopia. This study identifed that indices pertaining to vegetation, soil, biophysical factors, and water were particularly infuential, among other factors. This study examined the utilization of Sentinel 2 for predicting invasive species in multiple research studies. Reshi and Khuroo [\(2012](#page-8-14)) recommended a national alien invasive species information network for easier dissemination of information about invasive species. Saranya et al. ([2021\)](#page-8-15) predicted the suitable habitats of invasive plant species *C. odorata* and *L. camara*, using maximum entropy (MaxEnt), random forest, surface range envelope, boosted regression tree analysis, classifcation tree analysis, and a generalized boosted model in the Eastern Ghats. Singh et al. [\(2021](#page-8-16)) modeled the bioclimatic suitability of *P. julifora* in India using the MaxEnt model. Saranya et al. [\(2023](#page-8-17)) assessed the cumulative efects of multiple disturbance factors on plant diversity in the Similipal Biosphere Reserve. Ecological models simulate various scenarios, such as climate change impact or management intervention, providing insights into potential future distribution. Combining satellite imagery with feld surveys and environmental variables allows for precise range mapping and the identifcation of isolated populations.

#### Species traits (EBV-2)

Remote sensing technologies can capture certain traits, such as canopy structure, distinctive growth forms, leaf color, leaf morphology, leaf longevity, leaf onset, leaf offset, length of growing season, leaf type, leaf arrangements, fower characteristics, timing of fowering, prolifc seed production, vegetative reproduction, tolerance to environmental stressors, and monitoring changes in biomass and growth rate, which can aid in the identifcation and tracking of invasive species over large geographic areas (Kissling et al. [2018](#page-7-16)). Bradley [\(2014](#page-7-17)) has reviewed the mapping of plant invasive species using spectral classifcation and phenological observations at diferent resolutions of satellite data. Phenology based identifcation of plant invasions indicates diverse phenological events compared to native plant species. Phenological observations for diferent vegetation communities using MODIS data with vegetation indices in parts of New England, northeastern United States and southeastern Canada have been reported by Zhang et al. [\(2003](#page-8-18)). Spatial variability analysis and phenology study on six diferent phenological events for 29 perennial species in the Mediterranean region have been recorded by (Gordo and Sanz [2009\)](#page-7-18). Joshi et al. ([2006\)](#page-7-19) mapped seed-producing sites of *C. odorata*, that invaded the understorey forests of Nepal through the application of Landsat ETM+satellite imagery and neural networks. Hyperspectral and very high-resolution remote sensing techniques can directly measure plant traits like leaf N content, chlorophyll absorption, scattering, and refectance, as well as diferences in leaf water absorption (Homolová et al. [2013](#page-7-20); Niphadkar and Nagendra [2016\)](#page-8-19). Niphadkar and Nagendra ([2016\)](#page-8-19) reviewed scientifc research that uses plant functional traits for the mapping of invasive plant species. Invasive species often thrive in disturbed habitats, such as roadsides, construction sites, and agricultural felds. Their association with these areas can be a characteristic trait. The geographic range and distribution of invasive species, along with their historical records, can be important traits for mapping and monitoring efforts. Mielczarek et al.  $(2022)$  $(2022)$  assessed the use of dual-wavelength Airborne Laser Scanning (ALS) in categorizing the stages of the invasion by *Acer negundo* through sequential additive modeling.

## Community composition (EBV-3)

EBV-3 examines the composition of species within communities. Monitoring changes in community composition due to invasive species is vital for understanding their impact on native biodiversity. Remote sensing helps monitor shifts in species composition and diversity within ecosystems afected by invasive species. Multitemporal remote sensing data enable the assessment of changes in community composition due to biological invasions across land cover types. The study by Khanna et al. ([2012\)](#page-7-22) utilized multitemporal airborne HyMap spectrometry data to monitor the changes in plant communities by analyzing the distribution of *E. crassipes* detection in the Sacramento-San Joaquin Delta. This investigation observed that over time, *E. crassipes* decreased by control interventions while submerged aquatic plant cover increased, and vice versa. Vanderlinder et al. [\(2013](#page-8-20)) employed high-resolution aerial multispectral data over an 18-year period to quantify and analyze changes in vegetation during the study period. The research reveals the potential replacement of native wetland vegetation (*Schoenoplectus maritimus*) with invasive species (*Phragmites* and *Typha*). Pasha et al. [\(2014](#page-8-21)) conducted a study in the Great Rann of Kachchh to map the extent of invasive colonies, patchiness, coalescence, and rate of spread of *P.* 

*julifora*. This study has shown an increment of 42.9% of the area under *Prosopis* extent and cover in the Great Rann of Kachchh from 1977 to 2011. The study by Pasha et al. ([2015\)](#page-8-22) has reported a rapid invasion of *P. julifora* using multi-temporal satellite images from 1977 to 2011 in the Wild Ass sanctuary of Little Rann of Kachchh. Gong et al. ([2021\)](#page-7-23) employed multiseason Sentinel 2 and Landsat 8 imagery to delineate the community composition of both native and invasive plant species in the Yellow River Delta, China. They noted that there are critical times to extract the *Spartina alternifora* community (in October) and the *Phragmites australis* community (in May). Red edge bands signifcantly aided in the accurate mapping of these communities, according to the study. This investigation highlighted how the maps can be utilized for the eradication of *S. alternifora* and restoration of this ecosystem. Pasha and Reddy [\(2023](#page-8-23)) modelled the invasion trends of *P. julifora* in Kachchh Biosphere Reserve using space time pattern mining techniques.

## Ecosystem structure (EBV-4)

EBV-4 focuses on the physical and biological structure of ecosystems. Monitoring changes in ecosystem structure due to invasive species is essential to assessing their impact. Remote sensing reveals changes in vegetation structure and composition, helping identify shifts caused by invasive species' presence, which are often indicators of invasive species impacts. By analyzing landscape features, vegetation types, and environmental conditions, remote sensing helps identify areas susceptible to invasion. Asner et al. [\(2008](#page-6-5)) investigated the three-dimensional structure of Hawaiian rain forests that were altered by five invasive species (*Falcataria moluccana*, *Fraxinus uhdei*, *Hedychium gardnerianum*, *Morella faya*, and *Psidium cattleianum*) using airborne remote sensing. The fndings of this study indicate that a diverse range of alien plant species, each exhibiting a unique growth form or functional type, are signifcantly altering the fundamental three-dimensional structure of native Hawaiian rainforests. The study by Yang et al. ([2022\)](#page-8-24) analyzed the relationship between landscape patterns (compositional and structural heterogeneity) and Asian long-horned beetle (ALB) populations using a multivariable linear regression model and a linear mixed model.

## Ecosystem function (EBV-5)

EBV-5 evaluates the processes and functions that ecosystems perform. Invasive species can alter these functions, making this EBV critical for understanding their ecological impact. Remote sensing can aid in tracking changes in ecosystem functions, such as water flow, nutrient cycling, and carbon storage, infuenced by invasive species. A study by Große-Stoltenberg et al. ([2018\)](#page-7-24) assessed the impact of *Acacia longifolia* in a Mediterranean dune ecosystem. *A. longifolia* was mapped using spectral indices from hyperspectral images as well as LiDAR data using Random Forest. The Near-Infrared Vegetation Index, which is related to GPP (Gross Primary Productivity), increased linearly and signifcantly with increasing species extent and is responsible for changing ecosystem productivity.

# Genetic composition (EBV-6)

EBV-6 assesses the genetic diversity within species populations. Monitoring genetic changes in invasive species can help understand their adaptability and potential for hybridization. While remote sensing does not measure genetic composition, it can assist in identifying areas where hybridization or genetic changes may be occurring by tracking habitat alterations (Hoban et al. [2022](#page-7-25)).

# **Spatial decision support system development**

Developing a Spatial Decision Support System that integrates EBVs, remote sensing data, and GIS is required for informed decision-making. It involves a systematic approach that integrates spatial data, ecological knowledge, and decision-making tools. The system should be fexible and adaptable to changing conservation needs. The three stages of invasive species management include pre-invasion, during invasion, and post-invasion. Each stage of monitoring has unique information requirements on species inventories, invasibility, introduction, establishment, naturalization, spread, persistence, dominance, range extension, environmental impact, ecological modeling, planning, and restoration, including priorities that correspond to their spatial



<span id="page-5-0"></span>**Fig. 1** Framework for invasive species management using remote sensing and GIS

and species priorities (Fig. [1\)](#page-5-0). The four stages of development for national observation and monitoring systems are required to prepare a national list of invasive alien species, establish priority sites, assess the area occupied by species using UAVs and high spatial resolution and hyperspectral data, and establish a network of long-term monitoring sites involving ecological studies, remote sensing, and web-based information systems (Latombe et al. [2017](#page-7-26)). Remote sensing data can inform risk assessment by identifying areas vulnerable to invasion. This helps prioritize management efforts and allocate resources efectively. Designing an easy-to-use web interface that allows users to input parameters, view maps, and access information on management strategies would be the frst step in Decision Support System Development. To provide a comprehensive and efective Spatial Decision Support System for the management of biological invasions, highquality geospatial data is fundamental, including satellite imagery, aerial photographs, and environmental data. GIS-based integration of remote sensing data assists in delineating management zones where eradication, control, and restoration efforts are prioritized.

# **Challenges and future directions**

Despite the progress, challenges remain, including the need for improved accuracy in species identifcation, especially in complex ecosystems. The development of a standardized suite of EBVs for invasive alien species management involves several challenges, including the need for consistent data collection, validation, and integration into global biodiversity monitoring systems. The spatial, spectral, and temporal resolution of available data is insufficient to obtain accurate results for all invasive plant species. Techniques like camera traps, acoustic monitoring, and UAVs equipped with thermal and hyperspectral sensors allow for feld data collection. Hyperspectral remote sensing offers great potential to map invasive plants. The costs of data acquisition or reproducibility are expensive. The data can be analyzed using machine learning algorithms to automate species identifcation and track population trends. The development of reliable remotely sensed EBVs requires a precise defnition of their observation requirements, including temporal frequency, spatial resolution, and thematic accuracy. Spectral confusion, where native and invasive species share similar spectral signatures, can lead to misclassifcation. Additionally, the accurate identifcation of invasive species with similar phenology or spectral characteristics remains a challenge. An innovative approach to identifying occurrences of invasive species is the integration of remote sensingbased data, in-situ feld measurements, and a GIS. Artifcial intelligence and machine learning algorithms are being applied to enhance species identifcation and mapping accuracy. Research efforts have focused on integrating data from multiple remote sensing platforms to improve invasive species map-

ping and monitoring. Open-access satellite data and Earth Observation (EO) platforms, such as those provided by NASA, ESA (European Space Agency), and commercial entities like Google Earth Engine, have made EO data more accessible to researchers and conservation practitioners. Modern geospatial techniques can produce novel ways to view and predict. Predictive maps generated by ecological models assist in prioritizing areas for conservation, enabling efficient allocation of resources to mitigate invasive species impacts. Interdisciplinary strategies would provide better options in the management of invasive alien species. The impact of climate change on invasive species dynamics is an emerging research area that requires further investigation. Citizen science platforms and mobile apps encourage individuals to submit observations of invasive species occurrences.

# **Conclusions**

This review provides a synthesis of what is currently feasible in terms of remote sensing-based detection and monitoring of biological invasions. By combining standardized ecological measurements with highresolution remote sensing data, we can enhance our ability to monitor the impacts of invasive alien species. The combination of EBVs with remote sensing enabled variables represents a powerful tool for invasive alien species mapping and management. Earth observation strategies are revolutionizing management efforts by providing valuable tools for mapping, monitoring, and managing invasive alien species. As technology continues to advance, the accuracy and applicability of spatial data for invasive species mapping are expected to increase, contributing to more efective strategies for invasive species control and ecosystem restoration. The integration of remote sensing and GIS into Invasive Species Decision Support Systems represents a promising path toward a more proactive and efficient approach to addressing this global challenge.

**Acknowledgements** This research was conducted as part of a project titled "Biodiversity Characterization at the Community Level in India Using Earth Observation Data" funded by the Department of Biotechnology and the Department of Space, the Government of India. We are grateful to the Director, National Remote Sensing Centre, Hyderabad for encouragement.

#### **Funding** Applicable.

**Data availability** Not applicable.

**Code availability** Not applicable.

#### **Declarations**

**Confict of interest** The authors declare no confict of interest and have no known competing fnancial interests or personal relationships that could have appeared to infuence the work reported in this article.

**Ethical approval** This article does not contain any studies involving human/ animals performed by any of the authors.

#### **References**

- <span id="page-6-4"></span>Ahmed N, Atzberger C, Zewdie W (2021) Species distribution modelling performance and its implication for sentinel-2-based prediction of invasive *Prosopis julifora* in lower Awash River basin, Ethiopia. Ecol Process 10:18. [https://](https://doi.org/10.1186/s13717-021-00285-6) [doi.org/10.1186/s13717-021-00285-6](https://doi.org/10.1186/s13717-021-00285-6)
- <span id="page-6-1"></span>Andrew ME, Ustin SL (2008) The role of environmental context in mapping invasive plants with hyperspectral image data. Remote Sens Environ 112:4301–4317. [https://doi.](https://doi.org/10.1016/j.rse.2008.07.016) [org/10.1016/j.rse.2008.07.016](https://doi.org/10.1016/j.rse.2008.07.016)
- <span id="page-6-2"></span>Arasumani M, Singh A, Bunyan M, Robin VV (2021) Testing the efficacy of hyperspectral (AVIRIS-NG), multispectral (Sentinel-2) and radar (Sentinel-1) remote sensing images to detect native and invasive non-native trees. Biol Invasions 23:2863–2879. [https://doi.org/10.1007/](https://doi.org/10.1007/s10530-021-02543-2) [s10530-021-02543-2](https://doi.org/10.1007/s10530-021-02543-2)
- <span id="page-6-5"></span>Asner GP, Jones MO, Martin RE et al (2008) Remote sensing of native and invasive species in hawaiian forests. Remote Sens Environ 112:1912–1926. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.rse.2007.02.043) [rse.2007.02.043](https://doi.org/10.1016/j.rse.2007.02.043)
- <span id="page-6-3"></span>Becker RH, Zmijewski KA, Crail T (2013) Seeing the forest for the invasives: mapping buckthorn in the Oak openings. Biol Invasions 15:315–326. [https://doi.org/10.1007/](https://doi.org/10.1007/s10530-012-0288-8) [s10530-012-0288-8](https://doi.org/10.1007/s10530-012-0288-8)
- <span id="page-6-0"></span>Bolch EA, Santos MJ, Ade C et al (2020) Remote detection of invasive alien species. In: Cavender-Bares J, Gamon

JA, Townsend PA et al (eds) Remote sensing of plant biodiversity. Springer, Switzerland, pp 267–307

- <span id="page-7-17"></span>Bradley BA (2014) Remote detection of invasive plants: a review of spectral, textural and phenological approaches. Biol Invasions 16:1411–1425. [https://doi.](https://doi.org/10.1007/s10530-013-0578-9) [org/10.1007/s10530-013-0578-9](https://doi.org/10.1007/s10530-013-0578-9)
- <span id="page-7-4"></span>Bradley BA, Mustard JF (2006) Characterizing the landscape dynamics of an invasive plant and risk of Invasion using remote sensing. Ecol Appl 16:1132-<br>1147. https://doi.org/10.1890/1051-0761(2006)016. [https://doi.org/10.1890/1051-0761\(2006\)016](https://doi.org/10.1890/1051-0761(2006)016). (**[1132:CTLDOA]2.0.CO;2**)
- <span id="page-7-0"></span>CBD (2023) Convention on biological diversity. In: Convention on biological diversity. <https://www.cbd.int/>. Accessed 24 Sept 2023
- <span id="page-7-15"></span>Cord AF, Klein D, Dech S (2010) Remote sensing time series for modeling invasive species distribution: a case study of *Tamarix* spp. in the US and Mexico. International Environmental Modelling and Software Society (iEMSs), Ottawa
- <span id="page-7-2"></span>Dai J, Roberts DA, Stow DA et al (2020) Mapping understory invasive plant species with feld and remotely sensed data in Chitwan, Nepal. Remote Sens Environ 250:112037. <https://doi.org/10.1016/j.rse.2020.112037>
- <span id="page-7-14"></span>Gavier-Pizarro GI, Kuemmerle T, Hoyos LE et al (2012) Monitoring the invasion of an exotic tree (*Ligustrum lucidum*) from 1983 to 2006 with landsat TM/ ETM +satellite data and support vector machines in Córdoba, Argentina. Remote Sens Environ 122:134– 145.<https://doi.org/10.1016/j.rse.2011.09.023>
- <span id="page-7-1"></span>GEO-BON (2023) GEO BON: the group on earth observations biodiversity observation network. [https://geobon.](https://geobon.org/) [org/.](https://geobon.org/) Accessed 24 Sept 2023
- <span id="page-7-23"></span>Gong Z, Zhang C, Zhang L et al (2021) Assessing spatiotemporal characteristics of native and invasive species with multi-temporal remote sensing images in the Yellow River Delta, China. Land Degrad Dev 32:1338–1352. <https://doi.org/10.1002/ldr.3799>
- <span id="page-7-18"></span>Gordo O, Sanz JJ (2009) Long-term temporal changes of plant phenology in the Western Mediterranean. Glob Change Biol 15:1930–1948. [https://doi.org/10.1111/j.](https://doi.org/10.1111/j.1365-2486.2009.01851.x) [1365-2486.2009.01851.x](https://doi.org/10.1111/j.1365-2486.2009.01851.x)
- <span id="page-7-24"></span>Große-Stoltenberg A, Hellmann C, Thiele J et al (2018) Early detection of GPP-related regime shifts after plant invasion by integrating imaging spectroscopy with airborne LiDAR. Remote Sens Environ 209:780–792. [https://doi.](https://doi.org/10.1016/j.rse.2018.02.038) [org/10.1016/j.rse.2018.02.038](https://doi.org/10.1016/j.rse.2018.02.038)
- <span id="page-7-25"></span>Hoban S, Archer FI, Bertola LD et al (2022) Global genetic diversity status and trends: towards a suite of essential biodiversity variables (EBVs) for genetic composition. Biol Rev 97:1511–1538. [https://doi.org/10.1111/brv.](https://doi.org/10.1111/brv.12852) [12852](https://doi.org/10.1111/brv.12852)
- <span id="page-7-20"></span>Homolová L, Malenovskỳ Z, Clevers JG et al (2013) Review of optical-based remote sensing for plant trait mapping. Ecol Complex 15:1–16. [https://doi.org/10.1016/j.eco](https://doi.org/10.1016/j.ecocom.2013.06.003)[com.2013.06.003](https://doi.org/10.1016/j.ecocom.2013.06.003)
- <span id="page-7-7"></span>Ingole NA, Nain AS, Kumar P, Chalal R (2018) Monitoring and mapping invasive aquatic weed *Salvinia molesta* using multispectral remote sensing technique in Tumaria Wetland of Uttarakhand, India. J Indian Soc Remote Sens 46:863–871. [https://doi.org/10.1007/](https://doi.org/10.1007/s12524-018-0764-4) [s12524-018-0764-4](https://doi.org/10.1007/s12524-018-0764-4)
- <span id="page-7-12"></span>Izadi F, Chamani A, Zamani-Ahmadmahmoodi R (2022) How vegetation cover characteristics response to the spread of *Prosopis julifora*: a time-series remote sensing analysis in southern Iran. Environ Monit Assess 194:401. [https://doi.](https://doi.org/10.1007/s10661-022-09888-8) [org/10.1007/s10661-022-09888-8](https://doi.org/10.1007/s10661-022-09888-8)
- <span id="page-7-19"></span>Joshi C, De Leeuw J, Van Andel J et al (2006) Indirect remote sensing of a cryptic forest understorey invasive species. For Ecol Manag 225:245–256. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.foreco.2006.01.013) [foreco.2006.01.013](https://doi.org/10.1016/j.foreco.2006.01.013)
- <span id="page-7-3"></span>Kandwal R, Jeganathan C, Tolpekin V, Kushwaha SPS (2009) Discriminating the invasive species, 'Lantana' using vegetation indices. J Indian Soc Remote Sens 37:275–290. <https://doi.org/10.1007/s12524-009-0027-5>
- <span id="page-7-9"></span>Kattenborn T, Lopatin J, Förster M et al (2019) UAV data as alternative to feld sampling to map woody invasive species based on combined sentinel-1 and sentinel-2 data. Remote Sens Environ 227:61–73
- <span id="page-7-22"></span>Khanna S, Santos MJ, Hestir EL, Ustin SL (2012) Plant community dynamics relative to the changing distribution of a highly invasive species, *Eichhornia crassipes*: a remote sensing perspective. Biol Invasions 14:717–733. [https://](https://doi.org/10.1007/s10530-011-0112-x) [doi.org/10.1007/s10530-011-0112-x](https://doi.org/10.1007/s10530-011-0112-x)
- <span id="page-7-8"></span>Khare S, Latif H, Ghosh SK (2018) Multi-scale assessment of invasive plant species diversity using Pléiades 1A, RapidEye and Landsat-8 data. Geocarto Int 33:681–698. <https://doi.org/10.1080/10106049.2017.1289562>
- <span id="page-7-10"></span>Khare S, Latif H, Rossi S, Ghosh SK (2019) Fractional cover mapping of invasive plant species by combining very high-resolution stereo and multi-sensor multispectral imageries. Forests 10:540. [https://doi.org/10.3390/f1007](https://doi.org/10.3390/f10070540) [0540](https://doi.org/10.3390/f10070540)
- <span id="page-7-5"></span>Kimothi MM, Anitha D, Vasistha HB et al (2010) Remote sensing to map the invasive weed, *Lantana camara* in forests. Trop Ecol 51:67–74
- <span id="page-7-6"></span>Kimothi MM, Dasari A (2010) Methodology to map the spread of an invasive plant (*Lantana camara* L.) in forest ecosystems using Indian remote sensing satellite data. Int J Remote Sens 31:3273–3289. [https://doi.org/10.1080/](https://doi.org/10.1080/01431160903121126) [01431160903121126](https://doi.org/10.1080/01431160903121126)
- <span id="page-7-11"></span>Kishore BSPC, Kumar A, Saikia P et al (2022) Mapping of understorey invasive plant species clusters of *Lantana camara* and *Chromolaena odorata* using airborne hyperspectral remote sensing. Adv Space Res. [https://doi.org/](https://doi.org/10.1016/j.asr.2022.12.026) [10.1016/j.asr.2022.12.026](https://doi.org/10.1016/j.asr.2022.12.026)
- <span id="page-7-16"></span>Kissling WD, Walls R, Bowser A et al (2018) Towards global data products of essential biodiversity variables on species traits. Nat Ecol Evol 2:1531–1540
- <span id="page-7-26"></span>Latombe G, Pyšek P, Jeschke JM et al (2017) A vision for global monitoring of biological invasions. Biol Conserv 213:295–308. [https://doi.org/10.1016/j.biocon.2016.06.](https://doi.org/10.1016/j.biocon.2016.06.013) [013](https://doi.org/10.1016/j.biocon.2016.06.013)
- <span id="page-7-13"></span>Liu X, Liu H, Datta P et al (2020) Mapping an invasive plant *Spartina alternifora* by combining an ensemble one-class classifcation algorithm with a phenological NDVI timeseries analysis approach in middle coast of Jiangsu, China. Remote Sens 12:4010. [https://doi.org/10.3390/rs122](https://doi.org/10.3390/rs12244010) [44010](https://doi.org/10.3390/rs12244010)
- <span id="page-7-21"></span>Mielczarek D, Sikorski P, Archiciński P et al (2022) The Use of an Airborne laser scanner for rapid identifcation of invasive tree species *Acer negundo* in riparian forests. Remote Sens 15:212.<https://doi.org/10.3390/rs15010212>
- <span id="page-8-5"></span>Müllerová J, Brundu G, Große-Stoltenberg A et al (2023) Pattern to process, research to practice: remote sensing of plant invasions. Biol Invasions. [https://doi.org/10.1007/](https://doi.org/10.1007/s10530-023-03150-z) [s10530-023-03150-z](https://doi.org/10.1007/s10530-023-03150-z)
- <span id="page-8-19"></span>Niphadkar M, Nagendra H (2016) Remote sensing of invasive plants: incorporating functional traits into the picture. Int J Remote Sens 37:3074–3085. [https://doi.org/10.1080/](https://doi.org/10.1080/01431161.2016.1193795) [01431161.2016.1193795](https://doi.org/10.1080/01431161.2016.1193795)
- <span id="page-8-7"></span>Niphadkar M, Nagendra H, Tarantino C et al (2017) Comparing pixel and object-based approaches to map an understorey invasive shrub in tropical mixed forests. Front Plant Sci 8:892.<https://doi.org/10.3389/fpls.2017.00892>
- <span id="page-8-23"></span>Pasha SV, Reddy CS (2023) Trends in hotspots of Alien plant invasion in Kachchh biosphere reserve, India using spatial pattern mining tool. J Indian Soc Remote Sens 51:469– 481. <https://doi.org/10.1007/s12524-022-01637-1>
- <span id="page-8-21"></span>Pasha SV, Satish KV, Reddy CS et al (2014) Satellite image based quantifcation of invasion and patch dynamics of mesquite (*Prosopis julifora*) in Great Rann of Kachchh, Kachchh biosphere reserve, Gujarat, India. J Earth Syst Sci 123:1481–1490. [https://doi.org/10.1007/](https://doi.org/10.1007/s12040-014-0486-0) [s12040-014-0486-0](https://doi.org/10.1007/s12040-014-0486-0)
- <span id="page-8-22"></span>Pasha SV, Satish KV, Sudhakar Reddy C, Jha CS (2015) Massive invasion of mesquite (*Prosopis julifora*) in wild ass wildlife sanctuary, India. Natl Acad Sci Lett 38:271–273. <https://doi.org/10.1007/s40009-014-0321-9>
- <span id="page-8-2"></span>Pereira HM, Ferrier S, Walters M et al (2013) Essential biodiversity variables. Science 339:277–278. [https://doi.org/10.](https://doi.org/10.1126/science.1229931) [1126/science.1229931](https://doi.org/10.1126/science.1229931)
- <span id="page-8-3"></span>Reddy CS (2021) Remote sensing of biodiversity: What to measure and monitor from space to species? Biodivers Conserv 30:2617–2631. [https://doi.org/10.1007/](https://doi.org/10.1007/s10531-021-02216-5) [s10531-021-02216-5](https://doi.org/10.1007/s10531-021-02216-5)
- <span id="page-8-8"></span>Reddy CS, Diwakar PG, Krishna Murthy YVN (2017) Sustainable biodiversity management in India: remote sensing perspective. Proc Natl Acad Sci 87:617–627. [https://doi.](https://doi.org/10.1007/s40010-017-0438-6) [org/10.1007/s40010-017-0438-6](https://doi.org/10.1007/s40010-017-0438-6)
- <span id="page-8-4"></span>Reddy CS, Kurian A, Srivastava G et al (2021) Remote sensing enabled essential biodiversity variables for biodiversity assessment and monitoring: technological advancement and potentials. Biodivers Conserv 30:1–14. [https://doi.](https://doi.org/10.1007/s10531-020-02073-8) [org/10.1007/s10531-020-02073-8](https://doi.org/10.1007/s10531-020-02073-8)
- <span id="page-8-14"></span>Reshi ZA, Khuroo AA (2012) Alien plant invasions in India: current status and management challenges. Proc Natl Acad Sci India Sect B Biol Sci 82:305–312. [https://doi.](https://doi.org/10.1007/s40011-012-0102-5) [org/10.1007/s40011-012-0102-5](https://doi.org/10.1007/s40011-012-0102-5)
- <span id="page-8-0"></span>Ricciardi A, Palmer ME, Yan ND (2011) Should biological invasions be managed as natural disasters? Bioscience 61:312–317. <https://doi.org/10.1525/bio.2011.61.4.11>
- <span id="page-8-6"></span>Rouse JW, Benton AR, Toler RW, Haas RH (1975) Three examples of applied remote sensing of vegetation. In: NASA earth resources survey symposium. NASA, Houston, pp 1797–1810
- <span id="page-8-15"></span>Saranya KRL, Lakshmi TV, Reddy CS (2021) Predicting the potential sites of *Chromolaena odorata* and *Lantana camara* in forest landscape of Eastern Ghats using habitat suitability models. Ecol Inf 66:101455. [https://doi.org/10.](https://doi.org/10.1016/j.ecoinf.2021.101455) [1016/j.ecoinf.2021.101455](https://doi.org/10.1016/j.ecoinf.2021.101455)
- <span id="page-8-17"></span>Saranya KRL, Mandal KK, Kar T et al (2023) Efects of disturbance regimes on phytodiversity of similipal biosphere

reserve. India J Indian Soc Remote Sens. [https://doi.org/](https://doi.org/10.1007/s12524-023-01684-2) [10.1007/s12524-023-01684-2](https://doi.org/10.1007/s12524-023-01684-2)

- <span id="page-8-12"></span>Satish KV, Dugesar V, Pandey MK et al (2023) Seeing from space makes sense: novel earth observation variables accurately map species distributions over Himalaya. J Environ Manag 325:116428. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.jenvman.2022.116428) [jenvman.2022.116428](https://doi.org/10.1016/j.jenvman.2022.116428)
- <span id="page-8-10"></span>Shiferaw H, Bewket W, Eckert S (2019) Performances of machine learning algorithms for mapping fractional cover of an invasive plant species in a dryland ecosystem. Ecol Evol 9:2562–2574. <https://doi.org/10.1002/ece3.4919>
- <span id="page-8-9"></span>Simpson MD, Akbari V, Marino A et al (2022) Detecting water hyacinth infestation in Kuttanad, India, using dual-pol Sentinel-1 SAR imagery. Remote Sens 14:2845. [https://](https://doi.org/10.3390/rs14122845) [doi.org/10.3390/rs14122845](https://doi.org/10.3390/rs14122845)
- <span id="page-8-16"></span>Singh M, Arunachalam R, Kumar L (2021) Modeling potential hotspots of invasive *Prosopis julifora* (Swartz) DC in India. Ecol Inf 64:101386. [https://doi.org/10.1016/j.eco](https://doi.org/10.1016/j.ecoinf.2021.101386)[inf.2021.101386](https://doi.org/10.1016/j.ecoinf.2021.101386)
- <span id="page-8-1"></span>Van Rees CB, Hand BK, Carter SC et al (2022) A framework to integrate innovations in invasion science for proactive management. Biol Rev 97:1712–1735. [https://doi.org/10.](https://doi.org/10.1111/brv.12859) [1111/brv.12859](https://doi.org/10.1111/brv.12859)
- <span id="page-8-20"></span>Vanderlinder MS, Neale CM, Rosenberg DE, Kettenring KM (2013) Use of remote sensing to assess changes in wetland plant communities over an 18-year period: a case study from the bear river migratory bird refuge, great Salt Lake, Utah. West N Am Nat 74:33–46. [https://doi.org/10.3398/](https://doi.org/10.3398/064.074.0104) [064.074.0104](https://doi.org/10.3398/064.074.0104)
- <span id="page-8-11"></span>Walsh SJ, McCleary AL, Mena CF et al (2008) QuickBird and Hyperion data analysis of an invasive plant species in the Galapagos Islands of Ecuador: implications for control and land use management. Remote Sens Environ 112:1927–1941. <https://doi.org/10.1016/j.rse.2007.06.028>
- <span id="page-8-13"></span>West AM, Evangelista PH, Jarnevich CS et al (2016) Integrating remote sensing with species distribution models; mapping tamarisk invasions using the software for assisted habitat modeling (SAHM). JoVE. [https://doi.org/10.3791/](https://doi.org/10.3791/54578) [54578](https://doi.org/10.3791/54578)
- <span id="page-8-24"></span>Yang C, Zhan Z, Zong S, Ren L (2022) The relationship between landscape patterns and populations of Asian longhorned beetles. Forests 13:1981. [https://doi.org/10.](https://doi.org/10.3390/f13121981) [3390/f13121981](https://doi.org/10.3390/f13121981)
- <span id="page-8-18"></span>Zhang X, Friedl MA, Schaaf CB et al (2003) Monitoring vegetation phenology using MODIS. Remote Sens Environ 84:471–475. [https://doi.org/10.1016/S0034-4257\(02\)](https://doi.org/10.1016/S0034-4257(02)00135-9) [00135-9](https://doi.org/10.1016/S0034-4257(02)00135-9)

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional afliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.