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From Pixels to Plants: Remote Sensing of California Invasive Plants

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This Master's Project

From Pixels to Plants: Remote Sensing of California Invasive Plants

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List of Acronyms

AVHRR	Advanced Very High Resolution Radiometer
AVIRIS	Airborne Visible Infrared Imaging Spectrometer
AVIRIS-NG	Airborne Visible Infrared Imaging Spectrometer- Next Generation
CAL-IPC	California Invasive Plant Council
CASI	Compact Airborne Spectrometer Imager
CCR	California Code of Regulations
CDBW	California Department of Boating and Waterways
CDFA	California Department of Food and Agriculture
CFP	California Floristic Province
cm	centimeter
DEM	digital elevation model
DRAAWP	Delta Region Areawide Aquatic Weed Project
EDRR	Early Detection and Rapid Response
E.O.s	Executive Orders
FAV	floating aquatic vegetation
GPS	global positioning system
km	kilometer
L	Liter
LiDAR	Light Detection and Ranging
m	meter
MLC	maximum likelihood classifier
MNF	minimum noise fraction
NDVI	normalized difference vegetation index
NIR	near infrared light
nm	nanometer
OBIA	object-based image analysis
PPA	Plant Protection Act of 2000
ppm	parts per million
RGB	red-green-blue color
SAM	spectral angle mapper
SAV	submerged aquatic vegetation
SMA	spectral mixture analysis
sp.	species
spp.	several species
SVM	support vector machine
WRMP	Wetland Regional Monitoring Program
UAV	unmanned aerial vehicle
µm	micrometer
U.S.	United States
USD	U.S. Dollars
VIS	visible light

Abstract

Invasive plants cause significant impacts to ecosystems, the economy, and human health. California has experienced significant plant invasions and is well suited to future invasion because of its Mediterranean climate and human disturbance. Eradication or control of invasive plant species requires a detailed understanding of their spatial distribution, which typically involves on the ground surveys that can be expensive or inconsistent. Remote sensing offers a potential alternative or supplement to in-person invasive plant mapping. This study performed a comparative analysis of 41 remote sensing studies that mapped the distribution of California invasive plants. I found that while high spectral resolution hyperspectral imagery was most often and successfully used to map California invasive plant species, recent studies suggest that employing low cost, color or color-infrared imagery are capable of overcoming lower spectral resolution with higher spatial or temporal resolution. Imagery obtained by UAVs are becoming increasingly more accessible for the use of mapping invasive plants at the site-scale. From this study, I examine two case studies that illustrate the use of remote sensing for large scale invasive plant management. One case study examines the use of remote sensing to monitor widespread infestations of salt cedar (*Tamarix* spp.) across the Western U.S.. A second case study examines the use of remote sensing to monitor invasive plants in a complex and regulatorily challenging landscape: The Sacramento-San Joaquin Delta. I recommend that land managers can incorporate remote sensing to monitor invasive plants by using low cost, color or color-infrared imagery obtained by drone or UAVs, developing partnerships with other relevant agencies, and collecting in-person data using methods that facilitate remote sensing analysis.

1.0 Introduction

Invasive species have a measurably negative impact on native ecosystems (Pearson et al. 2018). Invasive species are of particular concern to the conservation and restoration of native ecosystems and are a contributor to biodiversity loss worldwide (Weidlich et al. 2020). In California, invasive species have contributed to altering nutrient cycling processes (Afzal et al. 2023) and altering fire regimes through increased fire intensity, severity, and frequency and by changing fuel loads and continuity within a landscape (Brooks et al. 2004).

The recovery and persistence of rare and endangered plants are threatened by invasive species due to increased competition, and invasive species control is often noted as a necessary management action in the recovery plans for 73% of federally listed endangered plant species (Lawler et al. 2002). Of the 958 species listed as federally threatened or endangered, 400 of them are impacted by competition with non-native species (Pimentel et al. 2005). Control of invasive plants is particularly important in ecological restoration, as invasive plants can prevent the establishment of desirable native plant communities (Weidlich et al. 2020).

Once established, invasive plants can be expensive to control and long-term results are difficult to achieve (Weidlich et al. 2020). The economic cost of invasive species to the U.S. economy in 2008 was been estimated to be between $131 and $185 billion USD, largely through impacts on agricultural production, fisheries, and recreation (Marbuah et al. 2014). In 2008, California spent $82 million USD to treat and control invasive species and to mitigate their impacts on impacted waterways, degradation of native ecosystems, and increased fire risk (Robison et al. 2010). Determining the geographic distribution of an invasive species is required before management actions such as treatment and control can be implemented (U.S. Department of the Interior 2016).

1.1 Research Objectives

Advances in remote sensing technologies may provide new opportunities for mapping the spatial distribution of invasive plant species (Robison et al. 2010). My project seeks to investigate the use of remote sensing for managing invasive plant species in California. Specifically, I seek to answer the following questions:

1) Which invasive species in California have been successfully identified and mapped using remotely sensed data, and how were they detected?

2) How has remote sensing of invasive species contributed to invasive species management, either through detection, treatment, or monitoring?

I plan to answer my first research question by synthesizing the available remote sensing literature about invasive species identification and mapping using remote sensing methods for California invasive plants, which I will obtain through a literature review. I will then perform a comparative analysis of these studies, comparing the methods used to detect tamarisk and which sensors were used. I plan to answer my second research question by two case studies: one that explores the role of remote sensing in managing tamarisk (*Tamarix* spp.), and one that discusses how remote sensing has contributed to invasive species management in the Sacramento-San Joaquin River Delta.

I hypothesize that many, but not all, invasive plants in California are capable of detection and mapping by remote sensing but that remote sensing is not a commonly used method for the detection and mapping of invasive plants in California. However, some cases exist where it has successfully been used for invasive species management. Finally, I hypothesize that while significant barriers to the detection of invasive species by remote sensing exist, it can still be a useful tool for land managers to detect invasive plant species at scale and that emerging tools and methods of data analysis will decrease barriers to use.

2.0 Invasive Species and the Role of Early Detection

2.1 Invasive Species

The California Floristic Province (CFP), which includes California west of the Great Basin and deserts, southern Oregon, and Baja California, is characterized by a Mediterranean climate with cool, wet winters and warm, dry summers (Keeley 2002). The CFP is a biodiversity hotspot with over 4,400 native plant species, half of which are endemic to the region, meaning they are only found within the CFP (Keeley 2002). However, roughly 25% of the plants species within the CFP are non-native, some of which are invasive, with the majority of non-natives originating from areas with similar climates such as the Mediterranean basin, North Africa, and Eurasia (Keeley 2002). This has led to the homogenization of California plant communities, particularly in developed regions where disturbance has facilitated the spread and establishment of invasive plant species and where there is less land held under public ownership for conservation (Schwartz et al. 2006).

Determining a consistent definition of an invasive species is necessary so that environmental managers can draw comparisons between the impacts of different invasive species and prioritize their control (Blackburn et al. 2011). Alien plants are those that have been introduced, either intentionally or accidentally, by humans outside of their native range (Richardson et al. 2000). Once introduced, alien plants may transition to naturalized or invasive plants if they are capable of overcoming barriers to survival, reproduction, and dispersal (Blackburn et al. 2011). Naturalized plants are alien plants that are capable of reproducing and sustaining populations without the help of human intervention, but generally do not disperse into adjacent areas (Richardson et al. 2000). Invasive plants are naturalized plants that have high reproduction rates and are capable of dispersing far away from initial populations (Richardson et al. 2000).

Invasive plants can further be differentiated from alien or naturalized plants by understanding their impacts on the ecosystems in which the spread. For example, the California Invasive Plant Council (CAL-IPC) defines invasive plants as “plants that are not native to the environment, and once introduced, [they] establish, quickly reproduce and spread, and cause harm to the environment, economy, or human health (CAL-IPC 2024a). This definition differs slightly from that proposed by Richardson et al. (2000) in that impacts to the environment are inherent to the definition of invasive species. Throughout this paper, I will be using the CAL-IPC definition for invasive plants. Further, invasive plants can be differentiated by traits that facilitate their reproduction and spread, such as leaf-area allocation, shoot allocation, growth rate, size, and fitness (van Kleunen et al. 2010).

2.2 History of Invasive Plants in California

Invasive species were first brought to California in the 16th century by Spanish settlers, who introduced many of the invasive forbs and grasses that are now prevalent throughout California (Keeley 2002). The transition to the Mexican Period (1821-1848) saw the widespread introduction of cattle to the region that, combined with an extreme drought, led to declines in native bunchgrass populations (Keeley 2002). Subsequently, introduced Mediterranean grasses and forbs that were both adapted to similar climatic conditions, disturbances, and grazing pressures in California rapidly expanded as available niches became available (Keeley 2002). Later, the Gold Rush (1848-1855) and American periods (1848-present) brought significant agricultural expansion and trade to the region, creating new pathways of invasion through infested seed and agricultural escapees (Rejmánek and Randall 1994).

Each period of California history saw landscape scale changes that facilitated invasion (Rejmánek and Randall 1994). The widespread implementation of agriculture to the state brought with it channelization of creeks, drainage of wetlands, and clearing of forests for agriculture, grazing, and timber (Rejmánek and Randall 1994). The construction of roads, railroads, and later highways created new pathways for introductions and fragmented existing habitats (Rejmánek and Randall 1994). Altered fire regimes arising from fire suppression policies and increased ignition sources have also changed invasion dynamics throughout California (Keeley 2002). Due to increases in tree density and ladder fuels caused by fire suppression policies, once resilient ecosystems such as coniferous forests have become more susceptible to invasion after fire events (Keeley 2002). Shifts from shrub-dominated communities to non-native annual grassland have been observed in areas close to urban centers due to more frequent fires caused by increases in ignition sources (Keeley 2002).

2.3 Policy Framework of Invasive Plants

While there are a variety of laws and policies that grant federal agencies the authority to regulate invasive plants, no single agency or law has full authority to manage invasive plants (Burgos-Rodríguez and Burgiel 2020). Executive Orders (E.O.s) 13112 and 13751 grant federal agencies the ability to implement invasive plant control programs (Burgos-Rodríguez and Burgiel 2020). The Plant Protection Act of 2000 (PPA) establishes regulations regarding inspection and quarantine of noxious weeds and potential plant pests, though these are generally targeted to crop pests (Burgos-Rodríguez and Burgiel 2020). Currently, two organizations are primarily responsible for prioritizing and ranking invasive plants in California (Brusati et al. 2014).

The California Invasive Plant Council (CAL-IPC) is non-profit research group that publishes an inventory of invasive plants that impact California's natural habitats (Brusati et al. 2014). Plants are rated on a scale from "High", "Moderate", and "Limited" based on the degree of their impacts on native impacts and how widespread they are across California (CAL-IPC 2024b). Additional ratings include "Alert", which describes "High" or "Moderate" rated species that have the potential to spread outside their limited range in California, and "Watch" which describes species not currently found in California but have the potential to be high risk (CAL-IPC 2024b).

The California Department of Food and Agriculture (CDFA) is a state agency with the legal authority to regulate plant species that pose a risk to agriculture (Brusati et al. 2014). Title 3 of the California Code of Regulations (CCR) Section 4500 lists species that qualify as noxious weeds and which fall under CDFA jurisdiction. Species are rated on a scale from A, B, C, D, or Q (California Department of Food and Agriculture 2024) where:

- A rated species: known to cause economic or environmental damage, are either not present in California or have limited distribution, are prohibited from entering the state, and are subject to state regulation.
- B rated species: known to cause economic or environmental damage, have limited distribution in California, have restrictions on entering the state, and are subject to regulation by county agricultural commissioners.

- C rated species: known to cause economic or environmental damage, can have widespread distribution in California, and are subject to regulation by county agricultural commissioners.
- D rated species: causes no or little economic or environmental damage, not subject to regulation
- Q rated species: suspected to cause economic or environmental damage, but not enough information is known to make a determination

2.4 Early Detection and Rapid Response

The establishment, spread, and impacts of invasive species can be prevented or controlled through effective management strategies (Weidlich et al. 2020). Early Detection and Rapid Response (EDRR) is a management framework that argues for identifying and eliminating initial infestations of invasive species before they become established and too costly and unmanageable to eradicate (U.S. Department of the Interior 2016). The U.S. Department of the Interior, the federal agency responsible for managing most of the open space in the U.S., defines EDDR as “a coordinated set of actions to find and eradicate potential invasive species before they spread and cause harm” (Reaser et al. 2020).

EDDR is based upon the conceptual framework of the “invasion curve,” which illustrates how the costs of managing an invasive species increase and the likelihood of eliminating that species decreases as its range increases and the longer it is established (Figure 1) (U.S. Department of the Interior 2016). The invasion curve proposes four management options for controlling invasive species that become progressively more expensive and time intensive as the infestation grows: Prevention, Eradication, Containment, and Long-Term Control (U.S. Department of the Interior 2016). All four management actions included in the EDRR framework require detection, or the verification of an invasive species presence (Reaser et al. 2020). Historically, detection was conducted through in person, visual surveys, though remote sensing may become a more feasible tool for detection as this technology advances (Reaser et al. 2020).

Prevention, the first management action under the EDDR framework, is the most cost-effective and includes any actions that prevent an invasive species from being introduced into a new ecosystem (Reaser et al. 2020). This is particularly important because many invasive species are introduced to new ecosystems, intentionally or not, by people through global trade (Early et al. 2016). For example, 63% of invasive species in California wildlands were introduced through the horticultural industry (Brusati et al. 2014). Prevention is a necessary step in the EDDR framework, as introductions of potentially invasive plants are believed to increase in the future due to climate change (Early et al. 2016).

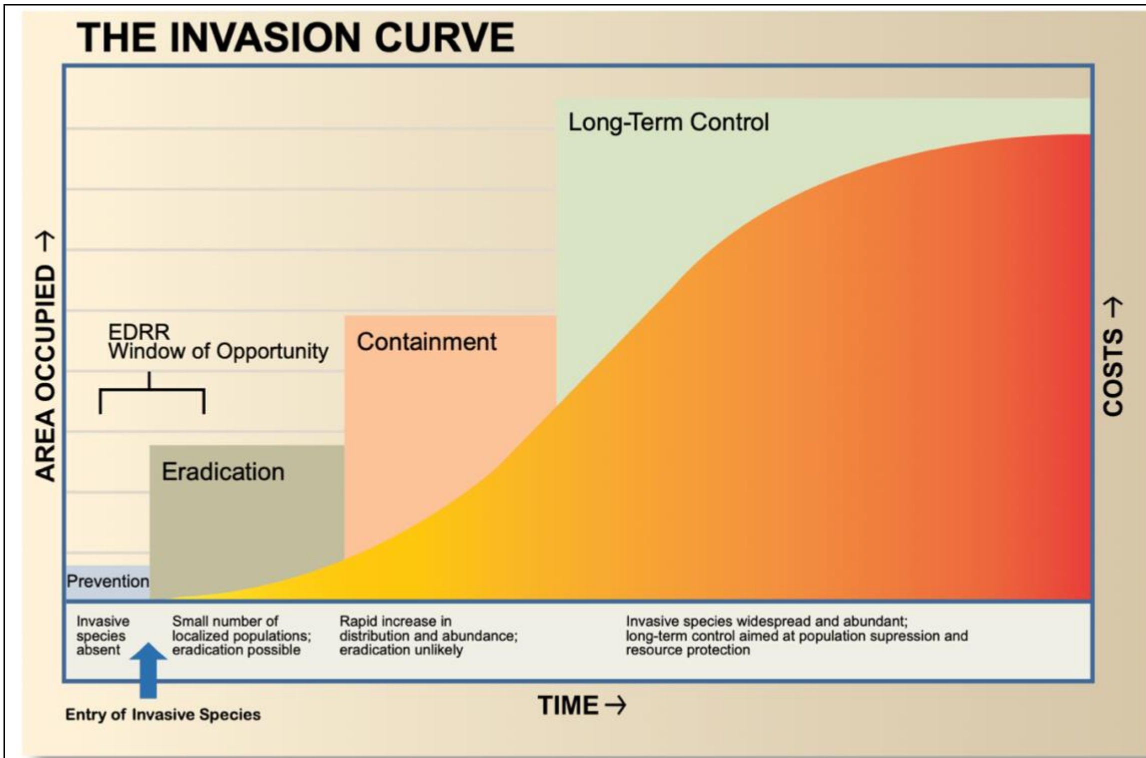

Figure 1: The invasion curve (U.S. Department of the Interior 2016)

Eradication, or the complete removal of an invasive species, is typically only successful for small populations of invasive species that have not had sufficient time to expand beyond their limited range (Reaser et al. 2020). For example, an invasive marine alga, *Caulerpa taxifolia,* was successfully eradicated in Southern California because treatment efforts were initiated seventeen days after it was first detected (Anderson 2005). However, the likelihood that an introduced plant species will become invasive increases the longer it is established in an area (Ahern et al. 2010). Herbarium studies have shown that non-native plant species with a higher Minimum Residence Time (an estimate of the time an introduced plant species has been established in an area based on herbarium collection dates) were more likely to become invasive (Ahern et al. 2010).

As environmental conditions within an ecosystem change, the ecosystem may become more susceptible to invasion (Rew et al. 2009). Climate change, for example, may open up available niches for new invasive species in native ecosystems (Hellmann et al. 2008), and established invasive species may see their ranges shift or contract as climate conditions change (Bradley et al. 2009). Additionally, longer residence times may provide sufficient time for genetic adaptations to accumulate within invasive plant populations that confer competitive advantages (Ahern et al. 2010). Regardless, detecting invasive or potentially invasive plants early in their establishment is a necessary first step to EDRR management actions such as eradication or containment (U.S. Department of the Interior 2016).

3.0 Remote Sensing Overview

Remote sensing is the practice of measuring an object from a distance using the light energy that is reflected off of a surface (Bradley 2014), and has been proposed as a promising method for detecting early invasions and mapping their distributions (Robison et al. 2010). Remote sensing requires a light source, a sensor, a target (in this case an invasive plant), and its interaction with electromagnetic radiation in order to gather information (Figure 2) (Macarringue et al. 2022).

Remote sensing has many applications in environmental management. Land use and land cover classification, which is the process of mapping the biophysical attributes of the Earth's surface and its use by humans, has long been conducted with satellite sensors because they can regularly acquire imagery across the entirety of Earth's surface (Macarringue et al. 2022). Remote sensing has a variety of applications for water resource management as well,

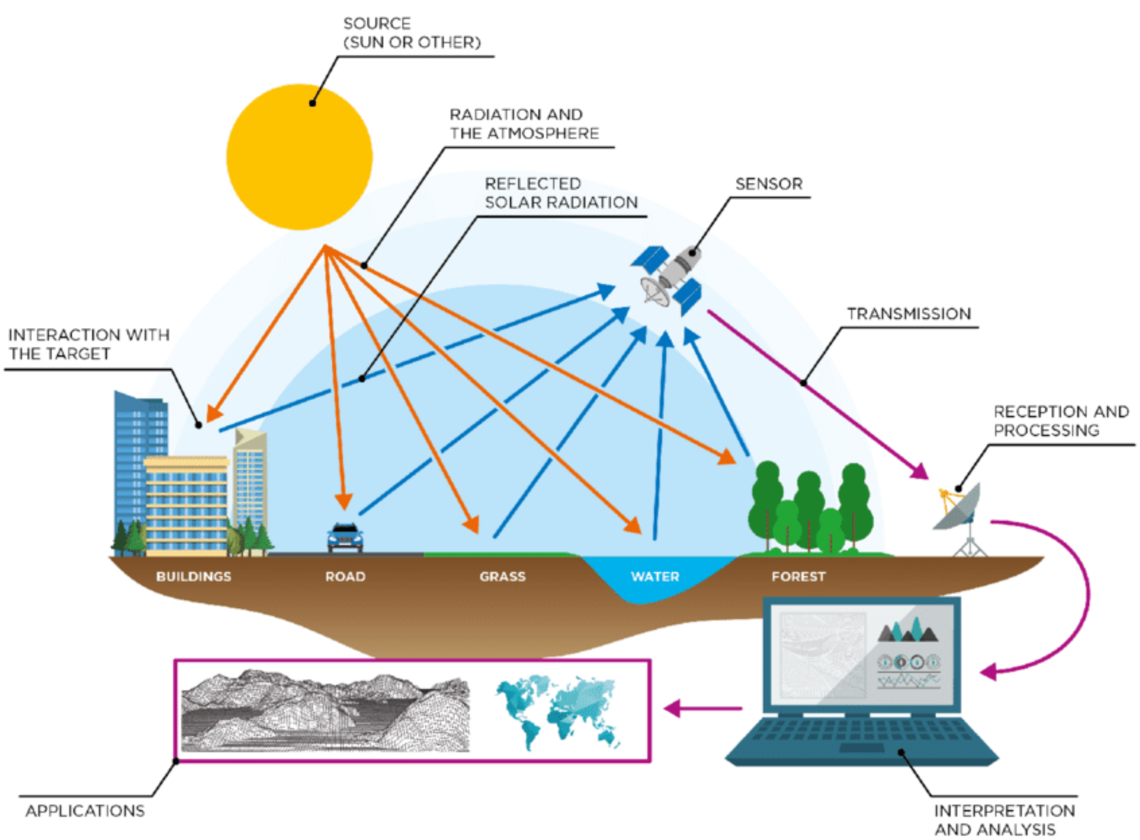

Figure 2: Overview of remote sensing process (Macarringue et al. 2022)

including measuring drought stress in agriculture, water quality monitoring, flood mapping, and mapping wetlands (Govender et al. 2009).

3.1 Sensor Properties

Sensors differ in both the source of light used for remote sensing and the resolutions at which they operate (Huang and Asner 2009). Sensors can be characterized as active if they provide their own light sources (e.g., LiDAR) or passive if they rely on solar reflectance for their light source (e.g., Landsat satellite) (Huang and Asner 2009).The spectral, spatial, and temporal resolutions of a sensor are of primary importance for the detection of plants by remote sensing (Huang and Asner 2009). Table 1 lists the resolution of many of the most used remote sensors used in detecting invasive plant species.

Table 1: Resolution of Different Remote Sensing Platforms (Adapted from Bradley 2014)

Imagery		Spatial Extent	Spatial Resolution	Temporal Resolution
Multi-Spectral	MODIS	2330 km	250-1000 m	Weekly composite
	Landsat 8	185 km	30 m	16 days
	Aster	60 km	15-30 m	Tasked
	Ikonos	11 km	1.8-4m	Tasked
	Quickbird	17 km	2.5 m	Tasked
	Worldview-2	16 km	1.8 m	Tasked
Hyperspectral	Hyperion	7.7 km	30 m	Tasked
	AVIRIS	2-11 km	4-20 m	Tasked
	CASI	Various	Up to 25 cm	Tasked
	HyMap	Various	3-10 m	Tasked
Aerial Photos	NAPP	9 km	1:40,000	Years
	NAIP	Mosaic	1 m	Years
	USGS DOQ	Mosaic	1 m	Years

Spectral resolution refers to the number of discrete regions within the visible (0.4 μm–0.7 μm) near-infrared (0.7 μm-1 μm), and short wavelength infrared (1 μm-2.5 μm) portions of the electromagnetic spectrum (called spectral bands) that are capable of being detected by a sensor (Bradley 2014). Multispectral sensors, such as Landsat, typically contain between 4-10 bands and can be described as having moderate spectral resolution (Bradley 2014). For example, the Landsat 5 near-infrared band measures wavelengths of light between 0.76 μm and 0.90 μm (Bradley 2014). Hyperspectral sensors on the other hand may contain hundreds of bands, with each band containing a narrower region of the electromagnetic spectrum, and can be classified as having high spectral resolution (Bradley 2014).

Spatial resolution, in this context, refers to how much area of land is contained within one pixel of a remotely sensed image (Bradley 2014). However, spatial resolution should not to be confused with spatial extent, which in this context is the total area of land covered by a remotely sensed image (Bradley 2014). Sensors with moderate spatial resolution (e.g. Landsat 8) may produce images with pixels anywhere between 30 m^2 to 250-1000 m^2 whereas high spatial resolution sensors (e.g. CASI) may produce pixels as low 25 cm (Bradley 2014). Figure 3 illustrates the difference between a moderate and high-resolution sensor.

Figure 3: Comparison of spatial resolution of true-color Landsat satellite imagery at 30-m resolution (left) and RapidEye satellite resolution imagery at 6.5-m resolution (right). Image: (Hill et al. 2016)

Lastly, temporal resolution refers to how often a sensor may return to the same location and acquire imagery (Bradley 2014). Satellite based sensors, such as Landsat 8, typically have fairly high temporal resolution as they capture imagery of the same footprint every 16 days (Bradley 2014). Aerial based imagery typically has lower temporal resolution, capturing the same footprint once every few years, or must be tasked, meaning that temporal resolution is defined by the user based on how often they choose to acquire imagery (Bradley 2014).

While higher spectral, spatial, and temporal resolution are useful in distinguishing one plant species from its surrounding environment, sensors must compromise between all types of resolution (Bradley 2014). Sensors with high temporal resolution typically exhibit a tradeoff between frequent imagery acquisition and low spectral or spatial resolution (Huang and Asner 2009). Likewise, sensors with high spatial or spectral resolution are typically drone or plane-mounted, which limits their availability and ease of access (Huang and Asner 2009). High spatial and spectral resolution imagery is also typically more expensive than moderate resolution imagery (He et al. 2011).

3.2 Detection of Plants by Remote Sensing

Methods for discriminating the signal produced by a remote sensor and assigning it to a particular category, in this case an invasive species, are generally characterized by spectral approaches, textural approaches, and phenological approaches (Bradley 2014).

Spectral approaches rely on the unique patterns of absorption and reflection that an object displays when interacting with light (Bradley 2014). By plotting the amount of light reflected off a surface over the wavelengths or spectra of light detected by a sensor, patterns called spectral signatures can be produced that may be unique to the material being sensed (Rocchini et al. 2022). For example, plant material can be distinguished from non-photosynthetic material such as soil or rocks based on the high reflectance of chlorophyll-a in the near-infrared region of light (He et al. 2011). Other leaf pigments such as carotenoids and anthocyanins, water, and other plant biochemicals, as well as unique leaf architecture can differentially reflect or absorb wavelengths of light, producing different spectral signatures (Blackburn, G. A. 2007). The relative abundance of any of these plant tissue constituents can differ greatly between species, and when an invasive species possess a substantially different spectral properties than surrounding vegetation, it may be capable of being detected using remote sensing methods (Bradley 2014). For example, leaf spectral signatures within the California flora have been shown to be more similar when plants shared a close evolutionary history, and that entire families of plants were spectrally distinct from one another, suggesting that remote sensing is a plausible tool for mapping vegetation diversity (Griffith et al. 2023). The spectral signatures of many different plant species and land cover types can be collected and stored in spectral libraries and used as reference spectra for later identification (Jiménez and Díaz-Delgado 2015). Pixels within a remotely sensed image that contain similar spectral signatures to those of a known invasive plant can be classified as such, producing maps of invasive species distribution (Bradley 2014). Hyperspectral imagery is typically believed to be superior for detection of invasive plants compared to multispectral imagery, as differences in reflectance can be distinguished by the numerous, high-resolution spectral bands (Figure 4) (Bradley 2014).

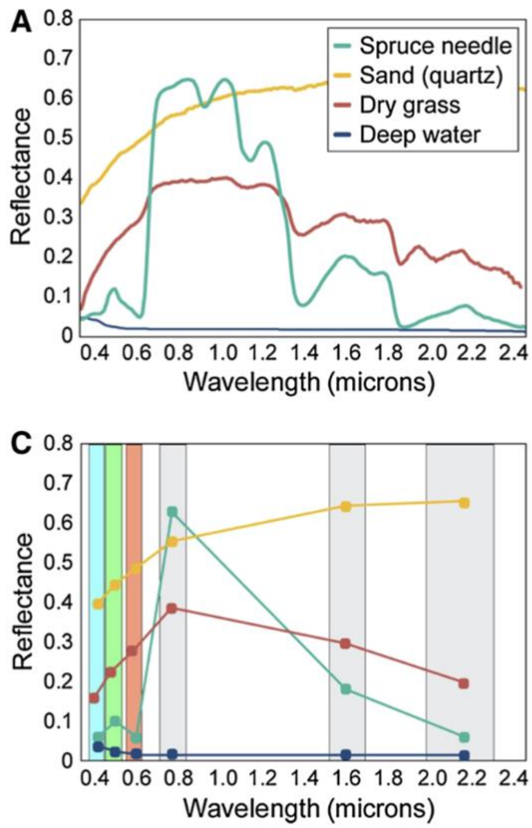

Figure 4: Comparison of spectral signatures for different cover types and tree species from hyperspectral and multispectral imagery (Bradley 2014)

Textural approaches rely on differentiating neighboring pixels from one another or grouping them together as opposed to classifying individual pixels (Bradley 2014). High spatial resolution is necessary for textural approaches, as spectral signatures must be compared to nearby neighbors (Bradley 2014). If pixels sizes are much larger than individual plants, then each pixel represents a mixture of different spectral signatures instead of a unique spectral signature that corresponds to a particular species (Bradley 2014). Additionally, target plant species must exhibit a different shape, growth habit, or density than native background vegetation to be detected by textural approaches (Bradley 2014).

Lastly, phenological approaches rely on growth patterns that are significantly different than background vegetation or native species (Bradley 2014). For example, invasive species that remain evergreen in deciduous ecosystems, become photosynthetically active earlier than native species or remain photosynthetically active later than native species can be differentiated through phenological approaches (Bradley 2014). Phenological differences between different landcover types or species can be expressed through the use of spectral indexes such as normalized difference vegetation index (NDVI), which is a ratio of near-infrared light (NIR) and the red portion of visible light (VIS) that displays areas of high photosynthetic activity and is calculated as $NDVI = (NIR - VIS)/(NIR + VIS)$ (Bradley 2014). Areas with higher NDVI represent vegetation that is greener, healthier, and more photosynthetically active than areas of lower NDVI (Bradley 2014).

3.3 Image Classification

Converting a remotely sensed image into a classified image requires preprocessing data, determining an appropriate classification system, training data, and an accuracy assessment (Lu and Weng 2007). Examples of image preprocessing include radiometric calibration, geometric rectification, atmospheric correction, and topographic correction (Lu and Weng 2007). Preprocessing data is particularly important for reducing the dimensionality of hyperspectral data, which would otherwise require exponentially more training data or computing power to compute the additional data (Chutia et al. 2016). Examples of preprocessing techniques for hyperspectral data include minimum noise fraction (MNF) and class-based principal component analysis (PCA) (Chutia et al. 2016).

Supervised classification approaches require training samples of a known spectral or textural value, which are then used to create thematic maps (Chutia et al. 2016). Common examples of supervised classification approaches include the maximum likelihood classifier (MLC), support vector machine (SVM), and object-based image analysis (OBIA) (Chutia et al. 2016). Alternatively, unsupervised classification approaches require no previous knowledge of what classifications are used, and often rely on fuzzy logic (Chutia et al. 2016).

Ensemble methods use a set of supervised learning using defined criteria algorithms to predict classification results (Chutia et al. 2016). Random Forests are one example of an ensemble method that is commonly used to classify hyperspectral images (Chutia et al. 2016), in this case calculating the probability that a pixel belongs to a certain class based on its spectral information (Macarringue et al. 2022).

Reference Data

	D	C	BA	SB	row total
D	65	4	22	24	115
C	6	81	5	8	100
BA	0	11	85	19	115
SB	4	7	3	90	104
column total	75	103	115	141	434

Land Cover Categories

D = deciduous
C = conifer
BA = barren
SB = shrub

OVERALL ACCURACY = 321/434 = 74%

PRODUCER'S ACCURACY

D = 65 / 75 = 87%
C = 81 / 103 = 79%
BA = 85 / 115 = 74%
SB = 90 / 141 = 64%

USER'S ACCURACY

D = 65 / 115 = 57%
C = 81 / 100 = 81%
BA = 85 / 115 = 74%
SB = 90 / 104 = 87%

Figure 5: Example of an error matrix (Congalton 1991)

Image classification accuracy can best be summarized using an error matrix, in which the number of pixels that were identified as a particular class and the true number of pixels belonging to that class are arranged in a series of columns and rows (Congalton 1991). From the error matrix, two metrics for validating image classifications can be calculated: the producer’s and user’s accuracy (Congalton 1991). The producer’s accuracy is a measurement of omission, which represents the chance that a correct identification what made classifying training data (Congalton 1991). Producer’s accuracy is calculated by dividing the number of correctly identified points from validation data by the total number of validation data points (Congalton 1991). User’s accuracy is a measure of commission error, which represents the probability that a classified pixel corresponds to the correct category in the real world (Congalton 1991). The user’s accuracy is calculated by dividing the total number of correctly classified points divided by the total number of points of that same classification within the dataset (Congalton 1991). Figure 5 shows an example of how to calculate producer's and user's accuracy from an error matrix.

3.4 Benefits of Remote Sensing in Invasive Plant Management

Remote sensing offers a potential alternative to on-the-ground reconnaissance of invasive species because maps can be produced for larger spatial scales in less accessible terrain and is only biased by the spatial extent of the sensor (He et al. 2011). This is important because early detection of invasive species is insufficiently conducted across the vast majority of California ecosystems (He et al. 2011). Most monitoring of invasive species occurs in person, limiting the scale of EDRR across large spatial extents and in difficult-to-access terrain, and is rarely repeated at regular time intervals (He et al. 2011). Further, efforts to document invasive plants is performed unequally throughout a landscape: most EDRR records and herbarium collections are from rare locations, which limits our understanding of the true distribution of invasive species (Bradley 2014).

An additional benefit of remote sensing methods is that a historical record of invasion spread over time and space is produced (He et al. 2011). Remote sensing may also provide further insights into the mechanisms of invasion (Bradley 2014) and resulting impacts on community structure and ecosystem processes (He et al. 2011). Remotely sensed data can also contribute to statistical models that predict the current distribution of individual plant species based on their known distribution and environmental conditions (Yannelli et al. 2022). These models can be updated with projected climate conditions to predict how species may respond to climate change (Yannelli et al. 2022).

3.5 Limits of Remote Sensing for Invasive Plant Detection

The resolution of a sensor can greatly impact its ability to differentiate an invasive plant species from surrounding vegetation (He et al. 2011). Imagery with coarse spatial resolution captures the spectral reflectance of multiple individual plants and potentially several species, which can introduce variations in spectral signatures both within and between species as well as spectral mixing (He et al. 2011). Alternatively, when pixel sizes are much smaller than the size of an individual of a plant species of interest, high spectral variance can occur as light reflects off different plant parts (He et al. 2011). Spectral signatures may also not represent discrete species, particularly if nearby species contain similar biochemical constituents (Rocchini et al. 2022).

Supervised classification methods rely on training data in order to create predictive models and validation data to measure their accuracy (Chutia et al. 2016). Yet, field data for training and validation can be lacking, particularly for species that are of emerging concern for environmental managers (Parker et al. 2021).

Because remote sensing typically measures a landscape from a birds-eye view, plant species below the canopy are typically missed, making remote sensing of understory species unfeasible (Rocchini et al. 2022). Other remote sensing technologies such as microwave remote sensing and synthetic aperture radar (SAR) are capable of penetrating through the canopy layer as well as through clouds, yet are more difficult to use (Parker et al. 2021). Phenological approaches also require that imagery is obtained at the same time distinct life stages such as flowering or senescence are occurring, which can occur asynchronously across a landscape (He et al. 2011).

Lastly, price and processing can preclude the use of higher quality data such as hyperspectral imagery (He et al. 2011). Hyperspectral imagery requires large amounts of data to store and technical capacity to process (He et al. 2011). Tasking flights to acquire hyperspectral imagery can often cost upwards of tens to hundreds of thousands of dollars (He et al. 2011).

4.0 Comparative Analysis of Remote Sensing for California Invasive Plants

There are a variety of different remote sensing platforms with varying degrees of spatial, spectral, and temporal resolution available to land managers interested in remotely sensing invasive species. Understanding the pros and cons of each sensor, the properties of each invasive plant that facilitates its detection via remote sensing, and data processing and classification methods are essential to mapping invasive plant species.

4.1 Methods

I conducted the literature review across multiple databases, including Fusion, Scopus, and Google Scholar with the search terms “remote sensing” followed by each species name in quotations to limit my results to studies containing each species in the CAL-IPC inventory as a keyword.

Plant species used in this comparative analysis were limited to those plants in the CAL-IPC inventory that were rated “high” (Table 2). These species were chosen to because their significant impacts would be of interest to environmental managers throughout California and would demonstrate the utility of remote sensing for invasive species monitoring over a variety of different ecosystems. For genera represented by more than one species in the inventory, only the genus was included in quotation marks. Approximately 5% of the studies were found through previously cited works within the papers I found or through incidental findings. Any studies that did not include a map illustrating the predicted distribution of the invasive species in question was excluded from analysis, as these end products are intended to be provided to resource managers. Studies performed outside of California were included so long as a species in the CAL-IPC inventory ranked “high” was one of the subjects of the remote sensing study.

For each study, I recorded the type of sensor used and its spectral, spatial, and temporal resolution, the type of study (e.g. single scene, time series, comparative study etc.), the property of the invasive species that permits its detection via remote sensing, data processing methods used, and the classification methods used to create distribution maps. Spectral resolution was broken down by hyperspectral imagery (imagery containing typically hundreds of spectral bands), multispectral (imagery containing four or more bands), Color-Infrared (imagery containing three color bands and one infra-red band) and RGB (imagery only containing three bands corresponding to red, green, and blue wavelengths of light). Spatial resolution was characterized as "coarse" (pixel size higher than 100 meters), "moderate" (pixel size between 10-100 meters), "high" (pixel size between 1-10 meters) and "very high" (pixel size smaller than 1 meter).

Table 2: High Rated Species in the CAL-IPC Inventory (CAL-IPC 2024)

Scientific name	**Common names**	**Scientific name**	**Common names**
Aegilops triuncialis	barb goatgrass	*Hedera helix*	English ivy
Alternanthera philoxeroides	Alligatorweed	*Hydrilla verticillata*	*Hydrilla*
Ammophila arenaria	European beachgrass	*Lepidium latifolium*	perennial pepperweed
Arundo donax	giant reed	*Limnobium spongia*	South American spongeplant
Brassica tournefortii	Sahara mustard	*Ludwigia hexapetala*	creeping waterprimrose
Bromus madritensis ssp. rubens	red brome	*Ludwigia peploides*	floating water primrose
Bromus tectorum	Cheatgrass	*Lythrum salicaria*	purple loosestrife
Carpobrotus edulis	highway iceplant	*Myriophyllum aquaticum*	parrotfeather
Carthamus lanatus	woolly distaff thistle	*Myriophyllum spicatum*	spike watermilfoil
Centaurea solstitialis	yellow starthistle	*Oncosiphon pilulifer*	stinknet
Centaurea stoebe ssp. micranthos	spotted knapweed	*Onopordum acanthium*	Scotch thistle
Cortaderia jubata	Jubatagrass	*Rubus armeniacus*	Himalayan blackberry
Cortaderia selloana	Pampasgrass	*Salvinia molesta*	giant *Salvinia*
Cytisus scoparius	Scotch broom	*Sesbania punicea*	scarlet *Wisteria*
Delairea odorata	Cape-ivy	*Spartina alterniflora x S. foliosa*	smooth hybrid cordgrass
Egeria densa	Brazilian water weed	*Spartina densiflora*	dense-flowered cordgrass
Ehrharta calycina	purple veldtgrass	*Spartium junceum*	Spanish broom
Eichhornia crassipes	water hyacinth	*Tamarix chinensis*	Chinese tamarisk
Elymus caput-medusae	Medusahead	*Tamarix gallica*	French tamarisk
Euphorbia virgata	leafy spurge	*Tamarix parviflora*	smallflower tamarisk
Genista monspessulana	French broom	*Tamarix ramosissima*	saltcedar
Hedera canariensis	Algerian ivy	*Ulex europaeus*	gorse

4.2 Results

A total of 41 studies were found using the above methods and included in my comparative analysis, representing 23 species or 57% of the high-rated species in the CAL-IPC inventory (Table 3). Shrubs were the most represented lifeform in the comparative analysis, with fourteen studies included. However, these were overwhelmingly represented by *Tamarix* spp. at eleven studies. Aquatic vegetation, including floating aquatic vegetation (FAV) and submerged aquatic vegetation (SAV), were also highly represented in the comparative analysis at eleven and six studies respectively. Annual herbs and perennial vines were the least represented in the comparative analysis at one study each, though *Rubus armeniacus*, which is a thicket forming vine, was recorded as a shrub in this analysis and could be included as a perennial vine.

Hyperspectral imagery was the most used type of sensor for detecting invasive plant populations having been used in 20 studies, followed by multispectral sensors in 14 studies, Color-Infrared (Color-IR) in 13 studies, and RGB Color sensors in six studies (Figure 6). Studies incorporating passive and active sensing (such as LiDAR) were only used in 4 studies. Of the studies using hyperspectral or multispectral sensors, the hyperspectral sensor HyMap was the most used with nine studies, followed by the multispectral sensor Landsat (comprising of the Landsat 5, Landsat Land Surface Reflectance, Landsat 7 Enhanced Thematic Mapper Plus scenes) at six studies. With the exception of Landsat (sixteen-day return interval) and MODIS (weekly composite), all sensors were tasked.

Of the 56 sensors used in the remote sensing studies, high spatial resolution (25 studies) and very high spatial resolution (19 studies) sensors were used most often to map invasive plant populations, followed by moderate spatial resolution (9 studies) and coarse spatial resolution (3 studies) sensors.

Populations of invasive plants were most often detected by spectral approaches (64%) followed by phenological approaches (23%). Combined spectral and textural approaches (7%) were used more than textural approaches alone (4%), and even fewer studies combined phenological, spectral, and textural approaches (2%).

4.3 Discussion

A majority of the species ranked as “high” in the CAL-IPC invasive plant inventory are capable of being mapped by remote sensing. This method of mapping invasive species provides a suitable means of mapping infestations across a variety of spatial scales using a repeatable

Table 3: Remote Sensing Studies of High Rated Species in the CAL-IPC Inventory

Study	Study Type	Species	Species Property for Sensing	Sensor Type	Resolution			Data Processing Methods	Classification Methods
					Spectral	Spatial	Temporal		
(Malmstrom et al. 2017)	Single Scene	*Aegilops triuncialis*	Phenological	Color-Infrared	4 bands	0.45 m	tasked	Spectral Indexes	Supervised and Unsupervised Classification
(Clements et al. 2014)	Single Scene	*Alternanthera philoxeroides*	N/A	RGB Aerial Imagery	3 bands	1 m	tasked	Segmentation	Machine Learning
(Sheffield et al. 2022)	Time Series	*Alternanthera philoxeroides*	N/A	RGB Aerial Imagery	3 bands	35 cm	tasked	N/A	Random Forest Algorithms
(Frati et al. 2020)	Time Series	*Ammophila arenaria*	Spectral	Hyperspectral and LiDAR	160 bands	5 cm	tasked	Spectral Indexes, SAM, MNF	Decision Tree
(Timm et al. 2014)	Single Scene	*Ammophila arenaria*	N/A	Color-Infrared	4 bands	1 m	3.5 days	Spectral Indexes	Linear Regression
(DiPietro et al. 2002)	Single Scene	*Arundo donax*	Spectral	Hyperspectral	165 bands	4 m	tasked	MNF, SAM	Supervised and Unsupervised Classification
(Ustin et al. 2002)	Single Scene	*Arundo donax*	Spectral and textural	Hyperspectral	224 bands	4 m	Tasked	Spectral Indexes, MNF, SAM	Supervised and Unsupervised Classification

(Yang et al. 2011)	Single Scene	*Arundo donax*	Spectral	Color-Infrared	3 bands	0.65 m	tasked	N/A	Supervised Classification
(Bradley and Mustard 2005)	Time Series	*Bromus tectorum*	Phenological	Multispectral	8 bands 4-6 bands	30 m 1 km	16 days Weekly	Spectral Index, Continuum Removal	N/A
(Weisberb et al. 2021)	Comparison	*Bromus tectorum*	Phenological	Color-Infrared	5 bands	2 cm	tasked	N/A	Random Forest Algorithm
(Innangi et al. 2023)	Comparison	*Carpobrotus edulis*	N/A	RGB Aerial Imagery, Color-IR	3 bands 4 bands	2-5 cm	tasked	Spectral Indexes, Image Segmentation	Random Forest Algorithm
(Underwood et al. 2007)	Comparison	*Carpobrotus edulis*	Spectral	Hyperspectral	174 bands	4 m	tasked	Continuum Removal, MNF	Supervised Classification
(Ustin et al. 2002)	Single Scene	*Carpobrotus edulis*	Spectral, Textural	Hyperspectral	224 bands	4 m	Tasked	MNF, Spectral Indexes, SAM	Supervised and Unsupervised Classification
(Miao et al. 2006)	Single Scene	*Centaurea solstitialis*	N/A	Hyperspectral	36 bands	1, 3 m	Tasked	Spectral unmixing, PCA	Monte Carlo Method
(Baron and Hill 2020)	Single Scene	*Centaurea stoebe ssp. micranthos*	Textural	Color-Infrared	4 bands	2.9 cm	Tasked	Spectral Indexes, OBIA	Random Forest Algorithms

(Underwood et al. 2007)	Comparison	*Cortaderia jubata*	Spectral	Hyperspectral	174 bands	4 m	Tasked	MNF	Supervised Classification
(Ustin et al. 2002)	Single Scene	*Cortaderia jubata*	Spectral and Textural	Hyperspectral	224 bands	4 m	Tasked	Spectral Indexes, MNF, SAM	Supervised and Unsupervised Classification
(Hill et al. 2016)	Time Series	*Cytisus scoparius*	Spectral	Multispectral	7 bands	30 m	16 days	Spectral Index	Supervised Classification
(Hestir et al. 2008)	Single Scene	*Egeria densa*	Spectral	Hyperspectral	128 bands	3 m	Tasked	SMA, SAM	Decision Tree
(Santos et al. 2009)	Time Series	*Egeria densa*	Spectral	Hyperspectral	128 bands	3 m	Tasked	Spectral Indexes, Spectral Unmixing, SAM	Decision Tree
(Underwood et al. 2006)	Comparative	*Egeria densa*	Spectral	Hyperspectral	128 bands	3 m	Tasked	SMA, Spectral Indexes	Decision Tree
(Bolch et al. 2021)	Comparative	*Eichhornia crassipes*	Spectral	Hyperspectral	128 bands 270 bands	1.7 m 5.4 cm	Tasked	MNF, Spectral Indexes, OBIA	Random Forest Algorithm
(Hestir et al. 2008)	Single Scene	*Eichhornia crassipes*	Spectral	Hyperspectral	128 bands	3 m	Tasked	SMA, SAM	Decision Tree
(Santos et al. 2009)	Time Series	*Eichhornia crassipes*	Spectral	Hyperspectral	128 bands	3 m	Tasked	Spectral Indexes, Spectral Unmixing, SAM	Decision Tree

(Underwood et al. 2006)	Comparison	*Eichhornia crassipes*	Spectral	Hyperspectral	128 bands	3 m	Tasked	SMA, Spectral Indexes	Decision Tree
(Dronova et al. 2017)	Single Scene	*Elymus caput-medusae*	Spectral, Textural, and Phenological	Color-Infrared	4 bands	0.15 m	Tasked	OBIA	Supervised and Unsupervised Classification
(Malmstrom et al. 2017)	Single Scene	*Elymus caput-medusae*	Phenological	Color-Infrared	4 bands	0.45 m	Tasked	Spectral Indexes	Supervised and Unsupervised Classification
(Weisberb et al. 2021)	Time Series	*Elymus caput-medusae*	Phenological	Color-Infrared	5 bands	2-5 cm	Tasked	N/A	Random Forest Algorithm
(Lake et al. 2022)	Time Series, Comparative	*Euphorbia virgata*	Spectral, Phenological	Multispectral Color-IR	8 bands 4 bands	1.8 m 3 m	Tasked Daily	N/A	Deep Learning, Image Segmentation
(Chance et al. 2016)	Single Scene	*Hedera helix*	Spectral	Hyperspectral and LiDAR	72 bands	1.0 m	Tasked	SAM	Random Forest Algorithm
(Khanna et al. 2023)	Time Series	*Hydrilla verticillata*	Phenological	Hyperspectral	430 bands 126 bands	3 m 2.5 m	Tasked	Spectral Indexes, Spectral Mixture Analysis, SAM	Random Forest Algorithm
(Andrew and Ustin 2008)	Site Scene	*Lepidium latifolium*	Spectral	Hyperspectral	128 bands	3 m	Tasked	Spectral Indexes, MNF	Aggregated classification and regression trees
(Hestir et al. 2008)	Single Scene	*Lepidium latifolium*	Spectral	Hyperspectral	128 bands	3 m	Tasked	MNF	Logistic regression

(Takekawa et al. 2023)	Single Scene	*Lepidium latifolium*	Spectral	RGB Aerial Imagery	3 bands	5 cm	Tasked	Spectral Indexes	Spectral Indexes
(Bolch et al. 2021)	Comparison	*Ludwigia spp.*	Spectral and Textural	Hyperspectral	128 bands 270 bands	1.7 m 5.4 cm	Tasked	Spectral Indexes, MNF, OBIA, Texture metrics	Random Forest
(Khanna et al. 2018)	Time Series	*Ludwigia sp.*	Spectral	Hyperspectral	430 bands 126 bands	3 m 2.5 m	Tasked	Spectral Indexes, Spectral Mixture Analysis, SAM	Random Forest
(Brooks et al. 2022)	Single Scene	*Myriophyllum spicatum*	Spectral	Multispectral	6 bands	2 cm	Tasked	Spectral Index	OBIA, Supervised Nearest Neighbor Analysis
(Khanna et al. 2023)	Time Series	*Myriophyllum spicatum*	Phenology	Hyperspectral	430 bands 126 bands	3 m 2.5 m	Tasked	Spectral Indexes, Spectral Mixture Analysis, SAM	Random Forest Algorithm
(Chance et al. 2016)	Single Scene	*Rubus armeniacus*	N/A	Hyperspectral and LiDAR	72 bands	1.0 m	Tasked	SAM	Random Forest Algorithm
(Everitt et al. 2002)	Single Scene	*Salvinia molesta*	Spectral	Color-Infrared	3 bands	0.6 m	Tasked	Iterative Self-Organizing Data Analysis	Unsupervised Classification

(Everitt et al. 2008)	Single Scene	*Salvinia molesta*	Spectral	Color-Infrared	4 bands	2.4 m	Tasked	Iterative Self-Organizing Data Analysis	Unsupervised Classification
(Akasheh et al. 2008)	Single Scene	*Tamarix spp.*	Spectral	Color-Infrared	3 bands	0.5 m	Tasked	N/A	Supervised Classification
(Bedford et al. 2018)	Time Series	*Tamarix spp.*	Spectral	Color-Infrared	4 bands	20 cm	Tasked	Spectral Index	Mahalanobis Distance Method
(Branskey et al. 2021)	Time Series	*Tamarix spp.*	Spectral	Multispectral	8 bands	2 m	Tasked	SAM	Supervised Classification
(Carter et al. 2009)	Comparative	*Tamarix spp.*	Spectral	Hyperspectral, Multispectral, Color-Infrared	220 bands 7 bands 4 bands	30 m 30 m 2.5 m	Tasked 16 days Tasked	Spectral Indexes, PCA, MNF	Supervised Classification
(Dennison et al. 2009)	Time Series, Comparative	*Tamarix spp.*	Phenological	Multispectral	3 bands 36 bands	15 m 250 m	Tasked Weekly	Spectral Indexes	N/A
(Evangelista et al. 2009)	Time Series, Comparative	*Tamarix spp.*	Phenological	Multispectral	7 bands	30 m	16 days	Spectral Indexes	Maxent model
(Hamada et al. 2007)	Single Scene	*Tamarix spp.*	Spectral	Hyperspectral	120 bands	0.5 m	Tasked	Spectral smoothing, spectral indexes, MNF	Stepwise Discriminant Analysis, Hierarchical Clustering
(Ji and Wang 2016)	Comparative, Time Series	*Tamarix spp.*	Phenological	Multispectral, Hyperspectral, RGB Aerial Imagery	36 bands 6 bands 61 bands 3 bands	250 m 30 m 1 m 1 m	Weekly 16 Days Tasked Tasked	N/A	SAM

(Ji et al. 2017)	Single Scene	*Tamarix spp.*	Phenological	Multispectral, RGB Aerial Imagery	36 bands 6 bands 3 bands	250 m 30 m 1 m	Weekly 16 Days Tasked	N/A	Stepwise generalized linear regression
(Sankey et al. 2016)	Time Series	*Tamarix spp.*	Phenological	Color-Infrared and LiDAR	4 bands	20 cm	Tasked	Spectral Indexes	Mahalanobis Distance Method
(Silván-Cárdenas and Wang 2010)	Comparative	*Tamarix spp.*	Spectral	Hyperspectral, Multispectral	61 bands 7 bands	1 m 30 m	Tasked 16 days	SMA	Spectral Unmixing Methods
(Granzig et al. 2021)	Single Scene	*Ulex europaeus*	Spectral, Textural	Multispectral, RGB Aerial Imagery	9 bands 3 bands	20 m 10 cm	5-10 days Tasked	Spectral Indexes, Textural Features	Random Forest Algorithm

process. However, the utility of remote sensing as a means for implementing EDRR programs can be limited depending on our understanding of novel invasive species, the spatial scale of the infestation, and the resolution of the sensor used.

Image classification of any plant species from remote sensing imagery requires that plant exhibits a spectral, textural, or phenological distinction between surrounding plant species. As new species are introduced, local land managers may not have sufficient knowledge of these potentially invasive plants to assess whether these distinctions exist. This may be especially problematic for cryptic invasive plants, which are misidentified as other species due to similar morphological traits (Morais and Reichard 2017). Additionally, closely related plants within the same genus in the CAL-IPC inventory were not capable of being differentiated from one another.

Spatial scale is another factor complicating the use of remote sensing to detect invasive plants as part of an EDRR management process. As illustrated by the invasion curve (Figure 1), newly introduced invasive plants are most cost-effective to manage early in their invasion process when populations occupy a small area and eradication is possible. Training data is required to teach image classification methods such as random forest algorithms or supervised classification methods to assign spectral properties as belonging to a unique species, and large amounts of training data may be necessary to account for intraspecific variation in spectral signatures or phenology.

The spatial resolution of a sensor is also important in preventing spectral mixing within a pixel, which will lead to inaccurate classifications and therefore inaccurate maps of invasive species distributions. Similarly, high spatial resolution often comes at the expense of high spectral resolution and spatial extent. It is possible to map small populations of invasive species using high spatial resolution imagery, but the scale at which mapping occurs is limited by the reduced extent of the imagery.

While remote sensing may have limited use in the early detection of invasive species, remote sensing can play an important role in mapping plants in the containment and long-term control phase of the invasion curve. As the occupied area of an invasive species expands beyond the point where eradication is possible, remote sensing offers a cost-effective strategy for monitoring invasive plant populations, understanding their spread, and evaluating how they respond to different management strategies across a variety of spatial scales.

4.3.1 Spectral Resolution

As previous studies have shown, hyperspectral data has several advantages to multispectral or color imagery for classifying plants to the species or genus level for mapping invasive plant populations (He et al. 2011), (Bradley 2014). The many narrow spectral bands used in hyperspectral imagery allow the unique spectral signature of different plants to be identified. For example, Chance et al. (2016) were able to use CASI hyperspectral imagery (72 bands at 1.0-meter spatial resolution) to distinguish the spectral signature of two species (*Hedera helix* and *R. armeniacus*) from surrounding vegetation based on higher reflectance of *H. helix* and *R. armeniacus* between the 749 nm and 1002 nm wavelengths of light (Chance et

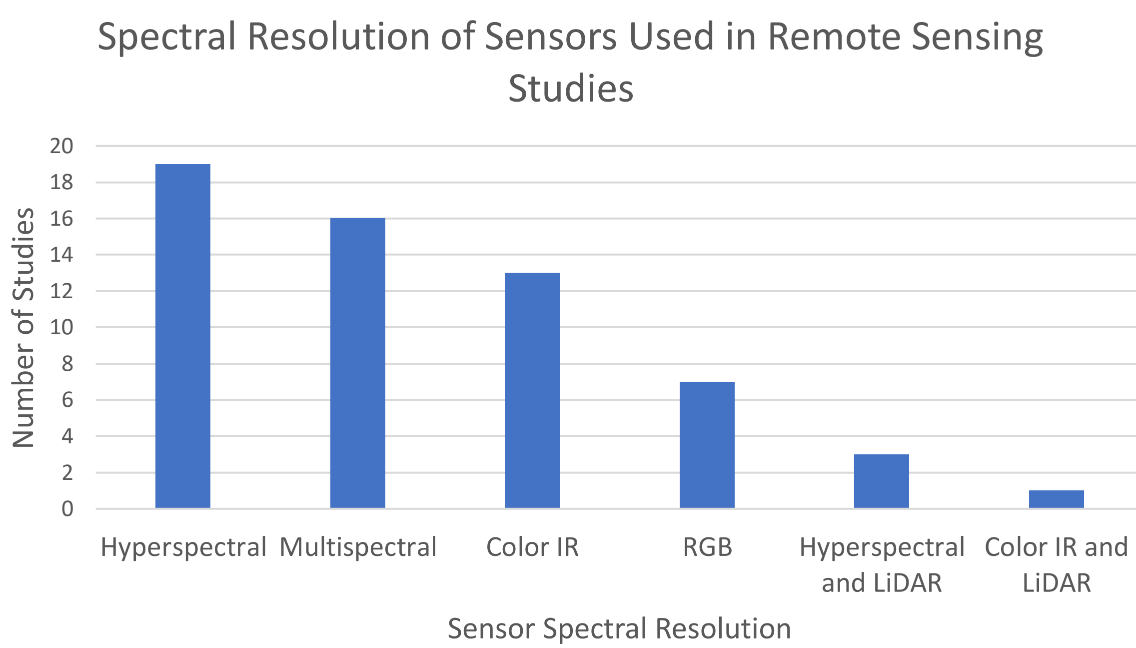

Figure 6: Spectral Resolutions of Sensors Used in Studies from the Comparative Analysis

al. 2016). Similarly, Underwood et al. (2007) were able to successfully map three invasive species using hyperspectral data in a coastal California setting: iceplant (*Carpobrotus edulis)*, jubata grass (*Cortaderia jubata)*, and blue gum eucalyptus (*Eucalyptus globulus*), the latter of which is not on the CAL-IPC high list) These species were able to be distinguished using hyperspectral imagery by taking advantage of the fact that these species exhibit slight differences in reflectance at high spectral resolutions (Underwood et al. 2007). *C. edulis* for example was successfully mapped at high spectral and spatial resolution (AVIRIS imagery with 174 bands at 4-meter spatial resolution) at high accuracy (92%) when growing within a chaparral ecosystem because *C. edulis* contains high amount of leaf water content, which was illustrated in the spectral signature as a strong dip in reflectance at 0.9 µm (Underwood et al. 2007). Similarly, *C. jubata* was successfully mapped at high accuracy (82%) with the same AVIRIS imagery because of the accumulation of dry, senesced leaves and inflorescences that collect on individual plants that strongly absorb at 1.7, 2.1, and 2.3 µm due to the high concentration of lignin and cellulose (Underwood et al. 2007).

Invasive species that grow in large, dense patches were most appropriate for tracking by high-temporal, multispectral sensors such as Landsat, Sentinel-2, and Worldview-2. The dense populations of these species were able to overcome the limited spatial resolutions of these sensors. For example, Gränzig et al. (2021) were able to map the fractional coverage of *Ulex europaeus* in Chiloé Island, Chile using Sentinel-2 satellite imagery (processed at 20-meter resolution, with the 60-meter bands B1, B9, B10 and 10-meter band B8 removed) when training data sets were made from high spatial resolution drone imagery. *U. europaeus* has bright yellow flowers that can easily be distinguished from surrounding land cover types via unmanned aerial vehicles (UAV) imagery (Gränzig et al. 2021). Older populations of *U. europaeus* grow in dense, large patches that can easily exceed the pixel size of the resampled Sentinel-2 imagery, allowing *U. europaeus* to be mapped across the entire 9,180 km^2 study site using four Sentinel-2 images (Gränzig et al. 2021).

Alternatively, high-temporal, multispectral sensors were capable of detecting some widespread species when they displayed significant phenological differences between native vegetation. Bradley and Mustard (2005) used Landsat TM and ETM+ imagery (30-meter resolution) and AVHRR (1-kilometer resolution) to map the distribution of cheatgrass (*Bromus tectorum*) across the entire Great Basin using phenological methods. *B. tectorum*, an annual grass that is a prevalent invader of sagebrush scrub and bunchgrass ecosystems, adapts to arid and drought conditions by responding rapidly to rainfall, using all of its available energy to seed production within a few weeks of germination (Bradley and Mustard 2005). Native bunchgrass and sagebrush on the other hand, invest the majority of their energy in belowground root growth, only slowly producing photosynthetic leaf material after rainfall (Bradley and Mustard 2005). After periods of high rainfall, areas of high *B. tectorum* cover exhibit pronounced increases in NDVI compared to areas of sagebrush or perennial grass cover (Bradley and Mustard 2005). By performing a change detection of NDVI across low and high rainfall years, Bradley and Mustard (2005) were able to use map areas of high change in NDVI, which corresponded to areas of *B. tectorum* cover for the entire Great Basin region, estimating that *B. tectorum* occupied 20,000 km^2 and was concentrated in the northern portion of the Great Basin.

While higher spectral resolution sensors are considered to be superior to multispectral or color-RGB sensors, I found nearly as many studies that used color-IR sensors as multispectral sensors (13 compared to 14). While color-IR sensors can be considered a subset of multispectral sensors, they typically differ from classic multispectral sensors such as Landsat in several ways. They typically only have 4 spectral bands (blue, green, red, and near-infrared, though some contain an additional band in the red-edge region of the electromagnetic spectrum) compared to Landsat, which extends into the shortwave-infrared (SWIR) region. With the exception of two sensors (Quickbird and Planetscope), these sensors were all tasked sensors mounted on UAVs and had sub-meter spatial resolution.

Similarly to Bradley and Mustard (2005), Malmstrom et al. (2017) were able to map two invasive annual grass populations, goatgrass (*Aegilops triuncialis*) and medusa head (*Elymus caput-medusae*), in a 6.8 km^2 non-native annual grassland in the Sacramento Valley with color-IR aerial imagery (Kodak Aerochrome III Infrared Film 1443 with four spectral bands via a fixed wing airplane with 0.39 to 0.45-meter resolution) by mapping differences in NDVI (Malmstrom et al. 2017). *A. triuncialis* and *E. caput-medusae* differ from the desirable non-native annual forage grasses present at the site (*Avena barbata, A. fatua, Bromus hordaceous*, and *Lolium multiflorum*) in that they have an extended growing season that lasts into late spring and early summer when the desirable annual grasses typically senesce (Malmstrom et al. 2017). Thus, *A. triuncialis* and *E. caput-medusae* populations could be mapped when NDVI values in March were subtracted from NDVI values in May (Malmstrom et al. 2017). Dronova et al. (2017) were also able to map populations of *E. caput-medusae* in a 368,000 m^2 grassland in the Sacramento Valley using color-IR imagery (Canon 5D Mark 2 cameras with four spectral bands at 0.15-meter resolution) using spectral, textural, and phenological characteristics. Both of these studies demonstrate how sensors with high spatial resolution can compensate for low spectral resolution when target species display significant differences in phenology or texture.

4.3.2 Spatial Resolution and the Role of Active Remote Sensing

In accordance with existing literature (He et al. 2011), larger plants such as shrubs were more capable of being detected by remote sensing (Figure 7). Within the CAL-IPC inventory ranked "high", these species include *Cytisus scoparius* (1 study), *R. armeniacus* (1 study), *Tamarix* spp. (11 studies), and *U. europaeus* (1 study) (Table 3). Alternatively, perennial vines and annual herbs were the least studied life forms within the CAL-IPC inventory ranked "high," with only *H. helix* (1 study) and *Centaurea solstitialis* (1 study) having a remote sensing study performed on them.

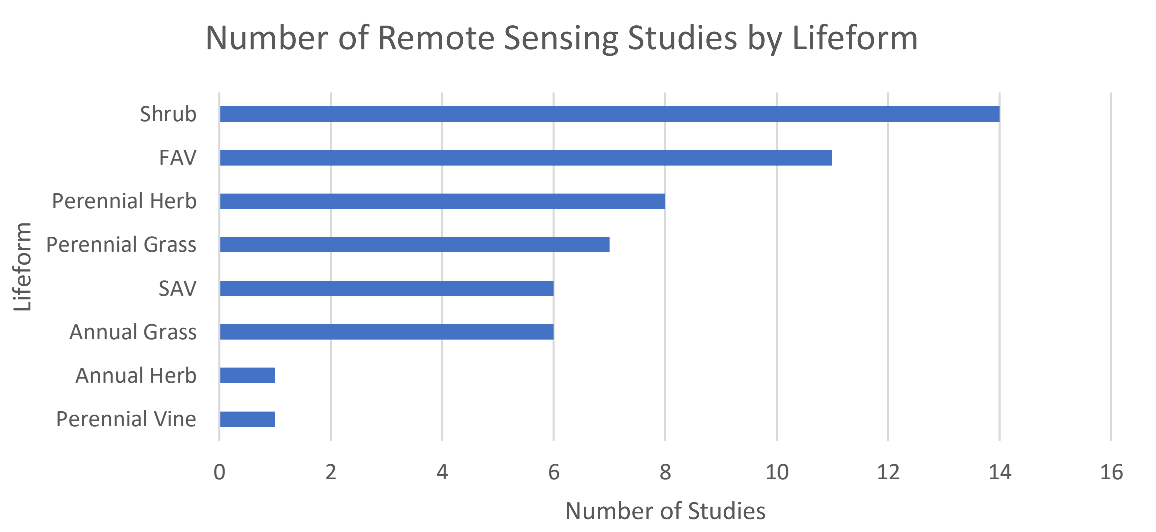

Figure 7: Number of remote sensing studies for high rated species in the CAL-IPC inventory by lifeform.

Appropriate spatial resolution is important for correctly classifying plant species with remote sensing imagery, and likely contributes to the high representation of shrubs present in the comparative analysis. Pixel sizes generally need to match the size of the object under study:

when they exceed the canopy of an individual plant then spectral signatures are mixed and averaged within a single pixel, but when pixels are much smaller than an individual plant canopy the variability of a spectral signature increases (He et al. 2011). For example, Underwood et al. (2007) found that when AVIRIS imagery was degraded from 4-meter spatial resolution to 30-meter resolution to mimic Landsat spatial resolution, accuracy results for *C. edulis* classification remained high (from 92% to 97%), but accuracy results for *C. jubata* substantially decreased (from 82% to 58%) when the same imagery was spatially degraded (Underwood et al. 2007). This was attributed to the fact that *C. edulis* would often grow in very large patches with dense cover such that even at 30-meter resolution, individual pixels would represent pure iceplant (Underwood et al. 2007). *C. jubata* on the other hand, individuals are roughly 4 meters in diameter, matching the spatial resolution of AVIRIS data so that the spectral signature of one individual *C. jubata* would be represented in a single pixel (Underwood et al. 2007). When the original AVIRIS imagery was resampled to 30-meter resolution, the spectral signature of *C. jubata* could no longer be distinguished from the spectral signatures of surrounding vegetation (Underwood et al. 2007).

When target plant species are much smaller than the spatial resolution of a remote sensor, or when multiple species with different spectral properties are present within a single pixel of remote sensing imagery, spectral mixing can occur (Miao et al. 2006). In order to map *C. solstitialis* with hyperspectral CASI-2 imagery (36 bands at 3-meter resolution), Miao et al. (2006) used linear spectral mixing models to determine the proportion of *C. solstitialis* present at their study site in the California Central Valley by calculating the contribution of *C. solstitialis* reflectance to the total reflectance of mixed pixels (Miao et al. 2006). While Miao et al. were able to map *C. solstitialis* at relatively high accuracy (r^2=0.88), the use of spectral unmixing models could have been avoided if higher spatial resolution sensors had been used.

Additionally, the lack of representation for vines in the comparative analysis results suggests they are poor candidates for detection by remote sensing, particularly if they grow in the understory. By recording the reflectance of top of surface materials, remote sensing is generally only able to classify vegetation growing with an exposed canopy layer. Images captured in deciduous forests during leaf-off conditions can reveal understory layers available for remote sensing analysis, but this requires acquiring imagery at specific time periods which can be difficult for hyperspectral imagery that is collected for other purposes (Chance et al. 2016).

Active remote sensors, such as LiDAR are able to penetrate the canopy layer and provide an estimation of understory structure that can then be used to model species composition (Chance et al. 2016). Chance et al. used hyperspectral CASI imagery (72 bands at 1.0-meter spatial resolution) to map the distribution of *H. helix* and *R. armeniacus* in the open canopy of an urban forest in British Columbia, Canada and LiDAR (point density 25 points/m^2) to map those species in the forest understory. These methods was relatively successful, though understory populations of *R. armeniacus* were slightly less accurately mapped (overall accuracy of 77.8% of understory populations compared to 87.8% for open populations) compared to *H. helix* (overall accuracy of 81.9% of understory populations compared to 82.1% for open populations) (Chance et al. 2016).

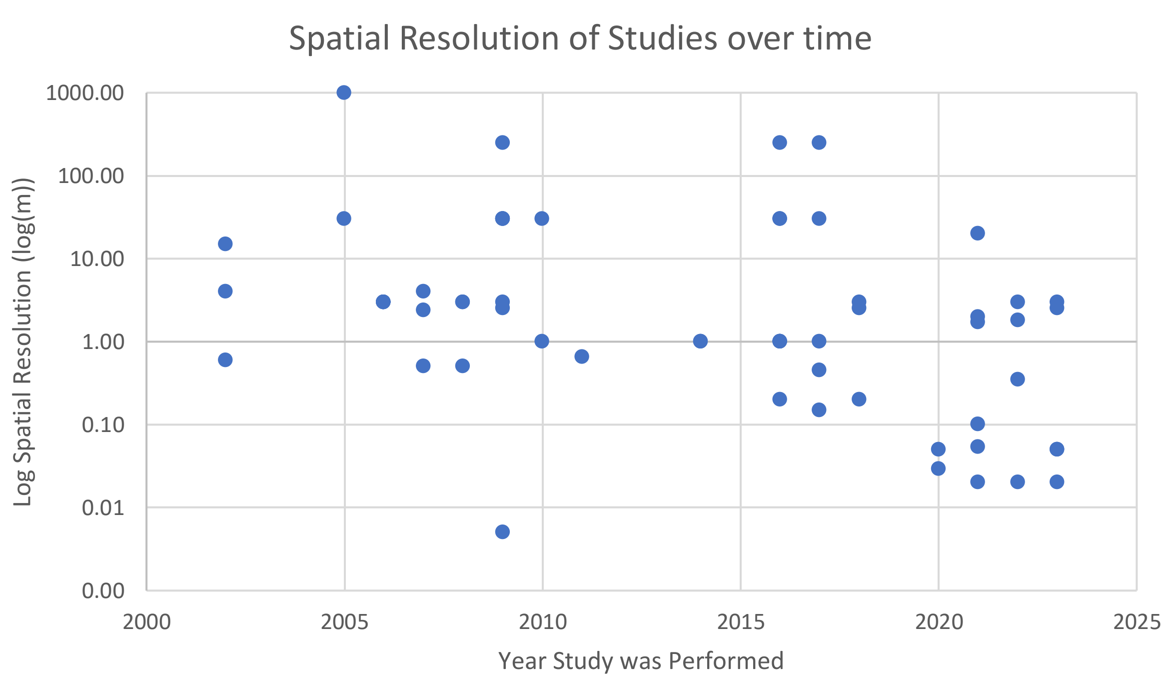

Figure 8: Log transformed spatial resolution of remote sensors used over time

While inclusion of LiDAR with hyperspectral imagery may increase the ability and accuracy of mapping understory invasive species, these tools are generally inaccessible to most land managers due to their expense and lack of availability. Thus, understory species such as vines may be poor candidates for mapping by remote sensing.

As mentioned in the previous section, the high spatial resolution of UAV or fixed-wing mounted aircraft RGB or Color-IR sensors can often overcome the limitations of their lower spectral resolution. This is particularly important for smaller plant lifeforms such as perennial herbs and annual grasses. Of the eighteen studies in the comparative analysis that used very high spatial resolution sensors (less than one-meter spatial resolution), only four studies used a shrub (*Tamarix* spp.) as their study species. There was also a trend towards the use of higher spatial resolution sensors in more recent studies, which is indicative of the improvements in sensor technology and the growing availability of drone and UAV based imagery (Figure 8).

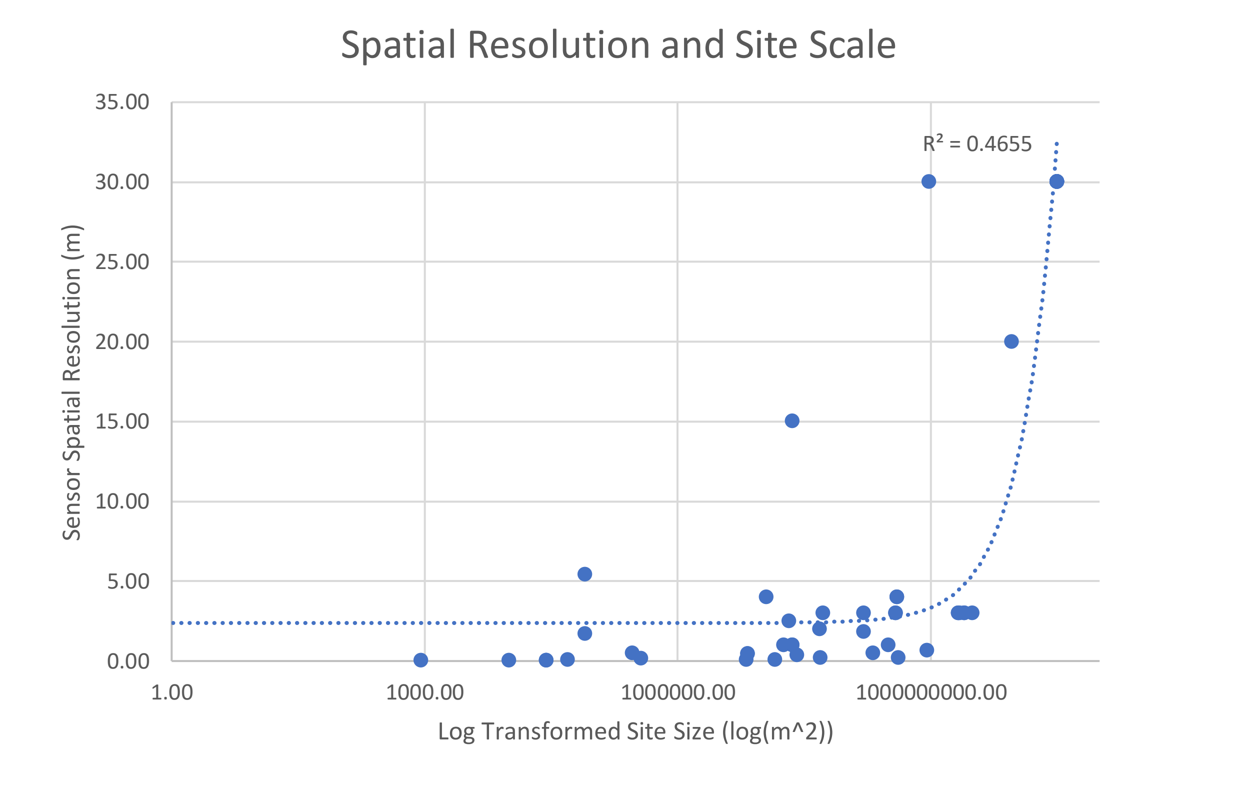

Figure 9: Spatial Resolution and Site Scale

Coarse resolution sensors were rarely used in remote sensing of invasive species, only being used in three studies. These sensors were rarely used to directly map the presence of invasive species, instead being used to determine the phenology of widespread or dispersed species. For example, Bradley and Mustard (2005) used an NDVI time series to determine appropriate imagery acquisition dates for Landsat scenes across the Great Basin to map *B. tectorum* (Bradley and Mustard 2005).

In general, the spatial resolution of the sensor used in a remote sensing study should be somewhat correlated to the spatial extent of a study site (Figure 9). Moderate to coarse scale sensors are most appropriate for studies that seek to monitor invasive plant populations across regional or large watershed scales. These types of sensors are likely to introduce too much spectral mixing to adequately classify all vegetation or land cover types present for small sites. Conversely, high resolution sensors may be more appropriate for relatively small sites, such as sub-watershed or local scale, as the spectral mixing would be reduced. Figure 9 shows a weak but consistent relationship between the log transformed site size of studies used in the comparative analysis and the spatial resolution of the sensor used in that study. Some inconsistencies between site size and sensor resolution can be resolved through the use of nested survey design, in which field data is obtained at corresponding spatial scales to the spatial resolution of remote sensors (Figure 10).

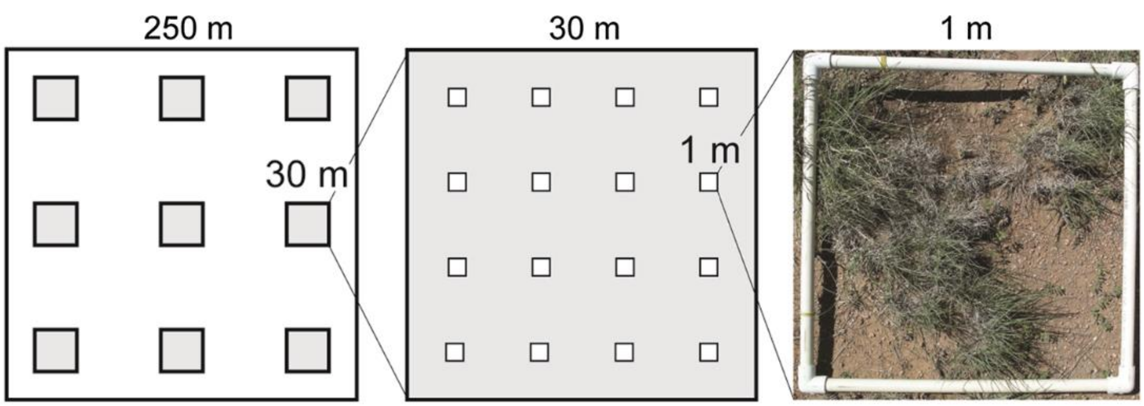

Figure 10: Example of a nested field sampling design that incorporates MODIS imagery (250 m^2 pixels), Landsat imagery (30 m^2 pixels) and 1 m^2 pixels that correspond to a sampling quadrat (Bradley et al. 2009)

4.3.3 Temporal Resolution

The vast majority of studies of California invasive plant species used sensors that were tasked (37 studies) (Figure 11). Of these studies, 9 were conducted using UAVs and 28 were conducted by aircraft. Of the satellite-based sensors, the majority (7 studies) had a temporal resolution of 16 days, all of which were represented by studies using Landsat imagery.

While there was no clear trend between temporal resolution, tasked sensors have several advantages over satellite-based sensors despite their inconsistent temporal resolution. Because these sensors are typically airborne or mounted on UAVs, they are able to achieve much higher spatial resolution than satellite-based sensors. This enables tasked UAV and airborne sensors to reduce the amount of spectral mixing within pixels that occurs with moderate spatial resolution sensors. Tasked sensors are able to acquire imagery when plants are at peak phenological states which can enable their detection via unique spectral attributes. Additionally, satellite-based sensors acquire imagery regardless of site-specific meteorological conditions such as high cloud cover. However, tasked sensors are generally less accessible than high-temporal resolution imagery from sensors such as Landsat, which are freely available

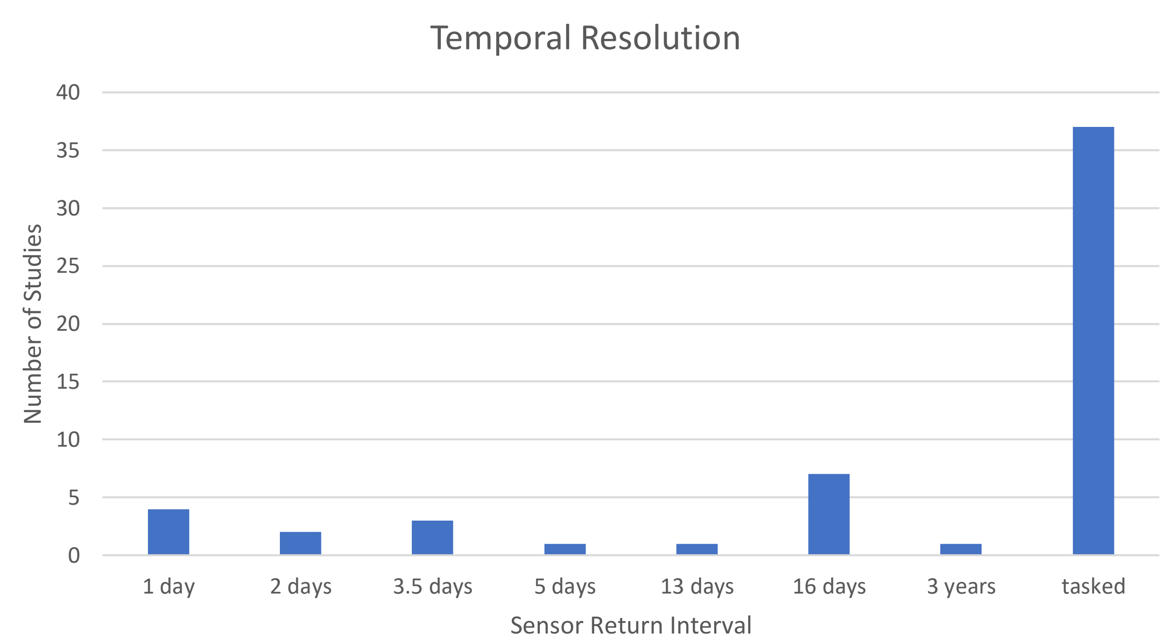

Figure 11: Temporal resolution of sensors used in comparative analysis studies

4.3.4 Potential for Remote Sensing of other California Invasive Plant Species

While I did not find remote sensing studies for 17 of the species rated as “high” in the CAL-IPC inventory, remote sensing has the potential to help land managers understand their impacts and distribution. For example, several remote sensing studies have been conducted in California and abroad on invasive *Spartina* species. *S. alterniflora* and the hybrid *S. alterniflora x foliosa* have been mapped in San Francisco Bay using LiDAR (Ustin et al. 2006). However, these mapping projects relied on differences between where these invasive species grow within estuarine environments compared to the native *S. foliosa* instead of unique spectral properties (Ustin et al. 2006). While all *Spartina* spp. will grow within saltmarshes, the invasive *Spartina* spp. are capable of growing in previously unvegetated mudflats, which causes accretion of sediment and a rise in elevation (Ustin et al. 2006). By conducting a change detection of vegetation height and elevation using LiDAR, Ustin et al. (2006) were able to demonstrate that invasive *Spartina* was expanding at a rate of 2.5 m/year at two sites in San Francisco Bay, even though these species can't be distinguished spectrally (Ustin et al. 2006).

Similarly, many species included not included in the analysis were in the same genus as plants that were the subject of a remote sensing study. For example, there were no studies conducted on *Cortaderia selloana* or *Myriophyllum aquaticum*, but two studies conducted on *C. jubata* and *M. spicatum* each. Because spectral approaches to remote sensing require plant species to be spectrally unique, and because plants within the same genus are closely related it should generally be assumed that they share similar spectral properties. For example, Khanna et al. (2018) do not differentiate between the two *Ludwigia* spp. (*Ludwigia hexapetala* and *Ludwigia peploides*) when mapping FAV in the Delta, and Bolch et al. (2021) do not differentiate between *M. spicatum* and other SAV species whether they are invasive, such as Brazilian water weed (*Egeria densa*) or native such as coontail (*Ceratophyllum demersum*).

I hypothesize that other species that were not the subject of a remote sensing mapping study may exhibit similar properties that would enable their detection via remote sensing. For example, several species rated high on the CAL-IPC inventory (*Cytisus scoparius*, *Genista monspessulana*, and *Spartium junceum*) contain similar properties as *U. europaeus*, which was mapped using Sentinel-2 imagery (Gränzig et al. 2021). All species are shrubs capable of forming dense stands with bright yellow flowers that may exhibit unique spectral signatures similarly to *U. europaeus*. Stinknet (*Oncosiphon pilulifer*) is a strong-smelling annual herb native to South Africa that can form dense monocultures in dunes, chaparral, and scrub habitats in southern California (CAL-IPC 2024b). The strong odor results from the unique sesquiterpene lactone chemicals that have medicinal properties that have been identified using spectroscopy in a lab setting (Pillay et al. 2007). Because there are native plants in the same genus found in

California, it may be possible to detect *O. pilulifer* based on its unique spectral properties. Further research into the spectral properties of these invasive plants could reveal unique properties that enable mapping infestations by remote sensing methods, offering land managers additional tools to prioritize control efforts.

4.3.5 Remote Sensing in Early Detection and Rapid Response

The resolution of most remote sensors is often inadequate to capture nascent populations of invasive plants. Image classification algorithms require training to recognize an image and associate a spectral signature as belonging to a particular plant species. This may be particularly challenging for new invasive plant species that we know little about. Some of these limitations could be solved by changing practices regarding collection of voucher specimens for newly discovered invasive species. For example, hyperspectral data could be collected in the field using hand-held spectrometers when botanists collect and voucher specimens for herbarium records, creating spectral libraries that serve as references for future generations of researchers (Davis 2023). People working in the field will still be needed to observe these alien plant species before remote sensing can applied to early detection of invasive plants.

Choosing the right sensor may enable remote sensing as complementary tool for early detection and rapid response. Higher spatial resolution sensors can often overcome the limitations of having lower spectral resolution by reducing the amount of spectral mixing that occurs within a pixel, thereby enabling classification of invasive plants in an image. These sensors, which are typically mounted on drones or airplanes, can also be tasked to acquire imagery under ideal circumstances for invasive species identification, such as ideal weather conditions or when invasive plants undergo phenological events such as flowering or senescence that make them spectrally distinct.

While remote sensing may not be an ideal method for detecting small early populations of invasive plants, it can be successfully leveraged to monitor plants later in the invasion process when containment and long-term control are more realistic goals (Figure 12) (Müllerová et al. 2023). For example, products derived from remote sensing can be used to create models that predict future expansion of invasive species and reactions to different control methods (Müllerová et al. 2023).

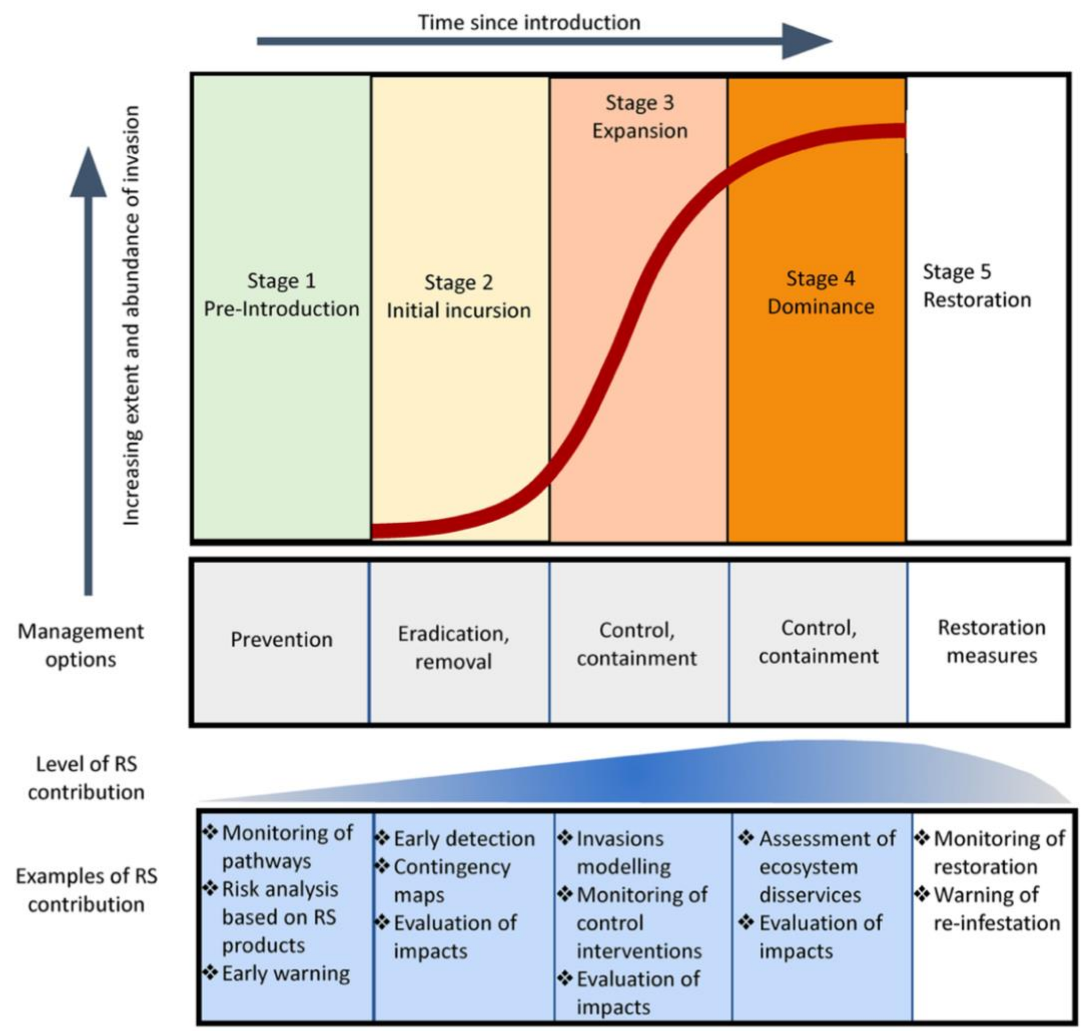

Figure 12: Applicability of remote sensing to invasive species control based on invasion stage (Müllerová et al. 2023)

Detecting small populations of early infestations may become more feasible in the future, as sensor resolution improves, UAV imagery becomes more accessible, and as flights become automated (Müllerová et al. 2023). For example, the Landsat Next mission (also known as Landsat 10), will significantly increase the spectral and temporal resolution of previous Landsat missions (U.S. Geological Survey 2024). Set to launch in 2030, Landsat Next will feature a three-satellite array of sensors with a temporal resolution of six days and spectral resolution of 26 bands at 10–20-meter spatial resolution for visible, near infrared, and shortwave infrared bands (U.S. Geological Survey 2024).

In the following sections I will demonstrate how remote sensing has contributed to management of invasive plant in two case studies: one using saltcedar (*Tamarix* spp.) as a case species, and a second using a site, the Sacramento-San Joaquin Delta, as a case site.

5.0 Tamarisk Management Case Study

Here I present a case study on the role of remote sensing for EDRR and management of the invasive shrub tamarisk. Drawing from the results of my comparative analysis, large plants such as trees and shrubs are particularly well suited for detection by remote sensing. While remote sensing has been used to understand the distribution of tamarisk throughout the western U.S., these studies have rarely been applied to tamarisk management in California. In the following sections, I will provide a brief overview of tamarisk biology, its history as an introduced species, tamarisk control methods and restoration efforts, and relevant studies using remote sensing to better understand tamarisk invasions and management efforts.

5.1 Tamarisk Background

Tamarisk distribution grew from 40 km^2 in the 1920s when it was first introduced to over 600 km^2 by 1987 (Di Tomaso 1998). Tamarisk was first introduced to the U.S. through the horticultural industry in 1823, and was widely planted for its ornamental and erosion control values throughout the mid 1800s and early 1900s (Brotherson and Field 1987). Tamarisk is currently established throughout the western U.S. and continues to spread north into Canada and south into Mexico (Di Tomaso 1998). It is estimated that tamarisk costs the economy anywhere between 28,000 to 45,000 USD/km^2 due to agricultural and municipal water loss, decreases in hydropower generation, flood control costs, and impacts on recreation (Zavaleta 2000)

Several factors facilitated the spread of tamarisk throughout the western U.S. (Di Tomaso 1998). Harvesting of native trees from riparian forests for building material and fuel opened up space for escaped tamarisk to grow (Brotherson and Field 1987). Later, changes to riparian hydrology due to dam construction, water extraction for irrigation, and stream diversions caused decreases in stream flows that reduced the ability of native riparian species to reproduce (Di Tomaso 1998). Intensive grazing of riparian forests by livestock also facilitated the spread of tamarisk by reducing competition from native species (Di Tomaso 1998).

5.2 Tamarisk Biology

5.2.1 Tamarisk Taxonomy and Identification

Tamarisk, represented by the genus *Tamarix*, are shrubs and trees that are natively distributed across the southern Mediterranean region through Mongolia and China (Di Tomaso 1998). Of the 54 species included in the *Tamarix* genus, eight species have been introduced to the United States, and five (*T. chinensis, T. gallica, T. parviflora, T. ramosissima,* and *T. aphylla*) are particularly invasive in the Southwest (Di Tomaso 1998) and are listed on the CAL-IPC inventory as having high degree of invasiveness (with the exception of *T. aphylla*, which is rated as limited) (CAL-IPC).

Tamarisk is also known as salt-cedar because their leaves, which exude salt, resemble the scale-like leaves of cedar trees (Di Tomaso 1998). Tamarisk flowers are small, usually pinkish to white and can be present on plants as young as one year old (Di Tomaso 1998).

5.2.2 Tamarisk Ecology

Tamarisk is a facultative phreatophyte, meaning that it typically requires access to groundwater in order to survive, but can also grow outside those conditions (Di Tomaso 1998). Mature tamarisks are capable of surviving without access to the water table (Brotherson and Field 1987). It is typically found in riparian areas with high water tables under 2100 m in elevation with silt loams or silty clay loams, but are capable of tolerating a variety of soil conditions (Di Tomaso 1998).

Adaptations to high soil soluble salt concentrations give tamarisk an important competitive advantage over native riparian species in arid environments (Di Tomaso 1998). Tamarisk is a facultative halophyte capable of surviving in a range of soil salt conditions (between 650 to 36,000 ppm) (Di Tomaso 1998). Salts within soil or groundwater are transported through xylem (Di Tomaso 1998) and later into leaf glands that are capable of storing and excreting salts (Di Tomaso 1998). These glands are non-selective to the type of salt present in the environment, making tamarisk highly adaptable to varying soil conditions (Di Tomaso 1998).

Figure 13: Tamarisk invaded riparian habitat in the lower Colorado River. Tamarisk is the lighter color shrub in the top picture and the understory of the bottom picture (Shafroth. et al. 2005)

5.2.3 Tamarisk Reproduction

Individual tamarisk seeds germinate readily, but are short-lived and require moist soil in order to germinate (Di Tomaso 1998). Mature plants are capable of producing over 500,000 seeds in one season (Brotherson and Field 1987). Blooms can extend from April through October, which gives tamarisk a competitive advantage over other riparian plants (Figure 13) (Di Tomaso 1998). Seed production for native riparian trees, such as willows (*Salix* spp.) and cottonwoods (*Populus* spp.), is synchronized with the typical timing of high flow events that produce moist bare ground which their seeds require in order to germinate (Di Tomaso 1998). Because tamarisk has a lengthier flowering period compared to native riparian vegetation, it is able to take advantage of optimal germination conditions that native riparian species cannot (Di Tomaso 1998). Seeds are light and contain hairs that aid them in wind-dispersion, which also assists them in invading new areas (Brotherson and Field 1987). Vegetative reproduction is also possible for mature tamarisk via adventitious roots (Brotherson and Field 1987).

5.2.4 Tamarisk Establishment

Seedlings require moist soil for the first several weeks of growth, bare sunny soil, and an absence of competition (Di Tomaso 1998).Tamarisk seedlings survive by growing deep taproots capable of reaching the groundwater table, which can be up to 50 m long upon maturity but are usually 5 m long (Di Tomaso 1998). Aboveground growth is rapid, with seedlings capable of reaching 3-4 m in their first year (Di Tomaso 1998).

Once established, tamarisk is resilient to a number of stressors and disturbances, including drought, floods, fires, and manual cutting (Di Tomaso 1998). Resprouting occurs rapidly after fire and grazing (Di Tomaso 1998). Tamarisk is drought deciduous and adapts to low moisture conditions by dropping its leaves to reduce transpiration rates (Di Tomaso 1998). Alternatively, mature tamarisk can survive intense flooding up to 70 days (Brotherson and Field 1987).

5.3 Tamarisk Impacts

5.3.1 Impacts on Water Resources

Because of its ability to tap into deep groundwater resources and its impact on stream geomorphology, tamarisk is of unique concern among water resource managers (Brotherson and Field 1987). Tamarisk alters stream hydrology through its dense root system that stabilizes bank structure, restricting channels from naturally migrating during channel forming events (Di Tomaso 1998). Eventually, stream channels incise which leads to higher flow rates and increases the potential for flooding (Di Tomaso 1998). These floods can provide suitable germinating conditions for tamarisk seedlings outside of the riparian zone, further spreading the extent of tamarisk infestations (Di Tomaso 1998). In the absence of flooding, channels continue to incise and cut off streams from their floodplains, which can lead to conversion of riparian forest to upland plant communities (Reynolds and Cooper 2011).

Tamarisk has a significantly higher evapotranspiration rate than native riparian plants in the southwest (Di Tomaso 1998). A 1965 study in the Safford and Gila River valleys of Arizona demonstrated that tamarisk was capable of consuming 4-to-5-acre feet of water per acre every year, the cost of which equaled between $200 to $1,000 per acre every year (Brotherson and Field 1987). Individual trees are capable of consuming using 760 L of water a day (Di Tomaso 1998), though more recent studies indicate this may be a gross exaggeration, and that individual trees consume closer to 127 L of water per day (Owens and Moore 2007).

5.3.2 Impacts on Fire

Tamarisk is notably more adapted to fire than native riparian species. It resprouts vigorously after fire and is capable of quickly taking advantage of mobilized nutrients and responding to reduced soil moisture post-fire (Busch and Smith 1993). Fuels are often higher in tamarisk dominated habitats due to the increase in leaf litter and dead woody material (Busch and Smith 1993). Fire return intervals are substantially higher in tamarisk invaded riparian forests, sometimes burning every 10 to 20 years (Di Tomaso 1998). Riparian forests dominated by tamarisk often experience more frequent fire than native riparian forests, which rarely experience wildfire, which has contributed to the conversion of willow and cottonwood riparian woodland to tamarisk stands (Di Tomaso 1998).

3.5.3 Impacts on Vegetation

Tamarisk is capable of producing dense, nearly monotypic stands of 70-80% pure tamarisk (Di Tomaso 1998). Native willows, cottonwoods, and herbaceous understory species struggle to access sufficient light and moisture to reproduce under dense tamarisk canopies (Di Tomaso 1998). Dense tamarisk infestations can consume all aboveground water in perennial streams and pools (Di Tomaso 1998). Further, tamarisk lower the water table through their extensive tap roots, leading to a loss of native riparian vegetation that depend on access to groundwater (Di Tomaso 1998).

The salts that tamarisk accumulate in their leaves eventually are deposited in the soil surface, leading to elevated soil salinity (Di Tomaso 1998). This can lead to declines in native riparian vegetation such as cottonwoods and willows, whose growth can be inhibited at salinities of 1,500 ppm or greater (Di Tomaso 1998). In communities dominated by tamarisk, the only native understory species capable of persisting are halophytic plants such as saltgrass (*Distichlis spicata*) (Di Tomaso 1998).

5.3.4 Impacts on Wildlife

Tamarisk dominated habitats are generally of lower quality than native cottonwood or willow dominated habitats (Di Tomaso 1998). Insect diversity is greater on native willow and cottonwood riparian forests than tamarisk dominated forests (Di Tomaso 1998). Native mammals, such as porcupines and beaver, generally prefer willow or cottonwood dominated riparian forests over tamarisk dominated forests (Di Tomaso 1998).

Avian communities show mixed responses to tamarisk dominated riparian forests (Di Tomaso 1998). Tamarisk can provide roosting and nesting habitat for several species of riparian-obligate birds, including Gambell's Quail (*Callipepla gambelii*), white-winged doves (*Zenaida asiatica*), and mourning doves (*Zenaida macroura*) (Di Tomaso 1998), and 49 species of native birds have been documented using tamarisk for nesting habitat (Sogge et al. 2008). However, all of these species are found in higher densities in native riparian forests, suggesting their populations could be even higher if tamarisk dominated forests were replaced with native riparian species (Di Tomaso 1998). Even when birds such as doves and quail use tamarisk forests for roosting habitat, they still rely on adjacent habitat or agricultural fields for foraging habitat due to the small size of tamarisk seeds and lack of invertebrate prey (Di Tomaso 1998). Tamarisk also fails to provide suitable habitat for nest specialists, such as woodpeckers or secondary-cavity nesters, as well as raptors (Sogge et al. 2008).

Of particular concern to environmental managers is the relationship between tamarisk and the federally endangered southwestern willow flycatcher (*Empidonax traillii exitmus*) (Sogge et al. 2008). Southwestern willow flycatcher are riparian obligate birds that were historically common throughout southern California (Kus et al. 2003). Southwestern willow flycatcher often choose breeding sites based on habitat structure instead of species composition, and tamarisk can provide structurally similar habitat as native willow-dominated riparian forest (Sogge et al. 2008). Tamarisk-invaded forests provide important breeding habitat for southwestern willow flycatcher, as these habitats provide roughly 25% of breeding populations are located in tamarisk dominated riparian forests (Sogge et al. 2008).

5.4 Tamarisk Management and Restoration

5.4.1 Methods for Controlling Tamarisk

Tamarisk can be managed through mechanical, chemical, and biological control methods, through the costs and effectiveness of each treatment method varies (Shafroth et al. 2005). As mentioned previously, cutting back tamarisk is ineffective at killing the plant as it is capable of resprouting from its roots (Di Tomaso 1998). However, when cut stumps and root balls are mechanically removed from the soil using heavy equipment, success rates can be high, as much as 99% (Shafroth et al. 2005). While effective, this technique can be expensive (\$150,000-170,000 per km^2) and require follow-up visits to ensure eradication (Shafroth et al. 2005).

Chemical methods of tamarisk control typically involve the use of the herbicide glyphosate and imazapyr (Shafroth et al. 2005). The preferred method for herbicide application are dependent on the surrounding vegetation (Shafroth et al. 2005). Large-scale, monotypic tamarisk infestations can be treated by airborne herbicide application, whereas infestations occurring within a native vegetation and tamarisk matrix can be treated by chain sawing tamarisk plants and treating with herbicide on the cut stump (Shafroth et al. 2005). Treatment of large-scale patches can typically be less expensive (\$240-248 per ha) than treating individual plants (\$400,000-620,000 per km^2) but can result in undesirable side effects such as pesticide drift or infiltration into groundwater (Shafroth et al. 2005). As with mechanical control methods, follow-up treatments are required for years in order to ensure complete eradication (Shafroth et al. 2005).

Biological control methods, which involve introducing specialist insects or diseases of the target plant species, have been developed for tamarisk, the most notable being the Mediterranean tamarisk beetle (*Diorhabda elongata*) (Shafroth et al. 2005). Tamarisk beetle feeds on tamarisk leaves, which can result in tamarisk mortality if plants are completely defoliated and are forced to consume the entirety of their stored energy (Sankey et al. 2016). The Mediterranean tamarisk beetle was introduced to six western U.S. states in 2001 after extensive testing revealed it nearly exclusively targeted tamarisk (Sankey et al. 2016). Initially, it was believed that physiological limitations would prevent tamarisk beetles from spreading further south than 38 degrees latitude, though they have since been found as far south as the Colorado River (Sankey et al. 2016).

Results of biocontrol for tamarisk have been mixed, with some previously defoliated areas experiencing re-growth, suggesting that biocontrol may not serve as a silver bullet for tamarisk eradication (Sankey et al. 2016). Remote sensing has been proposed as a potential method for monitoring the effects of tamarisk biocontrol due to its widespread distribution and inconsistent results (Sankey et al. 2016). Additionally, defoliation by tamarisk beetle may reduce the quality as breeding habitat for southwestern willow flycatcher by decreasing vegetative cover (Sogge et al. 2008).

5.4.2 Restoration of Tamarisk Invaded Areas

Riparian systems are highly desirable targets for restoration because of the ecosystem services they provide, including biodiversity, water quality, and recreation, all of which are threatened by tamarisk infestations (Harms and Hiebert 2006). Understanding existing site conditions such as surface and groundwater availability, native propagule sources, and soil chemistry is essential for successful restoration of tamarisk-invaded habitats (Shafroth et al. 2008).

Successful restoration of riparian ecosystems invaded by tamarisk requires establishing achievable goals and outcomes, determining existing ecological and social conditions, choosing appropriate restoration sites, developing site-specific restoration plans, monitoring post-project conditions, and preparing for adaptive management if project outcomes do not match project goals (Shafroth et al. 2008). This is particularly important in arid environments where passive restoration often fails to reinstate desirable native vegetation (Sogge et al. 2008). Re-invasion by species such as Russian thistle (*Salsola* spp.), perennial pepperweed (*Lepidium latifolium*), or Russian knapweed (*Acroptilon repens*) can occur if active restoration fails to occur (Shafroth et al. 2008). Even where native species passively recruit following tamarisk removal, they are more likely to consist of native upland species (Reynolds and Cooper 2011). Tamarisk removal projects that fail to re-establish native riparian vegetation risk further jeopardizing southwestern willow flycatcher breeding habitat (Sogge et al. 2008).

5.5 Remote Sensing of Tamarisk

5.5.1 Spectral Properties of Tamarisk

The phenology of tamarisk makes it particularly suitable to detection by remote sensing. During the growing season, the reflectance values of tamarisk is highly similar to those of co-occurring species in the visible wavelengths of light, and near-infrared reflectance values are identical to those of mixed herbaceous species (Everitt 1990). However, as tamarisk enters winter dormancy its leaves senesce and turn a yellow-orange to orange-brown color before dropping, which significantly changes its spectral properties (Everitt 1990). During this time, tamarisk leaves become noticeably more reflective at 0.55 µm and 0.65 µm than other riparian species (Figure 14) (Everitt 1990). Additional phenological stages, such as flowering, may also exhibit a unique spectral signature due to the pink colored flowers (Evangelista et al. 2009).

Distinguishing the spectral signatures of living (green), desiccated (yellow to brown), and dead tamarisk is necessary to conduct change detection for monitoring the effects of tamarisk control efforts (Dennison and Meng 2015). Green and desiccated tamarisk shows a sharp increase in reflectance between the visible red and near infrared light (also known as the “red edge”), while dead tamarisk shows a gradual shift in reflectance values in this region (Dennison and Meng 2015). The decrease in reflectance within the red wavelengths is explained by the loss of chlorophyll absorption of the Shortwave infrared (SWIR) regions of the electromagnetic spectra, which is sensitive to leaf water content, is also important for distinguishing between living green, desiccated, and dead tamarisk (Dennison and Meng 2015). Reflectance values in the SWIR region are highest for dead tamarisk, lowest for living tamarisk, and between these values for desiccated tamarisk (Dennison and Meng 2015). These patterns of spectral reflectance are important for monitoring the effects of tamarisk beetle biocontrol, as tamarisk leaves turn yellow to brown as the beetle consumes the mesophyll cells within tamarisk leaves, meaning that remote sensing can detect tamarisk stands that have been defoliated by tamarisk beetle (Dennison and Meng 2015).

There are several challenges to mapping tamarisk even though it exhibits spectral properties that make it highly suitable for detection by remote sensing. Several riparian corridors in the arid west grow through deep river canyons, which limits the amount of light that can reflect off the surface of tamarisk leaves and causes variable amounts of shadow (Bransky et al. 2021). Timing of phenological events such as flowering occurs inconsistently along latitudinal gradients due to variations in local climates, so multiple days of imagery acquisition may be necessary to map tamarisk across large landscapes (Evangelista et al. 2009). While tamarisk often grows in dense, monotypic stands, it can also grow intermixed with other species at lower densities which can introduce spectral mixing (Hamada et al. 2007). Moderate resolution sensors such as MODIS or Landsat are incapable of detecting Tamarisk at low densities because the spatial resolution of these sensors produces pixels that are far larger than the crown of a single tamarisk shrub (Silván-Cárdenas and Wang 2010).

5.5.2 Summary of Tamarisk Remote Sensing

Tamarisk is an ideal study species for mapping by remote sensing due to its unique spectral properties, large growth form, widespread distribution, and high impacts to water resources. Because of these properties, there is a lot of flexibility as to what methods and sensors can be used to map tamarisk using remote sensing methods. For example, Carter et al. (2007), Evangelista et al. (2009), Ji and Wang (2016), and Silván-Cárdenas and Wang (2010) were all able to successful map tamarisk distributions using moderate resolution multispectral imagery from Landsat.

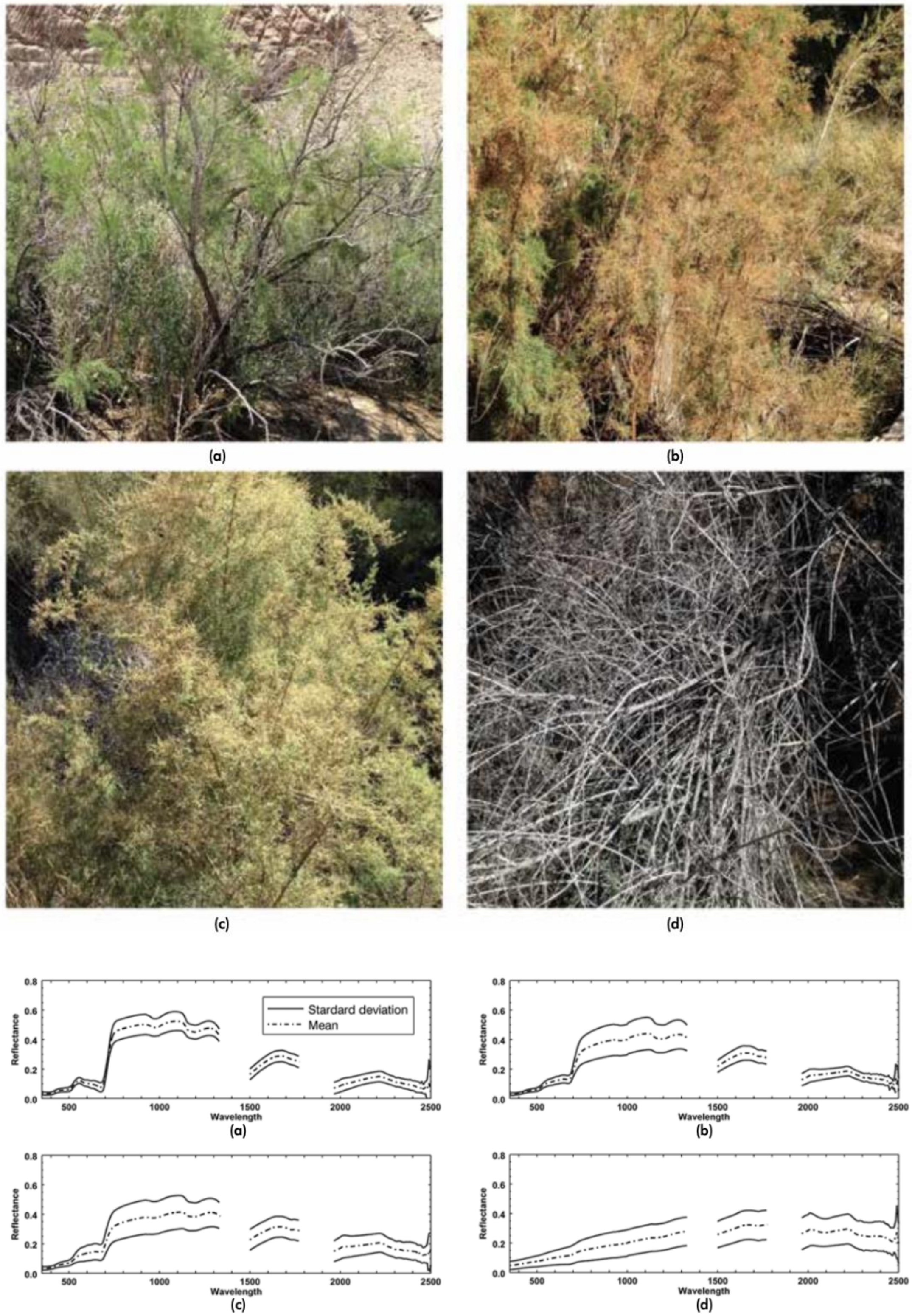

Figure 14: Photographs (above) and spectral signatures (below) of green (a), brown desiccated (b), yellow desiccated (c), and dead tamarisk (d) (Dennison and Meng 2015).

Carter et al. (2007) conducted a comparative analysis mapping tamarisk along the Colorado River near DeBeque, Colorado using moderate spatial resolution (30 m) multispectral imagery from Landsat TM5, high spatial resolution (2 m) multispectral imagery from Quickbird, and moderate spatial resolution (30 m) hyperspectral imagery from Hyperion. In order to acquire imagery from the same time period for all three sensors that corresponded with field-sampling, images from summer were used when tamarisk is actively growing and lacks the distinct yellow-orange color that spectrally distinguishes it. The authors used applied a maximum likelihood algorithm on several normalized-difference indexes to classify tamarisk presence. Even though the Quickbird imagery resulted in the overall highest classification accuracy (91%), Hyperion (88%) and Landsat (80%) imagery had high accuracy as well.

Evangelista et al. (2009) also mapped tamarisk in a comparative analysis, instead comparing the results of a single-scene of Landsat 7 ETM+ imagery with a time-series analysis for their study site in the lower Arkansas River in Colorado. The authors used a maximum entropy model with six Landsat scenes from April, May, June, August, September, and October and a time-series using all scenes. The authors used individual reflectance values for bands 1-5 and 7 from the Landsat data, as well as three vegetation indexes: NDVI, the Ratio Vegetation Index (RVI), and Tasseled Cap transformations, and the soil-adjusted vegetation index (SAVI) as their variables for the maximum entropy model. RVI is similar to NDVI in that it is a ratio of the reflectance in the red portion and the infrared portion of the electromagnetic spectrum, and is calculated by dividing Landsat band 4 by band 3 (Evangelista et al. 2009). Tasseled Cap transformations are used to measure soil brightness, vegetation greenness, and moisture in soil and vegetation, and is created by weighing composites of six Landsat bands (Evangelista et al. 2009). Lastly, SAVI is a spectral index that reduces the impacts of soil reflectance on image classification, and is calculated by using Landsat bands 3 and 4, as well as a correction factor that is based on the amount of vegetation cover (Evangelista et al. 2009). Accuracy was assessed through an AUC value, which ranges from 0 to 1, with an AUC score of 0.5 indicating that the model predicts tamarisk presence that are no better than a random guess, and scores equal to 1 mean that the model perfectly identifies all tamarisk present within a pixel (Evangelista et al. 2009). While all individual months of Landsat imagery had AUC scores above

0.88, indicating that they all predicting tamarisk distribution with high accuracy, AUC scores generally increased in the fall when tamarisk displays the spectrally unique yellow-orange color and when co-occurring plants are dormant (Evangelista et al. 2009). The time-series analysis had the highest AUC score, with variables from several different months contributing to the higher accuracy. This suggests that phenological cues from several months may be better at distinguishing tamarisk from co-occurring plants: for example, June tasseled cap wetness was the best overall predictor for tamarisk presence, which may be caused by the distinct purple-pink color of its flowers (Evangelista et al. 2009).

Since phenology plays an important role in identifying tamarisk by remote sensing, determining when to acquire imagery that corresponds to these phenological states is necessary to make accurate maps. As mentioned earlier, this can be difficult when plants undergo phenological events at different times due to local conditions. To resolve this issue, Ji and Wang (2016) used NDVI values derived from MODIS to determine tamarisk phenology in fall across two study sites in the Rio Grande River in Texas. From this data, the authors derived a linear model that estimated when tamarisk began to change color based on the timing of leaf drop, as previous studies showed that these traits were correlated for other woody tree species (Ji and Wang 2016). Landsat scenes that most closely matched the date obtained from the lead coloration linear model were selected to create a composite image of peak tamarisk phenology across the two Rio Grande River study sites. Hyperspectral reflectance measurements of tamarisk were obtained in the field and resampled to the same spectral resolution as the Landsat sensor, and the composite Landsat image was classified using the spectral angle method (SAM) algorithm. SAM classifies tamarisk as present when the angle formed between the training data (in this case the reflectance values obtained in the field) and the spectra from the imagery pixels is below a defined threshold (Ji and Wang 2016). The authors found that tamarisk does exhibit differences in phenology, with northern populations showing delayed onset of leaf coloration compared to southern populations. These phenology variations are evident even within a single Landsat image. While some single date Landsat scenes were able to achieve similar classification accuracies as the phenology-derived composite, omission errors were between two single-date images were very higher (0.75 for an October 31st image compared to 0.53 for a November 9th image), meaning that tamarisk cover was significantly underestimated when images were acquired just over a week apart. Thus, mapping widespread tamarisk infestations using moderate spatial resolution sensors such as Landsat may be less accurate when phenology is not taken into consideration.

5.5.2 Remote Sensing of Tamarisk Beetle Biocontrol

Monitoring the effects of tamarisk beetle defoliation is impractical from the ground due to the beetles' widespread distribution and difficulty in assessing its effects (Sankey et al. 2016). Therefore, remote sensing of tamarisk beetle biocontrol has been proposed as an alternative method of monitoring its impacts (Sankey et al. 2016).

Several of these studies have attempted to quantify the impacts of tamarisk beetle defoliation by conducting a change detection analysis of tamarisk cover before and after the beetles were first observed at their study site. For example, Bedford et al. (2018) used high spatial resolution, airborne color-infrared imagery to map tamarisk populations within a 412 km stretch of the Colorado River in the Grand Canyon, Arizona between 2009 when the beetles were first discovered in the study area and 2013. Tamarisk distribution for 2009 was determined using the Mahalanobis distance method, and the difference between NDVI values in 2013 and 2009 was used to determine areas of tamarisk beetle defoliation. The authors determined that the beetles defoliated 0.321 km^2 of the 2.144 km^2 of tamarisk present in the study site, leading to a 15% drop in tamarisk cover (Bedford et al. 2018). Sankey et al. (2016) performed a similar study within a smaller 24 km section of the same reach of the Colorado River, instead combining high spatial resolution color-infrared imagery with LiDAR to quantify the effects of tamarisk beetle defoliation on tamarisk biomass. The authors estimated that 24.7% of the tamarisk within their study site was defoliated, leading to a loss of 25,692 kg worth of tamarisk leaf biomass lost (Sankey et al. 2016).

Remote sensing studies have also revealed new insights into tamarisk beetle behavior that may have implications for future tamarisk control efforts. For example, Bedford et al. (2018) found that defoliation by tamarisk beetle was more likely to occur where tamarisk populations were large and dense. They also found that tamarisk beetle activity was more likely to occur within certain geomorphic sections of riparian areas, such as large confluences, sandbars, and debris fans. Through this finding, the authors speculate that tributaries may serve as migratory corridors to the Colorado River for the tamarisk beetles (Bedford et al. 2018). Identifying areas of tamarisk defoliation can also help land managers prioritize areas for restoration and replanting of native vegetation, as native birds are often impacted by the loss of nesting habitat that tamarisk provides and defoliated tamarisk stands may pose a fire risk (Sankey et al. 2016).

6.0 Sacramento-San Joaquin River Delta Case Study

Here I present my second case study the use of remote sensing in one of the most heavily invaded estuaries in the world, the Sacramento-San Joaquin River Delta (hereto referred to as the Delta). The Delta ecosystems' large area, array of hydrologic and environmental conditions, extensive history of biological invasions, and complex administrative landscape exemplify how remote sensing can overcome some the challenges of invasive species management in such as challenging setting. In the following section, I will provide a brief overview of the Deltas' biological setting, discuss relevant remote sensing studies of invasive species in the Delta, and how they have contributed to invasive species management and control efforts.

6.1 Delta Background

The Delta is located in Northern California at the confluences of the Sacramento and San Joaquin rivers and is roughly 3,237 km^2 large (Figure 15) (Whipple et al. 2012). Situated at the top of the San Francisco Bay Estuary, which drains 40% of the land surface of California, the Delta also experiences significant tidal and salinity gradients from east to west, with higher salinities and tidal influence in the west (Whipple et al. 2012). The climate is characterized as Mediterranean, with hot, dry summers and cool, wet winters, with precipitation gradients increasing from south (13-14 inches annual average precipitation) to north (19-20 inches annual average precipitation) and temperature gradients generally increasing from west to east (Whipple et al. 2012). These abiotic conditions have created a suite of different habitats, including open water, tidal wetlands, seasonal wetlands, perennial wetlands, riparian forests, grasslands, oak woodlands and savannas (Whipple et al. 2012).

Anthropogenic changes to the Delta landscape have significantly altered its ecosystem functions and processes (Whipple et al. 2012). Levees were first constructed in the Delta in the 1850s, both to protect the city of Sacramento from flooding and later to reclaim land for agriculture (Whipple et al. 2012). These alterations decreased the tidal prism of streams, disconnected rivers from their floodplains, and led to the loss of wetlands in the Delta (Whipple et al. 2012). Additionally, intensive farming in these former wetlands causes peat trapped within the soil to oxidize, leading to land subsidence of up to 26 feet (Whipple et al. 2012).

Channel straightening and dredging of the Stockton Deep Water Ship Channel in 1933 and the Sacramento Deep Water Shipping Channel would help facilitate transportation through the Delta led to channel morphology becoming deeper and more linear (Whipple et al. 2012). The construction of dams across most of the major rivers flowing into the Delta, combined with the transfer of water from the relatively wetter north to the drier south through the State Water Plan and Central Valley Project, significantly altered the seasonality, magnitude, and direction of freshwater flows into the Delta (Whipple et al. 2012). As result, salinity levels have increased in the western Delta leading to declining drinking water quality (Whipple et al. 2012).

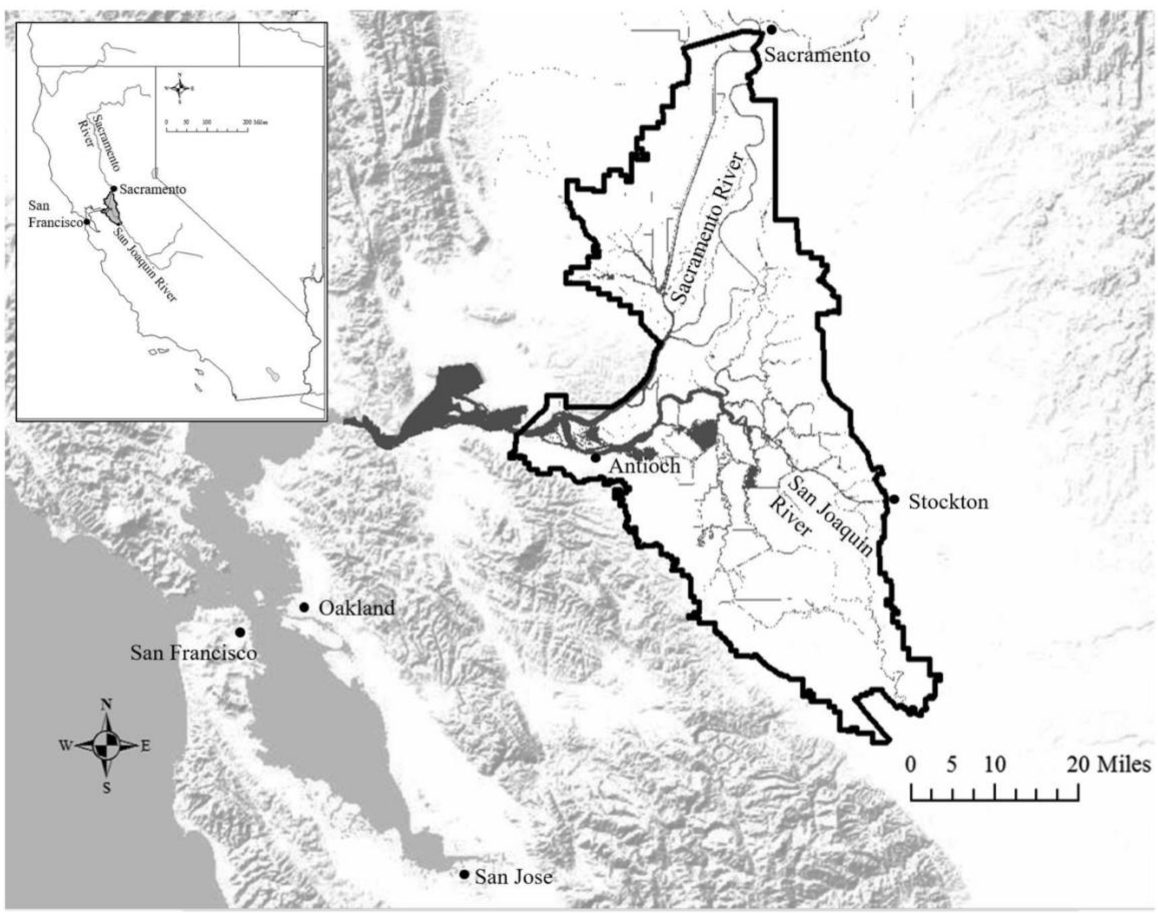

Figure 1. The Sacramento–San Joaquin Delta of northern California. Inset on left shows location in northern California. Larger map shows legal Delta boundary as dark line (DSC 2019a), the confluence of the Sacramento and San Joaquin Rivers, and the complex network of sloughs and canals, mostly built over the past 150 yr to drain land for farming. Map made by J. Miskella, USDA–ARS, Davis, CA using ArcGIS 10.6[1].

Figure 15: The Sacramento-San Joaquin Delta (Moran et al. 2021)

The Delta is currently targeted for large scale ecological restoration. The spread of invasive plants threatens the success of these projects maintaining ecological services, water infrastructure, and recreation opportunities (Conrad et al. 2023). In the Delta, SAV and FAV also threaten fish and wildlife habitat by outcompeting native plant species, and altering water velocity, sedimentation, temperature, and dissolved oxygen (Moran et al. 2021). Managing invasive species in the Delta has the potential to help recover endangered plant populations. For example, removal experiments of *L. latifolium* in Suisun Marsh was shown to increase populations of the federally endangered Suisun Marsh Thistle (*Cirsium hydrophilium*) (Schneider et al. 2024).

The regulatory landscape of the Delta is a complex mosaic of federal and state agencies with non-profit and academic partnerships playing a vital role (Ta et al. 2017). The California Department of Boating and Waterways (CDBW) is the lead agency for managing invasive aquatic plants in the Delta (Ta et al. 2017). CDBW has had jurisdiction to control FAV since the establishment of the Water Hyacinth Control Program in 1982, and received jurisdiction to control SAV since 2001 after the passing of a 1996 law that established the *E. densa* Control Program (Conrad et al. 2023). However, treating emergent species such as *Arundo donax* or *Phragmites australis* requires permitting for individual projects (Conrad et al. 2023). Each species needed to receive authorization every year from agencies such as USFWS and NIMS through a Biological Opinion or Letter of Concurrence, which often led to delays in treatment (Moran et al. 2021). Further, CDBW is required to coordinate with partner agencies such as California Department of Fish and Wildlife (CDFW) and CDFA in order to update the list of aquatic weeds managed under their programs as per AB 763 [2013] (Ta et al. 2017). Additionally, restrictions exist on the timing of herbicide application, which prevents treatment of early growth that is more effective (Khanna et al. 2023).

Funded between 2014 and 2018, the Delta Region Areawide Aquatic Weed Project (DRAAWP) was established to improve methods for weed control, improve understanding of weed growth using new methods, and streamline permitting and regulatory processes for invasive plant treatment (Moran et al. 2021). Remote sensing studies on invasive aquatic plant growth had a significant impact on the ability of DRAAWP member agencies to make informed decisions on where and when to treat invasive aquatic plants (Moran et al. 2021). For example, CDBW was able to use remotely sensed data to implement an adaptive control program for SAV and FAV, which has led to reductions in cover of invasive aquatic plants and higher native species diversity using less herbicide per unit area (Moran et al. 2021).

6.1.1 Invasive Plant Management in the Delta

Managing invasive species in the Delta is difficult due to logistical and regulatory challenges. The estuarine and riverine nature of the Delta makes accessing sites difficult due to the influence of tidal flows, and invasive plants can readily reinvade treated sites as they are transported downstream or through tidal action (Conrad et al. 2023). Chemical control methods, such as herbicides, can have limited effectiveness in tidal or riverine systems where untreated water can dilute herbicide concentrations below the level necessary to achieve desired results (Conrad et al. 2023). Herbicides require contact with plants for a minimum amount of time in order to kill plant tissue, making SAV particularly challenging to treat because they grow underwater (Conrad et al. 2023). FAV can escape chemical control when fragments break off and re-establish elsewhere (Conrad et al. 2023).

The development of slow-acting herbicides such as fluridone can be effective at controlling SAV when applied repeatedly at low-concentration, but require prolonged contact and need to be applied for several months in order to achieve plant mortality (Conrad et al. 2023). Effective herbicides for FAV, such as *Alternanthera philoxeroides* and *Eichhornia crassipes*, include the broadleaf specific 2,4-Dichlorophenoxyacetic acid dimethylamine salt (2,4-D), but due to its potential to damage agricultural crops it has been replaced by the non-selective herbicide glyphosate (Conrad et al. 2023). As our understanding of the risks that glyphosate poses to non-target vegetation, wildlife, and human health increases, alternative to glyphosate application will be necessary to control invasive plant in the Delta (Conrad et al. 2023).

Mechanical and physical approaches to invasive species control in the Delta have also been considered, but come with their own set of challenges. Hand removal, mechanical harvesters, disking, mowing, and suction devices have all been used to manage species such in the Delta, but can be expensive, labor intensive, and impractical at the spatial scales necessary to achieve long term control and risk spreading propagules (Conrad et al. 2023). Physical screens or barriers placed around FAV or SAV can prevent dispersal and limit light availability, but are only feasible for small populations (Conrad et al. 2023). Additionally, barriers can prevent oxygen and nutrient exchange for invertebrates and are susceptible to reinvasion once removed (Conrad et al. 2023).

Several herbaceous insects have been released as biocontrol agents to manage SAV and FAV in the Delta, though these results have not resulted in successful reductions of target invasive species (Conrad et al. 2023). Biological control of aquatic vegetation is often limited in California due to the region having an unsuitable climate for the known biocontrol agents for our species of interest, and few insects exclusively feed on SAV (Conrad et al. 2023). Sterile, triploid grass carp (*Ctenopharyngodon idella*) have been used as biocontrol agents in agricultural canals in the California Imperial Valley to manage *Hydrilla verticillata,* but these fish will consume any SAV and can consume non-target SAV as well (Conrad et al. 2023). Two species of insects have been released in California for biocontrol of *A. donax*: the shoot-tip galling wasp (*Tetramesa romana*) and the shoot-feeding armored scale (*Rhizaspidiotus donacis*) (Conrad et al. 2023). A third species, the leaf-mining fly (*Lasioptera donacis*), is under consideration for release (Conrad et al. 2023). While the first two insects have shown favorable results on *A. donax* control, their effectiveness in California has yet to be demonstrated (Conrad et al. 2023).

6.2 Remote Sensing of Invasive Plant Species in the Delta

From the studies used in my comparative analysis, six species were the focus of remote sensing in the Delta) *E. densa, E. crassipes, H. verticillata, L. latifolium, Ludwigia* spp., and *Myriophyllum* spp.). All were aquatic invasive plants (FAV or SAV) or perennial herbs that grow in wetland habitats.

Remote sensing of SAV and FAV is particularly challenging in the environmental context of the Delta. In order for a remote sensor to detect SAV, light must be able to pass through the water column and reflect off the surface of plant material (Hestir et al. 2008). Water is strongly absorbent of most spectral wavelengths, reflects light off the surface, and attenuates light that passes through, all of which can affect the magnitude and quality of the reflected spectral signal (Hestir et al. 2008). Tides and runoff can affect the amount of water present and the amount of suspended sediment can vary across the landscape, which affects the amount of light that can pass through the water column (Hestir et al. 2008). Errors between flightlines can also be introduced through the effects of weather and sun angles (Hestir et al. 2008). Additionally, imagery acquisition must occur when plants display unique phenological life stages, such as flowering or senescence, which can vary across the heterogenous Delta landscape (Hestir et al. 2008).

Other remote sensing studies in the Delta demonstrate how environmental heterogeneity complicates the detection of invasive plants species. Andrew and Ustin (2009) used HyMap hyperspectral imagery (3-meter spatial resolution) to map *L. latifolium* at three sites in the Delta that demonstrate the variety of ecological conditions and habitats present in the Delta:

1. 55 km^2 at Rush Ranch, a brackish tidal marsh in Suisun Bay dominated by tule (*Schoenoplectus californicus*), bulrush (*Schoenoplectus acutus*), pickleweed (*Salicornia virginica*), saltgrass (*D. spicata*), common reed (*Phragmities australis*), and cattail (*Typha* spp.).
2. 63 km^2 at The Greater Jepson Prairie Ecosystem: a vernal pool system within an annual grassland, riparian, and freshwater marsh wetland complex.
3. 40 km^2 at Consumes River Preserve: a mix of riparian forests, uplands, freshwater marshes, and agricultural fields.

While the authors were able to successfully map *L. latifolium* at both Rush Ranch and Jepson Prairie with high accuracies, omission and commission errors were very high at Consumes River Preserve. This means that a significant portion of pixels were excluded from classification, and a significant portion of pixels were misclassified. Several factors were attributed to the large discrepancy in accurate classification between the sites. The bright white flowers present on *L. latifolium* produced spectral signatures that were substantially different from those of other plants occurring at Rush Ranch. *L. latifolium* at Jepson Prairie, however, produced mixed spectral signatures because the spatial resolution of the imagery was coarse enough that pixels included other highly spectrally distinct species such as *C. solstitialis*. Plants were also in various stages of phenology at Jepson Prairie, which slightly decreased the spectral uniqueness of *L. latifolium,* but at the time of imagery acquisition it was the only green vegetation present which raised the accuracy of the image classification. Similarly, at Consumes River Preserve *L. latifolium* was present in all state of phenology due to variations in hydrology. Consumes River Preserve was also the most biodiverse of the three sites, which increased the likelihood that at least one other plant present at the site would be spectrally similar to *L. latifolium*. Dense patches of *L. latifolium* were also more likely to be accurately classified than sparsely populated patches. Small populations of invasive plants may be missed, particularly when spatial resolution does not match. While *L. latifolium* was successfully mapped in some contexts, this study also revealed some limitations of a remote sensing approach to invasive species mapping.

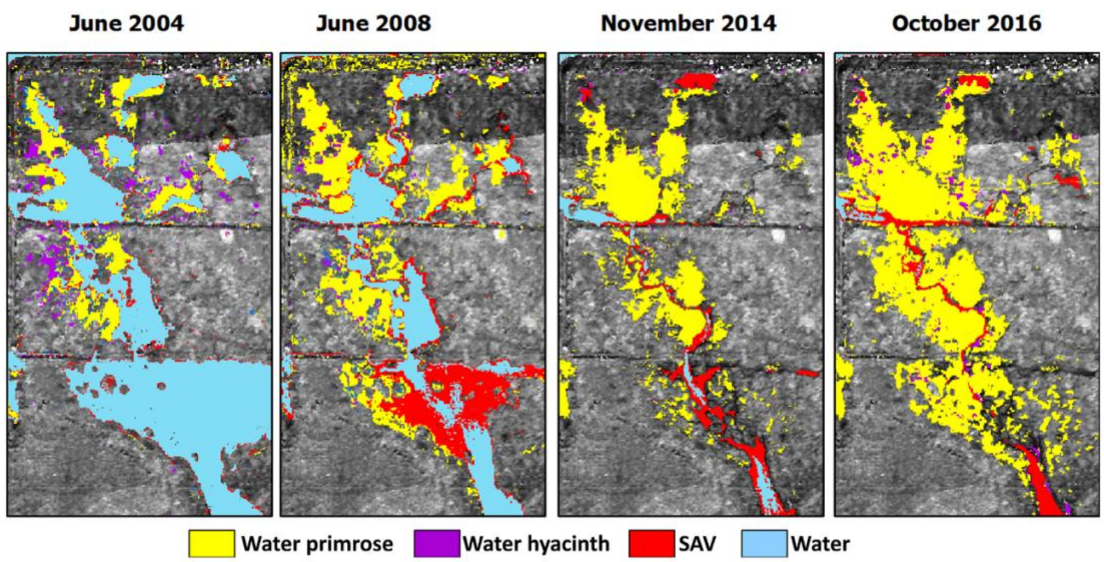

Figure 16: Spread of water primrose (Ludwigia spp.) into open water and SAV habitat in the Delta between 2008 and 2014 and into emergent marsh in 2016 (Khanna et al. 2018)

Remote sensing studies performed in the Delta in 2014 have been able to determine the extent of SAV (dominated by *E. densa*) and FAV cover (co-dominated by water primrose and water hyacinth) to be 7,550 acres and 3,180 acres, respectively (Ta et al. 2017). For example, Khanna et al. (2018) used AVIRIS-ng (3m spatial resolution) and HyMap (2.5m resolution) hyperspectral airborne imagery to map *Ludwigia* spp. across a 2500 km^2 swath of the Delta using imagery acquired in 2004, 2008, 2014, and 2016 (Figure 16). Training data was acquired by field crews who recorded the locations of 3 m^2 patches using GPS units that were dominated by a single species, which corresponded to the spatial resolution of the imagery. A random forest algorithm was applied to various outputs from the imagery to classify water, SAV, *Ludwigia* spp., *E. densa*, emergent vegetation, and non-photosynthetic vegetation. The authors then conducted a change analysis between different years of imagery by subtracting the percentage of pixels belonging to one class from another year. The authors found that between 2004 and 2016, *Ludwigia* spp. cover in their study area increased by 400%, from 121,800 m^2 to 471,300 m^2, and that this change accelerated the most between 2014 and 2016. Importantly, the authors note that this imagery was incapable of differentiating the two species of *Ludwigia* present at the site, indicating one potential shortfall of remote sensing as a means of EDRR. However, studies like this demonstrate how remote sensing may be useful in determining the spread of invasive plant species over very large spatial scales, in settings that are otherwise logistically challenging to access.

6.3 Management Implications for the Delta

Remote sensing studies have revealed important changes in invasion patterns for many high impact invasive species in California. These studies have demonstrated how *Ludwigia* for example, have caused significant changes to the ecology of the Delta. Khanna et al. 2018 showed that *Ludwigia* had begun invading emergent marshes, likely because it had completely filled all available niches within open water habitats. As *Ludwigia* cover expands across these open water habitats, its dense root system traps sediment. This increased rate of sedimentation has led to an expansion of emergent marshes within in the Delta at the expense of open water, as well as decreasing the turbidity of remaining aquatic habitat. The spread of *Ludwigia* across the Delta has likely occurred due to decreases in another co-occurring invasive plant, *E. crassipes*, which was a covered species under CDBW Water Hyacinth Control Program (Khanna et al. 2018). *Ludwigia*, which was not an authorized species under CDBWs invasive species control program, was likely able to exploit the available niches that were available as *E. crassipes* cover decreased due to management efforts.

Studies that determine the outcome of invasive species control programs across a large and heterogenous landscape like the Delta illustrate a particular strength of remote sensing approaches to invasive species mapping. Khanna et al. (2023) used AVIRIS-NG and HyMap hyperspectral airborne imagery to determine the effects of herbicide treatment of SAV, including but not limited to *E. densa* and *M. spicatum*, across a 2200 km^2 section of the Delta between 2014 and 2018. The authors found that several factors make SAV treatment the Delta unsuccessful due to several environmental and management factors. Wind speed and currents in a given location were likely to reduce the likelihood that pixels classified as SAV in 2014 would change to a different classification in 2018, indicating that these factors reduced the impact of the herbicide application, likely by diluting the effective dose required to kill the target plant species. This remote sensing approach to a landscape scale invasive plant treatment monitoring is useful, in that untreated reference sites could easily be included to determine if declines in SAV were due to treatment effects or other factors.

Additionally, advances in drone technology are facilitating the use of remote sensing to not only map the distribution of invasive species, but also to directly treat them. Takekawa et al. (2023) used an RGB color camera attached to a drone to collect aerial imagery of *L. latifolium* in Suisun Marsh at 5 cm^2 spatial resolution. The authors combined a red-green spectral index with a 1 m resolution Digital Elevation Model (DEM) to map locations of *L. latifolium* across 8 sites totaling 14.29 km^2. A spray drone was then used to treat *L. latifolium* at each site using transects that were mapped using the classification maps produced by the RGB imagery. After several weeks, a field crew manually surveyed each treatment site to determine the effects by measuring the percent cover of *L. latifolium* within a 1 m^2 quadrat and note if there appeared to be any evidence the area was sprayed and whether any *L. latifolium* present was experiencing dieback. The authors found that 49800 m^2 of *L. latifolium* that were mapped across the eight study sites, and there was an 87% success rate in *L. latifolium* mortality. Drone-delivered herbicide application had several benefits over traditional backpack or tractor-spraying methods. Drift rates were relatively low when herbicide was applied by drone due to the low altitude flight path and large droplet size used. Excluding the up-front costs of equipment, this method may be relatively cost-effective compared to contracting a field crew to backpack spray, costing an estimated 367,900 USD/km^2 compared to 4,569,500 USD/km^2. While there are concerns regarding the impact operating drones have on disturbing wildlife, this method also has the benefit of reducing herbicide contact with human applicators and associated health impacts.

Lastly, remote sensing has been proposed as a useful tool for wetland monitoring programs in the adjacent San Francisco Bay, where numerous restoration projects are taking place or are planned. The Wetland Regional Monitoring Program (WRMP) for San Francisco Bay was created to inform practitioners, scientists, and decision makers on how the San Francisco Bay estuary is changing over time and responding to restoration efforts (WRMP 2020). In order to do so, regular monitoring of environmental indicators is required from the site-specific to regional spatial scale (WRMP 2020). Many of these indicators, such as vegetation parameters, marsh elevation, and marsh extent, are capable of being measured by remote sensing techniques (WRMP 2020). Remote sensing across benchmark, reference, and project sites across the San Francisco Bay estuary can enable land managers to monitor invasive species establishment using a consistent method and to compare the effects of local influences or project design on invasive species establishment.

7.0 Conclusion and Recommendations

Invasive plants are a major contributor to environmental degradation and biodiversity loss in California. Introductions of novel plant species are likely to increase in the future due to human activity, some of which are likely to become invasive. Detecting invasive species early in their establishment and swiftly enacting control methods are the most effective methods for controlling invasive plants and preventing them from causing further ecological harm. The emerging science and practice of remote sensing offers a powerful tool for land managers to understand the spread of invasive plant species across spatial scales. High spectral resolution sensors are capable of distinguishing between several groups of vegetation by relying on unique spectral properties of plants. High spatial resolution sensors are capable of detecting very small patches of invasive plants. UAVs, drones, and aircraft can be deployed to obtain imagery at the precise temporal resolution necessary to capture plants at phenological life stages that enable their detection via remote sensing.

While significant limitations exist that limit the use of remote sensing for early detection, it has been demonstrated to be an effective means to monitor a variety of invasive plants in the containment and long-term management of invasive plants and understanding the impacts of large-scale treatment efforts. Our capacity to utilize remote sensing within the EDRR management framework will improve as new sensors are developed with better spatial and spectral resolution, and as UAV use becomes more widespread.

7.1 Management Recommendations

1. Use high spatial resolution multispectral, color-infrared, or color imagery when hyperspectral imagery is not available or practical. Several remote sensing studies have demonstrated that high spatial resolution imagery can often overcome the challenges imposed by lower spectral resolution. Higher spatial resolution may be better suited to detecting smaller, nascent and satellite populations of invasive plants known to occur in an area. This type of imagery, which is typically acquired through drone imagery or aircraft, can also be collected at precise times when target plants exhibit their unique spectral attributes or exhibit specific phenological life stages.

2. **Develop partnerships for acquiring hyperspectral imagery.** The power of remote sensing for invasive plant management lies in its ability to monitor at scale, across many political boundaries and jurisdictions. When more expensive hyperspectral imagery is necessary to map invasive plant populations, organizations within the same region that may find uses for this data should pool financial resources and expertise to obtain it. Such examples can be found between CDFW and CDBW use of hyperspectral imagery for invasive species mapping in the Delta.

3. **Collect field data that corresponds to remote sensing data.** At the present moment, remote sensing methods for invasive plant monitoring are too inadequate for fully replacing field surveys, and should instead be seen as a complementary tool. Combing remotely sensed data with field-collected date can be enhanced when field data is attained in way that facilitates its use with remote sensing data. For example, nested survey plots that match the spatial resolution of several remote sensors could be used to gather training data and extrapolate field monitoring to entire sites or adjacent landscapes.

4. **Spectral data for new invasive plant species should be collected in the field along with herbarium voucher specimens.** Herbariums play an important role as warehouses of botanical information. Voucher specimens stored in herbariums already play an important role in uncovering patterns of invasive plant spread and biotic homogenization. Recent advances have been made in utilizing the DNA within herbarium specimens to better understand phylogenetic relationships. Herbariums could also play a unique role as warehouses of spectral data, both from data collected from stored specimens and from in situ plants before collection. Processes for collecting spectral information from plants at the time of their collection should be developed and standardized so that herbariums can also serve as spectral libraries.

5. **Continue research and development into high resolution sensors.**

Sensor resolution is often the limiting factor in successfully identifying invasive plants through remote imagery. For example, high spectral resolution is necessary to distinguish similar plant species from one another and high spectral resolution is needed to separate nearby plants from one another. However, all sensors must make tradeoffs in design that limit their spatial, spectral, or temporal resolution. Newer, higher resolution sensors (e.g. Landsat Next) will become increasingly relevant to the application of remote sensing to invasive plant management as their higher spectral, spatial, and temporal resolution will increase the availability of high-quality data for making accurate assessments of invasive species cover. Continued development of higher resolution sensors should be a high priority for research agencies such as the U.S. Geological Service and private industry.

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