Emerging technologies to assess human benefits from and risks to water resources

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Abstract

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Humans benefit from water resources by deriving cultural ecosystem services (CES) such as numerous types of recreation (e.g., fishing, boating, swimming), improved mental health, and artistic inspiration. However, we also pose a significant risk to waterbodies by altering water chemistry, introducing invasive species, and degrading habitat quality. Thus, understanding human activity on freshwaters is critical for preserving not only aquatic ecosystems, but also the benefits we gain from them. Traditionally, human activity on waterbodies across time and space is inferred from sparsely conducted surveys that provide data with limited spatiotemporal scope. Volunteered geographic information (VGI) – user-generated, geotagged metadata from posts on mobile device applications – is a promising data source to examine human activity over broad scales of space and time.

Here, I show how technological innovations – particularly VGI – can be leveraged to support management and conservation of freshwaters. First, I offer a review of innovative technologies with applications for invasive species management related to pathway intervention, spread prevention, impact mitigation, and public engagement. I also explore challenges and opportunities for successful integration of emerging technologies into invasive species management, focusing on pipelines that enable practitioners to integrate tools into practice while recognizing logistic and financial constraints (Chapter 2). Next, I model visitation at lakes from multiple VGI sources to demonstrate that these data reflect empirical visitation. I also show that diverse VGI sources are likely to characterize the broad diversity of reasons motivating people to interact with nature (Chapter 3). My fourth chapter demonstrates the value of intentionally surveying waterbody visitors to identify their activities and desired amenities, thus informing the support of these activities across urban blue-green spaces. Improved access to close-to-home waterbodies and adjacent green spaces is fundamental to helping close the nature gap in urban environments where people of color, families with children, and low-income communities are most likely to be deprived of the benefits that nature provides (Chapter 4). Lastly, my fifth chapter visualizes and quantifies connections between waterbodies across the Western US in terms of the magnitude, direction and timing of human movements to identify potential invasion hubs. Identification of specific waterbodies at highest risk of invasive species introductions will allow state resource management partners to prioritize waterbody locations for preventative measures such as educational signage, boat inspection stations, and gear cleaning services (Chapter 5). Collectively, my research demonstrates the value of emerging technologies for informing freshwater conservation and management, as well as the integralness of quality empirical data for validating big data methods.

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Chapter 1. INTRODUCTION

1.1 BACKGROUND

Freshwater resources provide a suite of cultural ecosystem services (CES) to humanity. For example, lakes and reservoirs alone provide drinking water, habitat and population maintenance, spiritual spaces, and numerous types of recreation (e.g., fishing, boating, swimming, camping) (Reynaud and Lanzanova 2017). However, the interaction between and linkage of these services to one another remains a critical gap in our understanding and valuation of them (Hanna et al. 2018). Previous work has found that the valuation of water-based services varies spatially within and between watersheds, and thus understanding the spatiotemporal distribution of freshwater CES is critical to managing water resources with the goal of meeting and preserving societal demands and values (Chen et al. 2018).

A robust understanding of the geography and dynamics of lake visitation is critical for anticipating and minimizing human impacts. While water-based activities contribute to human well-being, they simultaneously impose stressors on aquatic systems such as depleting aquatic and riparian habitat quality, altering species' behaviors, and changing the biogeochemical cycles of aquatic ecosystems (Venohr et al. 2018). Humans are also traversing the landscape to experience different types of CES, and this creation of overland pathways can pose further harm to water resources. For example, human movement is a significant and growing source of invasive species transmission (Drake and Mandrak 2014). Angler and boater activities that entangle invasive organisms on fishing gear, boat hulls, and outboard engines, or use non-native species as live bait, serve as modes of introduction.

Traditionally, human activity on waterbodies across time and space is inferred from sparsely conducted surveys that provide data with limited spatiotemporal scope (Davis and Darling 2017). Conventional approaches typically rely on in-person surveys (often at boat launches) or mail-in questionnaires and thus only provide a limited snapshot in time of activity at a particular location (Rothlisberger et al. 2010; Anderson et al. 2014). An additional drawback of such methods for holistically evaluating water-based CES is their narrow targeting of specific user groups and associated activities (e.g., anglers and boaters).

Previous studies in a terrestrial context have found strong correlation between volunteered geographic information (VGI) – user-generated, geotagged metadata from posts on digital platforms (e.g., Twitter, Flickr) – and ground-truthed visitation estimates for points of interest. At US National Parks, for example, the relative numbers of monthly visitors counted at each park by the National Park Service are highly correlated with the relative number of photographs shared on Flickr from the same parks (Sessions et al. 2016). Significant positive correlation between empirical visitation estimates and VGI has also been quantified at New York City parks, Vermont state parks, and global recreational sites (Hamstead et al. 2018; Sonter et al. 2016; Wood et al. 2013). Despite these advances, such analyses are rarely done for blue spaces (lakes), and data validation is lacking for aquatic resources over varying spatial scales (Keeler et al. 2015; Fisher et al. 2018). In recent years, computational tools have maximized the use of VGI, which can provide a close to real-time understanding of human behavior and cost-effective monitoring (Deville et al. 2014; Venturelli et al. 2017; Xia et al. 2020).

Evaluation of water-based CES over a large spatiotemporal scale can aid in prioritizing additions and updates to waterbody infrastructure supporting recreation, evaluating the impact of environmental perturbations (e.g., algae blooms, wildfires, droughts) on the spatiotemporal distribution of waterbody use, estimating the likelihood of invasive species transmission based on propagule pressure, and assessing patterns in visitation before, during, and after the COVID-19 pandemic (e.g., Merrill et al. 2020, Ford et al. 2016, Fricke et al. 2020, Huang et al. 2020). In addition, climate change is projected to both increase and induce spatiotemporal shifts in demand for recreational ecosystem services on public lands (Fisichelli et al. 2015, Wilkins et al. 2021a). Recent studies have shown that daily weather conditions strongly influence patterns of recreation in parks, and social media data reveals that spatial trends in visitor behavior may change in response to increasingly frequent heatwaves (Wilkins et al. 2021b).

VGI are a highly promising resource, and yet their implementation presents many challenges. While most Americans own a cell phone (97%), ownership of smartphones in particular varies significantly by age, education, and household income. Consistent public sharing of VGI content is often limited to a small proportion of all VGI platform users who tend to fall at extremes in terms of their interest level and dedication to posting (Ruths and Pfeffer 2014; Gundelund et al. 2020). Significant variability in phone ownership, mobility, and social media use among demographic groups may also lead to biases in population-level estimates of point of interest visitation (Wesolowski et al. 2013; Malik et al. 2015; Feng et al. 2019).

Nevertheless, previous work has confirmed that VGI enhances visitation estimates, particularly at unmonitored sites and when parameterized with ground estimates (Wood et al. 2020). Compared to ground survey data, in urban parks VGI provide a greater magnitude of observations across a given area, thus offering park managers visitation data for locations with little or no in-person survey presence (Donahue et al. 2018). Optimal approaches will incorporate multiple streams (applications) of mobile data, as data from different types of applications (e.g., social media, citizen science, activity sharing) represent specific user groups and vary in their temporal and spatial granularity (Heikinheimo et al. 2020; Hanson et al. 2025).

The vast suite of available VGI offer a novel, yet rarely explored, opportunity to improve our understanding of human behavior and CES (Venturelli et al. 2017; Havinga et al. 2020). At the highest level, VGI can be categorized by how actively the user is involved in collecting the data. VGI generated by a user intentionally engaging with their device (e.g., posting photos, sending a tweet, logging a species observation) are types of active data, while VGI collected in the background once a user has downloaded an app and given permission for data collection (e.g., GPS location tracking) are passive (Wenz et al. 2019). Active data from mobile applications can be further classified by an application's purpose, such as social media (e.g., Twitter, Flickr), citizen science portal (e.g., iNaturalist, eBird) and outdoor activity-sharing platform (e.g., Gaia GPS, Strava), although these categories often overlap and many activity-sharig platforms contain features similar to social media (Havinga et al. 2020). These data can include geotagged user-generated records, text, and images.

Lakes and reservoirs are widespread and support critical ecosystem functions, provide numerous goods and services, and contribute to sustainable local and regional communities (Klessig 2001, Schindler 2009, Reynaud and Lanzanova 2017). Furthermore, blue spaces such as lakes in urban and suburban settings and adjacent green spaces (parks) serve as hotspots of connections to nature and offer heat stress relief in the midst of urban heat island effects (Gunawardena et al. 2017). Given lakes' multidimensional role in supporting human well-being, understanding human activity on them over vast spatiotemporal scales and assessing the benefits and risks associated with human water-based activities is critical for lake valuation and conservation.

1.2 RESEARCH OBJECTIVES

My dissertation capitalizes on large datasets from VGI to enhance our understanding and management of human activity on freshwaters by quantifying relative waterbody visitation, characterizing the CES associated with freshwaters, and visualizing the risk (via potential transmission of invasive species) we pose to lakes and reservoirs (hereafter, waterbodies). First, I summarize existing literature on the use of emerging technologies to manage invasive species (Fricke and Olden 2023, Chapter 2). Next, I quantify spatiotemporal patterns in waterbody visitation from multiple sources of VGI and show how multiple VGI estimates strengthen visitation estimates and represented CES (Chapter 3). In my fourth chapter, I sought to understand sociodemographic differences in waterbody use and accessibility by surveying Western Washington lake visitors about the CES they experience at lakes (Chapter 4). Lastly, my fifth chapter assembles a network model for the Western US from Flickr data to identify the magnitude and location of human movement between waterbodies as it relates to the potential for invasive species transmission (Chapter 5).

1.3 BROADER IMPACTS

This work demonstrates ways in which emerging technologies can be leveraged to assess human benefits from and mitigate risks our activities pose to water resources. My second chapter collates a broad suite of technologies targeted toward explicit invasive species management goals, and proposes areas to propel the use of technology within invasion science and provide guidelines for ensuring tool and data accessibility to end-users. In my third chapter, I show how multiple VGI sources reflect empirical visitation at waterbodies in Western Washington. Diverse VGI sources are likely to characterize the broad diversity of reasons motivating people to interact with nature, and my analysis reinforces the need for quality empirical data in tandem with VGI. My fourth chapter demonstrates the value of intentionally surveying waterbody visitors to identify their activities and desired amenities, thus informing the support of these activities across urban blue-green spaces. Improved access to close-to-home waterbodies and adjacent green spaces is fundamental to helping close the nature gap in urban environments where people of color, families with children, and low-income communities are most likely to be deprived of the benefits that nature provides. Lastly, my fifth chapter visualizes and quantifies connections between waterbodies across the Western US in terms of the magnitude, direction and timing of human movements to identify potential invasion hubs. Identification of specific waterbodies at highest risk of invasive species introductions will allow state resource management partners to prioritize waterbody locations for preventative measures such as educational signage, boat inspection stations, and gear cleaning services.

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Chapter 2. TECHNOLOGICAL INNOVATIONS ENHANCE INVASIVE SPECIES MANAGEMENT IN THE ANTHROPOCENE

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2.1 ABSTRACT

Curbing the introduction, spread, and impact of invasive species remains a longstanding management and policy prerogative. In recent decades, globalization and environmental change have further complicated efforts to execute science-based actions that address these challenges. New technologies offer exciting opportunities to advance invasion science knowledge, enhance management actions, and guide policy strategies, yet are increasingly complex and inaccessible to most practitioners. Here, we offer a synthetic perspective of innovative technologies with applications for invasive species management related to pathway intervention, spread prevention, impact mitigation, and public engagement. We also describe tools that augment big data processing required by some methods (e.g., remote sensing, mobile application data), such as automated image and text recognition built on machine learning. Lastly, we explore challenges and opportunities for successful integration of emerging technologies into invasive species management, focusing on pipelines that enable practitioners to integrate tools into practice while recognizing logistic and financial constraints.

2.2 Introduction

Nonnative, invasive species – species that have successfully been introduced, spread, and established beyond their native range – are responsible for profound, negative effects on biodiversity (Doherty et al. 2016), ecosystem functioning and services (Kumschick et al. 2015), human health (Ogden et al. 2019) and welfare (Jones 2017), and the economy (Haubrock et al. 2021). The importance of acting against invasive species globally is widely recognized (Pyšek et al. 2020), and includes the development of effective strategies to avoid or reduce the impacts of nuisance species in national-level policies (Early et al. 2016). Despite this challenge, human-mediated movement of invasive species will only continue to grow in response to synergies with other global changes (Seebens et al. 2021), thus widening the already significant gap between the societal need and the scientific capacity to inform management action.

Conservation technology – devices, software platforms, computing resources, algorithms, and biotechnology methods – is frequently identified as the next frontier to help scientists and practitioners address the 21st Century biodiversity crisis (Joppa et al. 2016, Berger-Tal and Lahoz-Monfort 2018, Iacona et al. 2019). Technological innovation has created the tools needed to collate, analyze, and disseminate data at scale, and offers new insight into how human activities are influencing biodiversity and integrity of ecosystems globally (Joppa et al. 2016). New technologies permeate all aspects of conservation by offering data on nature and people, enhancing data sharing and analytical methods, presenting new communication mechanisms, and enabling participatory governance (Arts et al. 2015, Lahoz-Monfort and Magrath 2021). Collectively, conservation technologies offer unprecedented opportunities to enhance management and policy actions both today, and in the future (Lahoz-Monfort et al. 2019).

Invasion science is a rapidly evolving interdisciplinary field (Vaz et al. 2017), and technological innovation is playing an increasing role in addressing the escalating extent and impacts of invasive species. In recent years, technological advances have provided insight across all stages of invasion. From identifying pathways of introduction to controlling and eradicating established invaders, these advances have also informed public opinion in invasive species management (Martinez et al. 2020). There is a long history of co-opting new technologies for the management of invasive species, spanning from initial detection with eDNA assays (Larson et al. 2020), to limiting species' spread in rivers with electric barriers (Jones et al. 2021), to controlling invasive predator populations with aerial baiting (Baker and Bode 2013), to aiding management and policy through hackathon-based development of public tools to track invasive species (Martinez et al. 2020). More recent developments in machine learning – artificial intelligence that allows models to learn from data – and digital interfaces offer additional prospects to improve data management and dissemination within invasion science, which in turn help enhance public engagement and policy efforts (Heger et al. 2021).

An ever-growing array of innovative technologies can help identify time- and cost-effective detection, deterrence, control, and eradication strategies for invasive species. However, as the number and intricacy of new approaches grow, so do the challenges to scientists to understand the choices of technology available to them and difficulties to conservation practitioners to effectively leverage these technologies for more informed management decisions. Here, we provide a comprehensive review of technology-based tools that aid in invasive species management, presenting examples of these approaches as they relate to specific management priorities ranging from pathway intervention to preventing spread to limiting impacts and increasing public engagement (Figure 2.1, Table 2.1). Though previous reviews have collated examples of some of these technologies (e.g., web scraping) within invasion ecology (Jaric et al. 2021), we include a broader suite of technologies targeted toward explicit management goals. In addition, we propose areas to propel the use of technology within invasion science and provide guidelines for ensuring tool and data accessibility to end-users. Our goal is to capture the pace and scope of recent and emerging technologies applied to invasion science and management, providing examples that are representative of this burgeoning area of innovation and discovery.

2.3 Identifying and Managing Introduction Pathways

Pathway management represents the first line of defense in preventing species invasions. Non-native hitchhikers make use of numerous transport pathways to spread from their native to introduced range, including movement associated with the intentional trade of non-native species. Unintentional examples include contaminated shipments of horticulture species and exotic pets, ballast water exchange associated with global shipping, recreational boat-facilitated movement (through hull fouling, plant entanglement, or still-water transport), and entanglement on fishing gear (Hulme 2009, Drake and Mandrak 2014). These human-assisted pathways and geographic routes of species movement have proven particularly difficult to pinpoint, characterize, and regulate (Pyšek et al. 2020, Ricciardi et al. 2021). Recently, however, spikes in smartphone use and ownership, innovations in smart fishing devices, and the proliferation of online live organism marketplaces have spurred new approaches leveraging mobile and online data to identify highly trafficked pathways for invasive species introductions.

The global pet trade is well recognized as a primary pathway for non-native species introductions, and in recent decades pet sales have rapidly expanded from physical retail stores to include an increasing number of internet marketplaces (Lockwood et al. 2019). In doing so, the Internet has created opportunities for new and long-distance trade routes (Lenda et al. 2014).

Online pet retail has also increased accessibility to new source pools of invasive species (Seebens et al. 2018), making an already challenging biosecurity problem even more difficult. Web scraping – or extracting data from websites – allows for better understanding of this emerging introduction pathway by tracking online sales of live organisms across international borders and identifying the most active trade routes for prohibited species. For example, use of automated web crawlers to collect data from online pet aquarium marketplaces revealed a diverse variety of freshwater species in trade and a concentrated network of trade routes that may serve as conduits of invasive species (Olden et al. 2021). In addition, systematic internet searching of posts or groups on social media have been used to identify invasive species within wildlife trade (Stringham et al. 2021).

Interception of potential invasive species at ports-of-entry is essential for effective biosecurity and biosurveillance programs, yet accurate identification of taxa remains a fundamental challenge because of the continued decline in systematics training and understaffing of inspection officials (Ricciardi et al. 2021). The use of molecular technologies to identify species by genetic fingerprinting or "barcoding" may help address these issues by developing a centralized database containing species information and standardized molecular markers to distinguish species (Cross et al. 2010). DNA barcoding could be especially effective for cryptic microorganisms for which traditional taxonomic classification is challenging, as Madden et al. (2019) demonstrated by finding DNA-based identifications of microlepidoptera (smaller moths) intercepted at U.S. ports-of-entry were more often correct than morphology-based identifications. Furthermore, comparisons of simplified metabarcoding (high-throughput sequencing and DNA-based identification) approaches to conventional DNA barcoding and visual surveys suggest that metabarcoding could also be a cost-effective solution for early detection (Borrell et al. 2017).

Determining the origin of an invasive species is critical for mobilizing a rapid response to limit the transport of additional individuals through a pathway and prevent the establishment of recently introduced incursions. For example, researchers used comparative DNA barcoding between wild and captive populations of the Julia butterfly (*Dryas iulia*) in Thailand to determine that Thailand's wild populations of the species originated from traded, captive individuals in butterfly houses (Burg et al. 2014). In other cases, managers may need to differentiate recently escaped or released individuals from previously established populations. Stable isotope analysis – quantifying the ratio of elements such as carbon, nitrogen, and sulphur in organisms to trace the flow of nutrients through food webs and assess trophic interactions – can help researchers understand individuals' environmental histories. Hill et al. (2020) showed that wild and captive red-eared slider turtles (*Trachemys scripta elegans*) exhibit distinct stable isotope ratios, thus allowing for the rapid identification of individual turtles' origins.

Propagule pressure – the repeated introduction of multiple individuals of a non-native species into a new environment over time – is a key determinant of invasion success (Lockwood et al. 2005, Reaser et al. 2008). Traditional approaches to estimating human traffic across the landscape, in which non-native propagules may be entrained, involve in-person surveys or mail-in questionnaires that are limited in their spatial scope and time periods of inference (Rothlisberger et al. 2010, Anderson et al. 2014). In recent years, smartphone applications and social media have enhanced our understanding of propagule pressure in freshwater ecosystems. Papenfuss et al. (2015) used angler posts to a popular mobile fishing application in Alberta, Canada, to quantify patterns of lake visitation and inter-lake angler movement across the entire province, a spatial extent not possible using traditional creel survey data. Furthermore, an analysis of passively collected angler location data from a sonar-enabled fishing bobber (linked to a mobile application) showed that nearly half of all user movements between waterbodies in the continental U.S. occurred within the desiccation tolerance window of many prevalent plant and animal invasive species (Fricke et al. 2020). Text and data mining of posts to popular social media platforms can also be leveraged to understand the spatiotemporal distribution of wildlife recreation activities (Monkman et al. 2018), and these same sources could also inform risk management for human-initiated invasive species transmission. These new mobile and web-based data sources are not a replacement of traditional in-person surveys of waterbody visitation, but when coupled with site-specific data models informed by smartphone-derived data are significantly more informative (Wood et al. 2020).

2.4 Detecting and Cataloging Presence in the Wild

Despite efforts to intercept invasive species prior to introduction, individuals repeatedly slip through to establish non-native populations. Early detection of newly introduced species is critical for enabling rapid implementation of control measures but remains challenging due to the large and diverse landscapes agencies are typically tasked with monitoring (Reaser et al. 2020). New technologies have enhanced our ability to effectively detect species outside their native range through camera traps, environmental DNA, and crowdsourcing of citizen scientist observations. The pace of detection can be further accelerated through artificial intelligence-based methods that automate species identification in imagery.

Locating target invasive species in the wild typically demands intensive and costly field campaigns that are limited by the number of personnel relative to a survey area. Remote camera traps that take photos when a sensor is triggered by the movement of an animal (using infrared and motion sensors), and increasingly transmit real-time images over cellular networks, can alleviate the long-term time commitment needed to effectively survey. For example, camera traps have been used to accurately detect invasive wild pigs (*Sus scrofa*) in South Carolina (U.S.) and invasive small and medium-sized terrestrial mammals on the island of Terceira (Davis et al. 2020, Lamelas-López and Salgado 2021). Furthermore, linking camera trap images with artificial intelligence-driven classification can expedite and automate the species identification process. Convolutional neural networks (CNNs) are computing systems inspired by biological networks of neurons that are commonly applied to image analysis. Willi et al. (2018) demonstrated the utility of CNNs for identifying specific species (89 to 93% accuracy) and differentiating from non-animal or empty images across multiple test datasets. Next-generation camera trapping will warrant technological modifications that expand the suite of potential species surveyed to smaller and more cryptic taxa (Delisle et al. 2021).

Detecting non-native species in elusive habitats, such as aquatic environments, is particularly challenging with traditional survey methods. Innovations in environmental DNA (eDNA) sampling, which uses genetic material extracted from environmental samples (e.g., soil, water, air) to identify species' presence – such as real-time PCR and high throughput sequencing – have increased the availability of this method and alleviated some of its costs (Larson et al. 2020). eDNA has proved to be an effective surveillance tool for highly invasive quagga and zebra mussels (*Dreissena* spp.) in novel waterbodies (Feist and Lance 2021), and it has enhanced border detection of non-native fish species through cross-referencing the eDNA of live trade shipments to DNA sequence libraries (Roy et al. 2018). Furthermore, portable field-based platforms for testing for invasive northern pike eDNA have been shown to take only a fraction of the time needed for lab-based approaches and offers an opportunity for rapid screening of invasive species presence (Sepulveda et al. 2018). A recent feasibility study demonstrated that retrofitting existing U.S. streamflow gauges with environmental sample processors (e.g., electro-mechanical robots that autonomously filter and preserve water samples) may offer a powerful way to overcome the human resource challenges of collecting samples for eDNA bio-surveillance of rivers over long time periods and across large geographic areas (Selpulveda et al. 2020).

Traditionally, monitoring for invasive species has been largely dependent on organized, on-the-ground campaigns by trained professionals, which are largely limited in their time and spatial scope. Dedicated citizen-science initiatives facilitated by web or mobile application interfaces – such as iNaturalist, eBird, and apps developed to target a specific species or region – are now enhancing knowledge of novel occurrences of invasive species beyond previously feasible scales (Johnson et al. 2020). These digital sharing platforms have enabled data collection to identify new populations of invasive eastern grey squirrel (*Sciurus carolinensis*) in Italy (Mori et al. 2016) and reconstruct the history of non-native monk parakeets (*Myiopsitta monachus*) in Mexico in relation to changes in legal regulations on pet trade importations (Hobson et al. 2017). Citizen observations can also allow managers to rapidly detect and respond to novel non-native and invasive species within their region, such as when Rojas and Jackson (2018) described the first account of the European firebug (*Pyrrhocoris apterus*) in Canada, the significance of which was recognized when the author submitted photographs to the community science project iNaturalist. Third-party expert confirmation of app-based sightings can initiate rapid response efforts, as the data processing flow for New Zealand's Find-A-Pest app exemplifies (Pawson et al. 2020) (Box 2.1).

2.5 Monitoring and Limiting Spread

A key component of managing species invasions is limiting their spread into adjacent regions through natural dispersal. New methods based on digital image analysis, social media scraping, and remote sensing offer more time- and cost-effective means to track species' spread and respond quickly. Next-level monitoring for invasive species detection in remotely collected imagery and community science data could transform from explicit (i.e., designating invasive species of concern to search for) to implicit (e.g., automatic recognition) approaches by leveraging new advances in computer vision systems trained to automatically recognize species (Joly et al. 2016, Demertzis and Iliadis 2017).

Traditional ground monitoring approaches for invasive species are dependent on well-trained human identification of non-native species, which can be prone to long processing times and varying levels of error. Numerous breakthroughs in automating image analysis – or the extraction of information from photos by classifying objects – have facilitated new approaches to identifying invasive plant species remotely and at scale. Morphological Spatial Pattern Analysis, which classifies and quantifies features within digital images according to shape, was more accurate at identifying invasive winter heliotrope (*Petasites fragrans*) than standard visual estimation methods (Carlier et al. 2020). Machine learning based approaches for identifying invasive *Hydrangea* built on convolutional neural networks achieved a near perfect accuracy (99.7%) on test datasets, suggesting that this is a highly effective method for automating recognition of invasive species within digital imagery (Ashqar and Abu-Naser 2019).

Mapping of invasive species across vast landscapes poses challenges in regions with difficult terrain and limited access infrastructure. Traditional large-scale surveys occur predominantly from helicopters or fixed-winged aircraft, both of which can be expensive.

Remote sensing – encompassing an array of tools from high-resolution satellite imagery to small, unmanned aerial vehicles (UAVs, or drones) – has been used to map the distribution of invasive animals, pests, weeds, and diseases at more than ten times less than the cost of manned flights (Jurdak et al. 2015) (Box 2.2), and it offers an opportunity to automate data processing and species recognition. Airborne imaging spectroscopy and laser scanning were used to map the distribution of *Eucalyptus* spp. and black wattle (*Acacia mearnsii*) in eastern African regions where they are invasive, and the authors used a one-class biased support vector machine built on machine learning to identify the target species (Piiroinen et al. 2018) (Box 2.3). Tesfamichael et al. (2018) further demonstrated the ability of remote sensing to automate invasive alien plant species identification by quantifying the efficacy of spectroradiography in distinguishing between similar invasive and non-invasive plants with narrow leaf structures; the results indicated high classification accuracies (83-97%). Drone imagery processing with deep neural networks built on machine learning has also enabled the detection of invasive green anole (*Anolis carolinensis*) in the Ogasawara Islands of Japan (Aota et al. 2021). While UAV use is substantially less expensive than fixed aircraft, mapping with ground surveys is often still the most cost-effective option (Sladonja 2022). Remote sensing has also been employed below the ocean's surface, where deep sea video surveys have revealed the range expansion of Humboldt squid (*Dosidicus gigas*) into waters off central Florida (Zeidberg and Robison 2007).

The development of predictive models to forecast invasive species spread is often hindered by limited available data on species distributions over time, as traditional ground monitoring methods require significant time and resources. With the influx of observation data now available through species-specific mobile applications and social media, however, managers now have the option of crowdsourcing public data to inform species distribution models.

Researchers and management entities designed the community science mobile application "BugMap" to elevate scientific understanding of invasive brown marmorated stink bug (*Halyomorpha halys*) – an agricultural pest – behavior and distribution (Malek et al. 2018). Collected data informed forecasts of the species predicted distribution in a newly invaded region of Northern Italy and led to the discovery of the insect's seasonal invasion dynamics, thus allowing researchers to model areas most likely to be invaded next. Community science data have also informed predictive species distribution models of plants in New England (Botella et al. 2018) and aided in tracking the spread of the invasive harlequin ladybird (*Harmonia axyridis*) in Britain and Ireland (Brown et al. 2018). Van den Burg et al. (2020) further demonstrated the utility of mobile data by developing species distribution models for invasive common green iguana (*Iguana iguana*) in Singapore and Thailand from photos and video on social media (Facebook, Instagram, iNaturalist) and photo-sharing websites (Flickr, iStock Photo, Shutterstock).

Containing invasive species, or preventing their subsequent dispersal into new, adjacent regions can prove challenging, particularly in riverine habitats where managers are simultaneously seeking to maintain habitat connectedness for native species across physical barriers (Rahel 2013). New advances in riverine barrier management offer opportunities to limit species range expansions into new river sections. Artificial barriers that selectively allow fish passage for only native species can be implemented through high-precision classifiers which automatically identify species upon their entry into a barrier passageway. For example, image recognition built on deep convolutional networks achieved a test prediction accuracy of 97% for 13 species in the Great Lakes, including invasive sea lamprey (*Petromyzon marinus*) and four major Asian carps (bighead carp (*Hypophthalmichthys nobilis*), silver carp (*H. molitrix*), black carp (*Mylopharyngodon piceus*), and grass carp (*Ctenopharyngodon idella*)) (Eickholt et al. 2020) (Box 2.3). In addition, bubble curtains, strobe lights, and acoustic barriers targeting the audiovisual systems of invasive carp have also shown some success in providing selective passage for native species, though potential long-term effects of these systems on native populations and their efficacy at deterring invasive species over longer timescales remains unknown (Zielinski et al. 2014, Jones et al. 2021).

2.6 Quantifying and Addressing Ecological Impacts

An integral part of assessing the damage leveed by invasive species is quantifying and addressing the ecological impacts to individuals to ecosystems. Developments in camera trapping, ecoacoustics, and DNA-based methods have recently tackled longstanding challenges in measuring ecological impacts of invasive species across and space and time.

Understanding interactions between invasive predators and their native prey has traditionally depended on first-hand observations of encounters between invasive and native species. However, remote cameras and vehicles now offer an opportunity to document and address these interactions in hard-to-reach locations, and genetic approaches are enabling researchers to parse apart complex interactions. For example, camera traps have been used to identify nest predators of native bird species across tropical rainforests in Brazil (Ribeiro-Silva et al. 2018). In addition, managers have recently demonstrated the use of drones to identify nuisance seagull (*Larus* spp.) nests in France and spray them with a sterilizing fluid, suggesting that remote vehicles could be an effective tactic for not only identifying but also controlling non-native species (Culbertson 2015). To understand more complex interactions between invasive and native species, researchers have increasingly turned to fatty acids and stable isotopes as complementary biomarkers to quantify the trophic ecology of invasive species (Androuin et al.

forthcoming) and trace predator-prey relationships (King et al. 2017, Rubenson et al. 2020). In addition, compound specific stable isotope analysis – or the comparison of isotopic signatures for individual groups of chemicals to examine trophic relationships – revealed that the invasive amphipod *Dikerogammarus villosus* does not primarily impact native populations through predation (Sahm et al. 2020).

Documenting community change due to invasive species introduction typically relies on effort-intensive sampling of species for relative abundance and other community metrics. In support of developing more time and cost-effective measures for quantifying community change, recent advances in ecoacoustics have proposed using sound from the activity of an animal community as an indicator of environmental conditions or ecological changes (Pijanowski et al. 2011). For example, acoustic tools have been used to monitor the distribution of invasive freshwater drum (*Aplodinotus grunniens*) in the Hudson River, New York, which produce sound with a special set of muscles in their body cavity that vibrate against the swim bladder during spawning (Rountree and Juanes 2017). Similarly, the density and presumed impact of the invasive electric ant (*Wasmannia auropunctata*) was estimated according to reductions in calls of the native cricket community in New Caledonia (Gasc et al. 2018). Acoustic techniques for detecting community structure reflect seasonal and spatial changes in species' distributions, providing real-time and constantly updating information on individuals' location and movement (Chhaya et al. 2021).

2.7 Controlling and Eradicating Populations

Once a nuisance species has become established, managers may seek to eradicate a targeted population for a variety of ecological and economic reasons. The heterogenous nature of landscapes in which non-native species establish often makes locating and eliminating all individuals of an introduced species a daunting, and near impossible task. However, enhanced capability to build robots, edit and inhibit species' genes, and identify species in real-time has spearheaded novel approaches to capturing invasive individuals, limiting their reproduction, and assessing the effectiveness of removal efforts.

Significant time and personnel are often needed to execute removal efforts, such as in aquatic environments where underwater dive times are limited and surveying for mobile species' locations in advance requires an extensive additional investment. Remotely operated vehicles (ROVs) offer a solution to locate both stationary and mobile underwater species from above the surface (Sward et al. 2019), and certain models can also interact with or capture target species (Box 2.2). By creating a robotic predator programmed to biomimic the behavior of natural predators of the invasive western mosquitofish (*Gambusia affinis*) researchers showed that even a brief (15 minute) weekly exposure to the robot effectively depletes the mosquitofish' energy reserves and deteriorates its body condition (Polverino et al. 2019). To aid spear-hunting divers in finding and identifying invasive red lionfish (*Pterois volitans*), a small ROV with integrated camera programmed using deep learning showed success in real-time assistive identification of the species and allowed divers to plan their dive prior to entering the water, thus maximizing their catch under time constraints (Naddaf-Sh et al. 2018). Beta-testing by private companies has gone one step further by developing an underwater vehicle, the Guardian LF1 Robot, intended to identify and capture red lionfish (Knight 2021). However, the efficacy of this ROV at trapping red lionfish over broad scales has yet to be tested.

Monitoring of invaded regions during and after removal programs is fundamental to ensuring successful invasive species control (Kettenring and Adams 2011). In the past, program evaluations have depended on time-intensive repeated manual field surveys, but new breakthroughs in remote sensing with drones and ROVs are now enabling scientists to quantify the effectiveness of invasive plant removal from afar. Brooks (2020) used drones and multispectral imagery to compare the reduction level of multiple treatment methods (mechanical harvesting, biological control, and diver-assisted suction harvesting) for Eurasian watermilfoil (*Myriophyllum spicatum*) removal. Autonomous surface vessels on lakes have also been developed to monitor Eurasian watermilfoil growth through imagery and depth information collection, with future work intended to distinguish between Eurasian watermilfoil and native plants (Codd-Downey et al. 2021). Remote sensing also aided in understanding the extent of invasive red imported fire ant (*Solenopsis invicta*) in Southeast Queensland, and in the future aims to confirm eradication of the species in regions treated with removal (Wylie et al. 2021).

Large-scale invasive species control can pose risks to the integrity of ecosystems (e.g., removing non-target native species), and with traditional removal methods, managers must consider the trade-offs of removal and its potential repercussions (Kopf et al. 2017). The development of highly targeted invasive plant herbicide application through helicopter ballistic technology has allowed managers to significantly reduce non-native plant populations on Santa Cruz Island in California with limited damage to non-target species (Cory and Knapp 2014). Recent advancements in the development of smart trapping devices equipped with sensory attractants and automated species recognition can also address this challenge by selectively attracting and capturing target species. Acoustic traps – physical traps equipped with speakers broadcasting reproductive calls – have shown promise as potential control mechanisms for invasive round goby (*Neogobius melanostomus*) in the Great Lakes (Isabella-Valenzi and Higgs 2016) and the invasive pest Asian citrus psyllid (*Diaphorina citri*) in California (Rene Fernandez 2020). Furthermore, scented traps with behavior-modifying semiochemicals are effective at capturing invasive sea lamprey (*Petromyzon marinus*) in experimental settings (Hume et al. 2015). Newly developed "smart pig traps" enhanced with image recognition capability detect and confirm the identity of wild pigs in traps prior to closing their doors (SSU 2019).

Large, well-established, mobile, and rapidly reproducing populations of invasive species are often difficult to control because of the sheer number of individuals in the wild. However, as the potential for genetic manipulation has expanded rapidly in recent years across sectors, we now have a large suite of tools capable of influencing the trajectory of invasive species from within their own ranks (Box 2.4). Gene drives – the use of genetic engineering to propagate a particular suite of genes throughout a population – offer managers a set of tools to influence the reproduction and survival of invasive species on the population scale (Teem et al. 2020). For example, researchers have proposed releasing engineered mice into island rodent populations that only produce male offspring to create a population incapable of reproduction (Leitschuh et al. 2018). Similarly, the development of a CRISPR gene drive targeting spermatogenesis in invasive common wasps (*Vespula vulgaris*) in New Zealand has been proposed as means to reduce or eliminate invasive species outside their native range (Lester et al. 2020). Pathogen introduction has also been proposed as a biocontrol agent, with researchers suggesting that the release of cyprinid herpesvirus 3 (CyHV-3) could be an effective control mechanism for invasive common carp (*Cyprinus carpio*) in Australia (McColl et al. 2016). However, this project is controversial given the uncertainty of potential ecosystem-wide impacts of mass fish kills. Lastly, the development of large biological databases has allowed scientists to effectively screen candidate molecules that may aid as bioinhibitors in invasive species control. Raschka et al. (2018) demonstrated the utility of their Screenlamp modular toolkit for identifying candidate proteins that may inhibit reproductive pheromone receptors in invasive sea lampreys. While genetic manipulation research suggests these technologies are a promising tool for invasive species management, scientists caution that acquiring public support for such programs will require substantial investment in open communication, intensive study of target nuisance species' reproductive biology and genetics, and physical and molecular containment of modified test organisms prior to implementation in the wild (Dearden et al. 2018).

2.8 Public Engagement in Invasive Species Management

Public sentiment toward invasive species management and trust in managers' ability to effectively manage non-native species can determine societal support for conservation actions (Bremner and Park 2007, Wald et al. 2019). Failure to adequately gather public perspectives could result in the public's refusal to engage in management efforts related to invasive species or outright opposition to planned actions (Kapitza et al. 2019). New innovations in social media scraping and web-based tools have enhanced our ability understand public discourse around invasive species and proactively educate and engage the public in management efforts.

Culturomics, or the study of human behavior and cultural trends through analysis of digital text and images, offers valuable insight into human attitudes around conservation and invasive species (Box 2.5). Information on human-nature interactions and human thoughts and attitudes about conservation is available through social media, smartphone applications, and online forums, and offers data at previously unfeasible spatial and temporal scales (Correia et al. 2021). Data mining of existing online networks and forums within naturalist, hunting, and angling communities can provide managers valuable information about public sentiment around invasive species (Jaric et al. 2021). A manual analysis of Tweets shared through the micro-blogging platform Twitter containing messages related to three invasive alien species (oak processionary moth *Thaumetopoea processionea*, emerald ash borer *Agrilus planipennis*, eastern grey squirrel *Sciurus carolinensis*) showed that social media channels are an extensive source of observational data and elucidate the nature of public discourse surrounding invasive species (Daume 2016). In addition, Sbragaglia et al. (2020, 2021) demonstrated through a content analysis of angler comments on YouTube videos that anglers hold contrasting sentiments towards invasive species, and thus control measures may accrue the support of only some, but not all, stakeholders.

When empowered with adequate tools and education, the public can also aid in removal efforts. Social media and web-based platforms provide an opportunity to solicit public assistance and make invasive species information available on a global scale. For example, social media networking was used to organize and facilitate a grass-roots red lionfish removal program in the British Virgin Islands (Forrester et al. 2021). In New Zealand, the Find-A-Pest cell phone application (http://www.findapest.nz/) was developed through a co-design effort involving indigenous tribes, agricultural and forestry sector representatives, iNaturalist, and regional and national government agencies. This mobile application allows users to report potential sightings of invasive weeds, insects, fungi, and other non-native animals via photographs or identification based on species' factsheets. App users collectively identify reported sightings via iNaturalist New Zealand, and those confirmed as potential invasive species are then forwarded to Biosecurity New Zealand. In a 3.5-month case study of 471 observations covering 176 taxa, crowd-sourced citizen identifications were correct 95.5% of the time (Pawson et al. 2020). Researchers have also proposed the development of a global open, zoomable atlas of invasion science which would provide critical information to both the public and policymakers on species' distributions and impacts (Jeschke et al. 2021).

2.9 Challenges and Opportunities for Management Success

Emerging technologies in invasion science offer much promise for expanding the scope and improving the effectiveness of management tactics and policy actions. The new technological methods we have described are often based on remotely sensed or web and cell-based data sources, which serve as cost-effective, automatically updating sources of data collection for ecological monitoring. Drones, ROVs, DNA barcoding, web scraping, smartphone applications, and image classification are just a handful of the new tools available to enhance the tracking and management of invasive species.

Although the growing utility of new technological innovations within invasion science is promising, numerous challenges related to the uptake of new technologies by practitioners in remote regions continue to hinder the integration of these data into management systems (Daume 2016). Here, we discuss specific barriers to the application of new approaches within invasion science and outline key areas to propel the use of new technologies in management. Enhanced technologies alone will not improve conservation; only by establishing the pipelines needed to provide these tools to end-users can we hope to improve invasive species management.

Invasive species management trails other fields in its implementation of emerging technologies. Indeed, a recent survey of conservation practitioners and academic researchers found that automated processing of data streams was the greatest need to expediate the uptake of technologically innovative methods (Hahn et al. 2022). Greater investment in collaborations with disciplines possessing a longer history of implementing automated methods, such as engineering and computer science, will undoubtedly aid invasion science in the integration of new technologies. Furthermore, big crowd-sourced data are not necessarily the panacea to data limitations currently facing the field of invasion science. For example, a study using the community science sourced Invasive Plant Atlas of New England found that the predictive ability of abundance models for invasive plants were poor, suggesting that the inconsistent nature of occurrence reports from applications may not effectively represent a species distribution over some scales (Cross et al. 2017).

Despite such limitations, however, we believe by addressing a handful of significant barriers, invasion science can make significant strides in harnessing new technologies for management good. First, formalizing data sharing guidelines is critical for developing regional partnerships. Data must be seen as products of research rather than as solely stepping-stones to publications (Hampton et al. 2013), and data acquired through drones, remote cameras, and web scraping methods must traverse the fine line between prioritizing human anonymity and explicitly detailing how they were procured (Sandbrook et al. 2021). A recent review of community science initiatives collecting invasive species observations found that just half (54%) of programs had a practice of data sharing, which may be impeding more widespread use of these data (Johnson et al. 2020). In decision-making programs aiming to integrate multiple types of data, it is also vital that resource managers understand the strengths and weaknesses associated with each methodological approach and communicate this to future users (Kamenova et al. 2017).

Second, end-users are in desperate need of powerful interfaces to readily access and disseminate the large datasets used in many of these new technological approaches. Numerous monitoring and reporting frameworks for managing invasive species across networks have been proposed, but these ambitious management schemes are only feasible through large-scale information collation supported by easy-to-use interfaces (Shackleton et al. 2020). Digitization of data collection can facilitate more timely analysis leading to faster management decision making during rapid response efforts (Will et al. 2014), but the pace of data integration depends on the extent of digital infrastructure connecting an observation of an invasive species to the relevant management agency. Furthermore, the most useful research outcomes may be those that directly integrate large datasets into decision support tools. For example, Bradie et al. (2021) developed a decision tool with Transport Canada to prioritize locations for ballast water compliance monitoring based on rankings of invasive species establishment risk.

Third, the uptake of new technologies by resource managers may be further spurred by enriched interactions between technology developers, end-users, and stakeholders, with a focus on identifying opportunities for co-generation of knowledge. For many decades researchers and managers have advocated for increased collaboration in invasive species science and management (Vaz et al. 2017), and the adoption of technologically enhanced approaches warrants a renewed emphasis on working together. Engagement of partners from other sectors, particularly computer science, engineering, and industry, could spur novel technological applications within invasive species management (Joppa 2015, Martinez et al. 2020). Collaborators should endeavor to first understand the technical knowledge of their management partners though, as field-specific understanding can strongly influence managers' perceptions of new conservation methods (Bernos et al. 2022). Moreover, crowd-sourced technologies such as community science applications and social media sites offer an opportunity to recruit contributors to conservation science, educate users, and serve as a medium for open and responsive communication of management intentions (Di Minin et al. 2015, Crowley et al. 2017).

Fourth, many new technologies are expensive and will remain out of reach to scientists and practitioners in many regions unless costs are reduced. For example, image recognition built on artificial intelligence can require significant hardware, software, and specialist staff, which may be unattainable to many (Lamba et al. 2019). Despite reductions in the cost of some technological methods since their initial development (e.g., eDNA), prohibitive cost is the most cited barrier limiting technology uptake within the conservation community (Hahn et al. forthcoming). Future technological development should prioritize methods that are financially accessible to practitioners globally.

Lastly, training skills enabling practitioners to readily use new technologies are not universally available. While disparities in technology accessibility are starting to narrow across the globe, support services integral to the sustained use of conservation technology (e.g., product maintenance, technical advice, and training on data collection, management, and analysis) continue to be limited (Lahoz-Monfort et al. 2019). Furthermore, projects often lack a designated technologist to offer technical support (Hahn et al. 2022). Open-source software and hardware (e.g., Raspberry Pi, Arduino) have created development environments for computational and tactile tools that may alleviate cost and access barriers, yet acquiring the knowledge base to develop technical products and analyses for specific management purposes remains challenging. For management entities lacking internal technical expertise, the development of cross-boundary networks sharing technical knowledge and methods for invasive species management is crucial.

2.10 Conclusions

Uptake of new technologies within invasive species management holds considerable promise for improving our ability to recognize and respond to novel species' invasions quickly and efficiently. However, as with any new technology, one must show its equivalence or advantages over the current methods. Furthermore, for the democratization of new technologies to be fully realized, significant work is needed to implement the data sharing practices and platforms necessary to integrate big data into management networks. Future investments should also focus on supporting application in remote and low-technology environments where frontline management actions are critical. In an increasingly connected world, both physically and digitally, the potential for invasive species to occur in new locations seems limitless. Rather than solely responding to the impacts of globalization and technological innovation, it is time for invasive species scientists and managers to turn the tables and leverage technology to their advantage. In the face of rapid human-assisted movement of invasive species, it is paramount to develop new tools and harness those at our disposal to identify, prevent, control, and eradicate harmful species.

2.11 Acknowledgment

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2.12 TABLES, FIGURES & BOXES

Table 2.1 Examples of new technologies for managing invasive species. Listed by type of technology, strengths and weaknesses of each technology, and the invasion stage that each example addresses.

Technology	**Strengths**	**Weaknesses**	**Stage**	**Citation**	**Summary**
Acoustic Barriers	Inexpensive, can be species-selective, and applicable in both lotic and lentic aquatic environments.	Passage rates of native species are rarely evaluated, and efficacy has yet to be tested long-term.	Spread	*Jones et al. 2021*	Reviewed use of acoustic and light barriers to limit the spread of aquatic invasive species.
				Zielinski et al. 2014	Showed bubble curtain can contain invasive common carp spread.
Acoustic Traps	Low-impact method that does not reduce native species numbers.	Mating disruption does not impede species migration, and audio distance to attract pests is unknown for some species.	Control	*Fernandez 2020*	Developed a prototype acoustic trap with open-source software for invasive citrus psyllid.
				Isabella-Valenzi & Higgs 2016	Captured more invasive round goby with acoustic traps broadcasting reproductive calls than control.
Camera Traps	Significantly reduces the time and cost of sampling labor, particularly for low-density species.	Trade-offs between number of cameras (most significant cost factor) and detection bias.	Detection in Wild	*Davis et al. 2020*	Showed cameras were more cost effective than DNA or trapping to estimate invasive pig density.
				Lamelas-López & Salgado 2021	Inventoried invasive mammals on an oceanic island and estimated abundance and detection capability.

				Willi et al. 2018	Identified species in images and differentiated from non-species images using image recognition.
			Ecological Impacts	*Ribeiro-Silva et al. 2018*	Identified bird nest predators from camera trap images and quantified percent depredation.
DNA Barcoding	Presents cost-effective opportunity to develop an early detection system (particularly at ports).	Reference library development is needed to increase the number of cataloged species.	Introduction Pathways	*Borrell et al. 2017*	Detected invasive invertebrates in port water with high-throughput DNA sequencing.
				Burg et al. 2014	Determined the wildlife trade origin of invasive butterflies by comparing wild and captive DNA.
				Madden et al. 2019	Identified invasive moths at U.S. ports-of-entry based on DNA matches.
Ecoacoustics	A non-intrusive, and relatively inexpensive approach to implement over large spatiotemporal scales.	Call absence does not mean species is absent, and ability to detect distribution may be seasonal based on mating.	Ecological Impacts	*Gasc et al. 2018*	Demonstrated the utility of reductions in cricket calls as an indicator of invasive ant presence.
				Rountree & Juanes 2017	Quantified the distribution of invasive freshwater drum by monitoring the species' distinct sound.
eDNA	Techniques like qPCR and high-throughput sequencing are increasing available and affordable to facilitate early detection of introduced species.	Potential for false negatives and false positives, and requires technical expertise for laboratory processing or contract services.	Detection in Wild	*Clare et al. 2022*	Collected eDNA from the air to identify mammal and bird species in a wildlife park.
				Feist & Lance 2021	Reviewed advanced eDNA methods for zebra and quagga mussel detection.
				Roy et al. 2018	Tested live trade shipments of freshwater fish for eDNA of invasive species.

				Sepulveda et al. 2018	Demonstrated the efficacy of a field-based platform to rapidly screen for invasive northern pike eDNA.
				Sepulveda et al. 2020	Showed the utility of retrofitting existing streamflow gauges with eDNA surveillance.
Genetic Manipulation	Biocontrol methods are more humane than traditional chemical controls, and may require less time to carry out that traditional methods.	Connectivity between native and invasive range may prevent implementation, and the inability to regulate gene edits once released into wild populations could result in unintended consequences for native and non-native species.	Control	*Bhattacharyya et al. 2020*	Optimized a model of genetically modified supermale fish introduction to eradicate invasive species.
				Evans et al. 2019	Released transgenically modified mosquitoes, and genome was incorporated into target population.
				Garbian et al. 2012	Fed honey bees RNA that is transferred to their mite parasites, inducing gene silencing and parasite decline.
				Leitschuh et al. 2018	Proposed releasing engineered mice which only produce males into island rodent populations.
				Lester et al. 2020	Suggested development of a CRISPR gene drive to eliminate invasive common wasps.
				McColl et al. 2016	Proposed release of cyprinid herpesvirus to control invasive common carp.
				Reinders et al. 2022	Showed the SmartStax PRO pesticide silences western corn rootworm genes, reducing adult survival.
Machine Learning	Can enhance the speed of other innovative methods	Requires technical expertise to assemble,	Spread	*Ashqar & Abu-Naser 2019*	Classified invasive Hydrangea in an image dataset with neural network analysis.

	(e.g., camera traps, remote sensing) by automating image processing or even identifying species in real-time.	and may be expensive to contract assistance.		*Carlier et al. 2020*	Classified invasive winter heliotrope in photographs with morphological analysis.
				Eickholt et al. 2020	Automated recognition of invasive sea lamprey and Asian carp to prevent passage through barriers.
				Kedia et al. 2021	Mapped invasive vegetation in an arid region with machine learning classification of drone imagery.
				Piiroinen et al. 2018	Mapped invasive tree distribution with machine learning-based classification of drone imagery.
			Control	*SSU 2019*	Enhanced feral pig traps with image recognition to confirm species identity before closing.
Remote Sensing	UAVs cost substantially less than manned aircraft, can survey remote environments, and can hover over regions for long time periods for temporal monitoring.	Though cheaper than manned crafts, UAVs are still costly. Furthermore, their use is not permitted in certain management areas (e.g., wilderness).	Spread	*Ahmed et al. 2021*	Modeled the distribution of an invasive plant in Ethiopia with satellite imagery.
				Aota et al. 2021	Detected an invasive lizard species with neural network analysis of drone imagery.
				Gong et al. 2020	Distinguished native from invasive species in the Yellow River Delta, China with satellite imagery.
				Jurdak et al. 2015	Reviewed autonomous technologies for biosecurity surveillance.
				Kattenborn et al. 2019	Combined satellite and UAV data to map invasive woody species in Chile.
				Sladonja et al. 2022	Used drones to map the distribution of invasive plants along riverbanks in Croatia.

				Tesfamichael et al. 2018	Compared the invasive plant classification accuracy across five different satellite imagery datasets.
			Control	*Brooks 2020*	Compared the reduction of treatment methods for watermilfoil with drones and multispectral imagery.
				Wylie et al. 2021	Calculated the extent of invasive ants and will confirm eradication through removal treatments.
ROVs	Can be equipped with underwater cameras and sensors to identify and capture invasive species, and reduce the time and manpower needed to inspect ship for hull fouling.	Development of ROVs for specific intervention tasks can be expensive, and non-autonomous vehicles require a permanent connection to a power source.	Spread	*Mehler et al. 2018*	Modeled distribution of zebra/quagga mussels with underwater ROV imagery.
			Control	*Codd-Downey et al. 2021*	Monitored watermilfoil growth with autonomous surface vessel imagery.
				Culbertson 2015	Identified nuisance seagull nests with drones and sprayed with sterilizing fluid.
				Knight 2021	Developed a robot to identify and capture invasive red lionfish.
				Naddaf-Sh et al. 2018	Conducted in-water video surveys to aid in planning and effectiveness of removal dives.
				Polverino et al. 2019	Created a robotic predator to biomimic the behavior invasive mosquitofish' natural predators.
				Zeidberg & Robison 2007	Quantified the range expansion of Humboldt squid with deep sea video surveys.
			Ecological Impacts	*Guedes and Araujo 2022*	Used ROV imagery to survey fish communities across depth zones in a Brazilian reservoir.

Scented Traps	Increases the efficacy of trapping, as more individuals navigate to the trap faster.	Species can respond differentially in lab and field settings, and trap effectiveness may vary by location.	Control	*Hume et al. 2015*	Decreased arrival time of invasive sea lamprey in traps with strategic repellent odor distribution.
				Johnson et al. 2009, 2013	Lured female invasive sea lampreys into traps with male mating pheromones.
Smartphone Apps	Low-cost opportunity to crowdsource data from app users and community scientists.	Specialized app development requires significant time input and technical expertise, and app user populations can be biased.	Introduction Pathways	*Fricke et al. 2020*	Calculated angler movement frequencies within invasive species' desiccation tolerance.
				Papenfuss et al. 2015	Quantified lake visitation and angler movement patterns from posts to a fishing application.
			Detection in Wild	*Pawson et al. 2020*	Described the Find-A-Pest smartphone application for reporting invasive species in New Zealand.
			Spread	*Malek et al. 2018*	Designed the community science mobile app "BugMap" to forecast invasive stink bug distributions.
Social Media	Web and app-based platforms are a low-cost opportunity to both collate species observations and disseminate educational materials to the public.	Subject to significant biases within user populations, and access to specific platforms can change rapidly as tech companies adjust their policies. Social media data can complement, but generally not replace, expert species distribution datasets.	Introduction Pathways	*Monkman et al. 2018*	Scraped online social media forums to quantify the spatiotemporal distribution of angling recreation.
				Harrington et al. 2021	Examined exotic pet trade by extracting information from exporters' public Facebook accounts.
			Detection in Wild	*Botella et al. 2018*	Compared invasive species distribution models from app-based observations to expert inventories.
				Brown et al. 2018	Collated a dataset of invasive harlequin ladybird observations through app and online reporting.

				Hobson et al. 2017	Quantified historic invasive parakeet abundance from eBird and iNaturalist observations.
				Mori et al. 2016	Identified new populations of invasive eastern grey squirrel with iNaturalist observations.
				Rojas & Jackson 2018	Described the first account of invasive European firebug in Canada from an iNaturalist observation.
			Spread	*Allain 2019*	Showed Flickr records of introduced turtles reflect the spatiotemporal distribution of traditional observations.
				van den Burg et al. 2020	Developed distribution models for invasive iguana from social media and photo-sharing websites.
			Public Engagement	*Daume 2016*	Analyzed Tweets to understand public discourse around three common invasive species.
				Forrester et al. 2021	Organized a grass-roots lionfish removal program with social media networking.
				Mehmet et al. 2018	Assessed the polarity of stakeholder attitudes toward invasive carp management.
				Mittermeier et al. 2021	Quantified Wikipedia page views for hundreds of bird species.
				Sbragaglia et al. 2020, 2021	Examined angler comments on YouTube to characterize sentiments toward invasive species.

				Wyckhuys et al. 2019	Assessed internet salience of invertebrate biological control agents.
Stable Isotopes	Can determine the environmental history and diet of invasive species.	Requires intensive lab analysis, though the cost of sample testing has declined in recent years.	Introduction Pathways	*Hill et al. 2020*	Demonstrated distinct stable isotope ratios of invasive wild and captive red-eared slider turtles.
			Ecological Impacts	*King et al. 2017*	Used stable isotopes and fatty acids to understand the fish consumption of cormorant populations.
				Rubenson et al. 2020	Quantified introduced smallmouth bass impacts on Chinook salmon with stable isotopes and fatty acids.
				Sahm et al. 2020	Examined the trophic interactions of invasive amphipods with compound specific stable isotopes.
Web Scraping	Facilitates identification of new species entering the exotic pet and wildlife trades.	Users often post species with colloquial names, which can make identification challenging.	Introduction Pathways	*Olden et al. 2021*	Scraped data from online aquarium marketplaces to reveal potential trade routes for invasive species.
				Stringham et al. 2021	Provided guidance for wildlife trade surveillance through web-based interfaces.
Web Tools	Can disseminate information on invasive species in a centralized, easily accessible manner.	Uptake is dependent on public choosing to actively engage with the web tool.	Public Engagement	*Jeschke et al. 2021*	Proposed development of an open, global atlas of invasion science for public and policymakers.

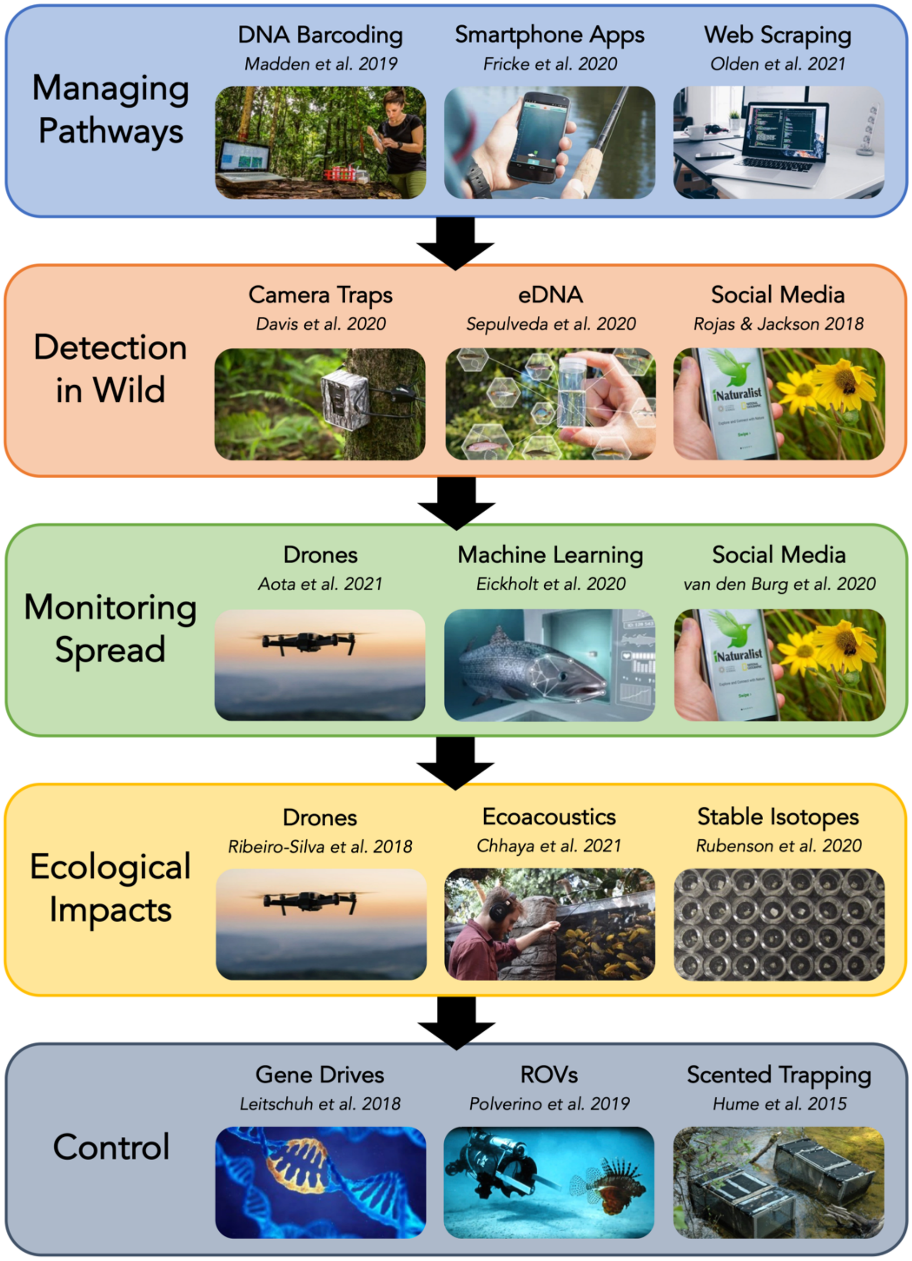
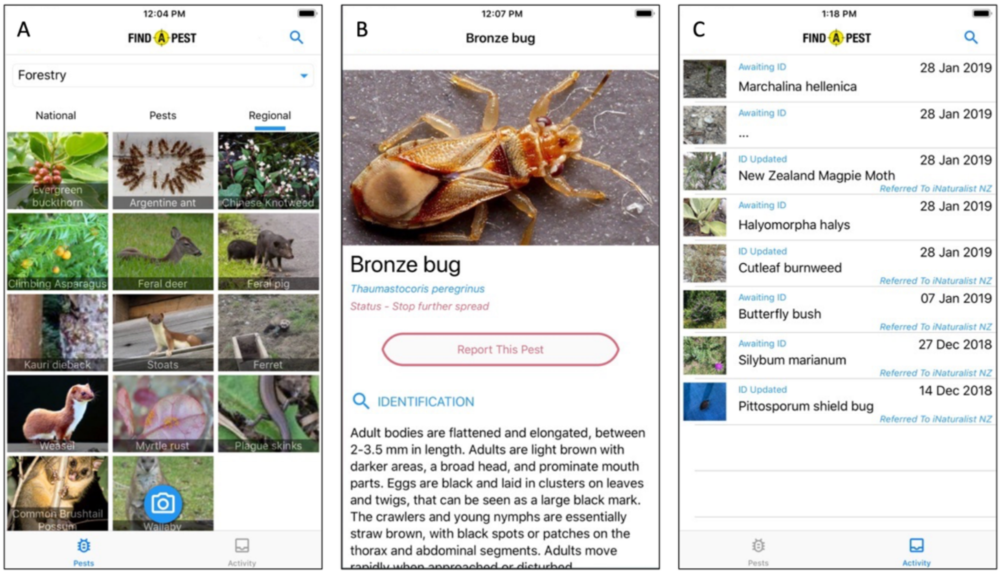
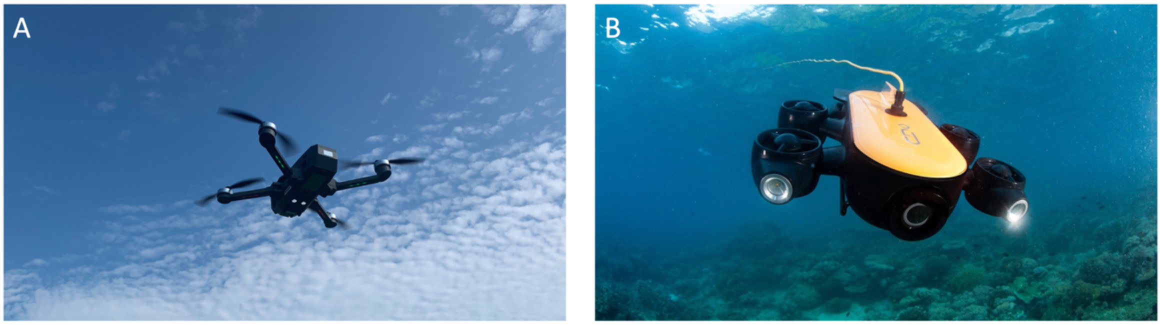


Figure 2.1 New technologies offer exciting opportunities to advance knowledge in invasion science, enhance management actions, and guide policy strategies. Shown here are example technologies, with representative citations, grouped by the stage of invasion (left) they have been used to address. Arrows indicate the progression of introduced species through the stages of invasion. All photos licensed under Creative Commons.



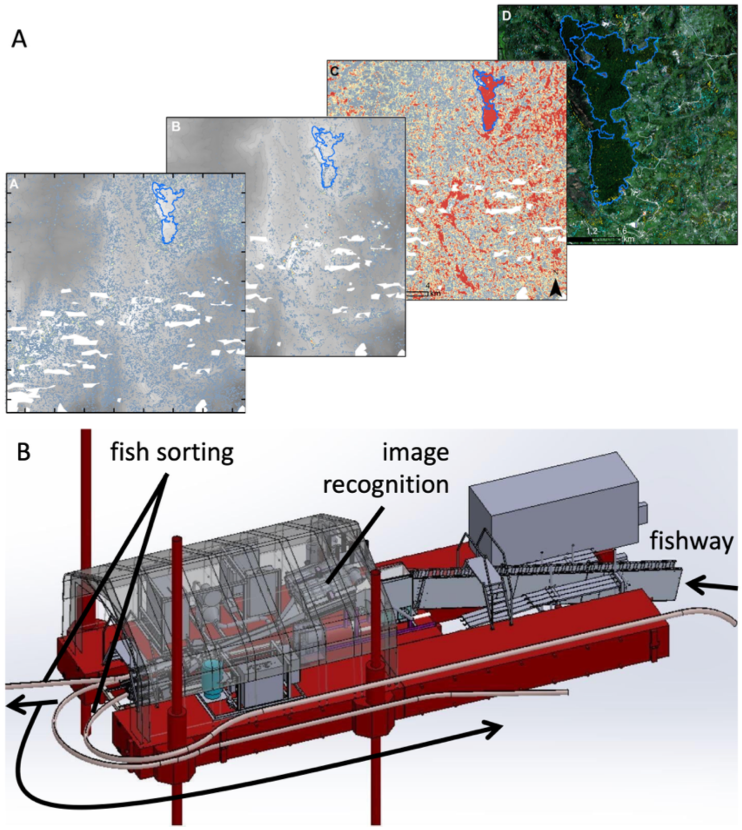
***Box 2.1** Mobile applications and social media data offer new avenues for streamlining species observation processing and initiating rapid responses to species invasions*

Social media and cell phone applications are dramatically altering the landscape of data available on invasive species distributions, as well as opening opportunities for the development of dedicated platforms to rapidly identify and respond to novel invasions. Social media posts to both wildlife-specific platforms (e.g., iNaturalist, eBird) and broader social sites (e.g., Twitter, Instagram) can be leveraged to identify species introductions and spread. For example, records of introduced freshwater turtles in the United Kingdom from the photo-sharing application Flickr largely reflect the spatiotemporal distribution of traditionally reported observations (Allain 2019), and researchers may be able to track the trade of exotic pets by monitoring distributors' Facebook pages (Harrington et al. 2021). Ultimately, mobile platforms which integrate species observations into expert-verified reporting systems – such as New Zealand's Find-A-Pest application – may be the most effective avenues for leveraging community science sightings and initiating a rapid response to new species invasions (Pawson et al. 2020). This application allows users to view invasive species within a selected region (A), peruse the profile and biography of invasive species (B), and monitor the status of their submitted observation (e.g., awaiting identification, referral initiated) (C) (Photo credit: iTunes Search API). Despite the growing number of invasive species reporting applications available, these platforms still lack the user engagement (e.g., gamification of invasive species identification and reporting) needed to promote widespread and sustained use (Howard et al. 2022).



Box 2.2 *Remote-operated vehicles and remote sensing improve invasive species monitoring*

Remote-operated vehicles (ROVs) and remote sensing have enhanced our ability to monitor and detect species underwater and in remote land regions. Satellite imagery from Earth observation systems such as Sentinel-2 and the Landsat program have enabled species distribution mapping of the invasive plants *Pinus radiata*, *Ulex europaeus* and *Acacia dealbata* in Chile, *Spartina alterniflora* in China, and *Prosopis juliflora* in Ethiopia – to name a few examples (Kattenborn et al. 2019, Gong et al. 2020, Ahmed et al. 2021). Unmanned aerial vehicles (UAVs), or drones (A), have further enhanced aerial mapping by allowing cameras to fly at lower elevations necessary for capturing high-resolution imagery to differentiate between species. This capability is particularly useful in arid regions where species tend to be smaller, and in finer-scale areas of species cover such as riverbanks (Kedia et al. 2021, Sladonja et al. 2022). In aquatic environments, underwater remote operated vehicles (ROVs) (B) equipped with cameras can map the distribution of invasive species such as zebra mussel (*Dresseina* spp.) (Mehler et al. 2018). Video footage from ROVs has also been used to quantify spatiotemporal shifts in fish communities, providing evidence that native catfish (*Loricariichthys castaneus*, *Pimelodella lateristriga*) in a Brazilian reservoir have moved to deeper water in response to the introduction of exotic cichlids (*Cichla spp., Coptodon rendalli*) which prefer shallower zones (Guedes and Araújo 2022).



Box 2.3 *Enhancing image analysis and invasive species identification through machine learning approaches*

Machine learning is rapidly enhancing invasive species management through automated recognition and classification of image and text data. For example, Piiroinen et al. (2018) mapped the occurrence of invasive trees *Eucalyptus* spp. and black wattle *Acacia mearnsii* in Kenya using a combination of airborne imaging spectroscopy and laser scanning, followed by machine learning-based classification of imagery. The authors classified crowns separately for the two species of interest using a biased support vector machine algorithm – a type of one class classification approach for image recognition which only requires labeled training data for the positive class (i.e., a single tree species). Species occurrence in relation to environmental variables was then used to predict its distribution over the entire area, enabling region-wide mapping of occurrence for each species (A). In addition to automating image processing, machine learning can also aid in real-time identification of individuals as native or non-native. Eickholt et al. (2020) tested this concept by passing specimens of 13 fish species (including invasive sea lamprey and Asian carp) through a fish imaging scanner developed by Whooshh Innovations (B). Images were then classified with deep convolutional neural networks and achieved an accuracy of 97% on a test dataset of species' images, thus demonstrating the viability of automated, image recognition in fish passage systems.

Box 2.4 *New methods for genetic manipulation provide opportunities to identify and suppress invasive populations*

Genetic-based techniques for invasive species identification and suppression – including but not limited to eDNA, gene drives, transgenes, gene silencing, and supermales – have revolutionized invasive species management. Our ability to extract and classify trace amounts of species DNA within environmental samples from land, water, and even air has expanded rapidly with increasingly accessible and affordable techniques such as qPCR and high-throughput sequencing (Larson et al. 2020, Clare et al. 2022). eDNA can aid in invasive species detection by allowing managers to search widely for new species within an environment or target specific nuisance species. Transgenes – or the introduction of one or more foreign DNA sequences from another species by artificial means – could serve as an effective control method for invasive species through the introduction of modified individuals containing detrimental genes. For example, to suppress mosquito-borne diseases transgenic mosquitoes *Aedes aegypti* with a dominant lethal gene were introduced and incorporated into the genome of a mosquito population in Brazil (Evans et al. 2019). Furthermore, prevention of gene expression through gene silencing has reduced populations of the honeybee ectoparasite *Varroa destructor* and nuisance western corn rootworm *Diabrotica virgifera virgifera* (Garbian et al. 2012, Reinders et al. 2022). Lastly, supermale fish – individuals with a YY sex chromosome – have been introduced into invasive fish populations to skew the gender ratio towards males, ultimately causing population eradication (Bhattacharyya et al. 2020).

Box 2.5 *Computational social science to understand public attitudes toward invasive species management*

The study of human behavior and attitudes through analysis of digital data can inform invasion science by revealing human sentiment toward and awareness of invasive species (Jaric et al. 2021). Analyses within this sub-field have quantified polarity of stakeholder attitudes toward invasive fish management, Google search volumes for invasive fire ants, internet salience of invertebrate biological control agents, and Wikipedia page views for hundreds of bird species (Mehmet et al. 2018, Fukano and Soga 2019, Wyckhuys et al. 2019, Mittermeier et al. 2021). In addition to estimating the efficacy of invasive species management based on public interest and support, computational social science also offers an opportunity to leverage digital activity for early detection of invasive species in global trade. Enhancing international biosecurity and identifying global dispersal networks of invasive species is a top priority for invasion science (Ricciardi et al. 2021). Biosecurity management could employ computational methods by monitoring digital species trade forums for mentions of new species and shipping destinations and anticipating the locations and type of potential new species' introductions in advance (Olden et al. 2021).

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Chapter 3. MULTIPLE SOURCES OF VOLUNTEERED GEOGRAPHIC INFORMATION STRENGTHEN HOLISTIC ESTIMATES OF LAKE VISITATION

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3.1 ABSTRACT

Lakes provide human societies with a wide range of cultural ecosystem services (CES), yet these benefits are rarely quantified. Site visitation is frequently used to assign CES values to recreational destinations, but traditional approaches for estimating lake visitation have limited spatiotemporal extent. Visitation estimates increasingly leverage volunteered geographic information (VGI) to address this challenge. We compared the utility of five different sources of VGI from Flickr, eBird, iNaturalist, Twitter, and Gaia GPS, which broadly encompass lake users with different motivations for interacting with nature. We evaluated the potential for predicting on-site visitation from in-person counts by testing models informed by unique combinations of VGI sources at urban and suburban lakes in western Washington. Additionally, we investigated the amenities driving differences in relative lake visitation by modeling visitation as a function of lake attributes (e.g., tree cover, water quality, built infrastructure). All VGI sources were included in the top-performing visitation models, suggesting they provide significant and unique contributions to estimates of overall lake use (*combined* $R^2 = 0.85$). Given that these VGI sources reflect different types of lake users seeking unique CES, we conclude that holistic VGI visitation estimates should incorporate a diversity of VGI sources. Our results also reveal that built lakeside infrastructure is the predominant driver of visitation at lakes in western Washington, suggesting that spatially equitable updates to amenities will encourage public lake use. We urge

greater consideration of the accessibility of different lake-based CES across the landscape and among diverse communities in future lake recreation planning, and suggest that VGI-based estimates of lake visitation offer a robust way to inform this process.

3.2 INTRODUCTION

Ecosystem services represent a valuable lens by which to understand the diverse benefits humans derive from the natural world. Freshwater ecosystems, such as lakes and reservoirs, offer drinking water, support biodiversity, and provide numerous types of recreation opportunities (e.g., fishing, boating, swimming, camping), all of which are highly valued by people (Reynaud and Lanzanova 2017, Vári et atl. 2022). Additionally, non-material cultural ecosystem services (CES) such as sense of place, physical and mental health, and spiritual or aesthetic value are supported, despite being markedly undervalued both globally and in freshwater ecosystems, including lakes (Gascon et al. 2017, IPBES 2019). The value of water-based services varies spatially within and between watersheds, highlighting that understanding the spatiotemporal distribution of freshwater CES is critical to managing water resources with the goal of meeting and preserving societal demands and values (Wantzen et al. 2016, Tomscha et al. 2017).

Lakes and reservoirs are globally ubiquitous and support critical ecosystem functions, provide numerous goods and services, and contribute to sustainable local and regional communities (Klessig 2001, Reynaud and Lanzanova 2017). Furthermore, lakes (and their adjacent parks) in urban and suburban settings serve as hotspots of connections to nature and offer heat stress relief in the midst of urban heat island effects and more intense and frequent climate-induced heatwaves (Gunawardena et al. 2017). Given lakes' multidimensional role in supporting human well-being, understanding human activity on them is important for natural resource valuation, prioritizing restoration and conservation efforts and ensuring equitable access for people (Hossu et al. 2019, Meyerhoff et al. 2022). This necessity only heightens when considering the magnitude of human impacts on freshwater ecosystems, both today and projected in the future (Jenny et al. 2020, Woolway et al. 2022).

Human visitation is one fundamental metric by which researchers commonly assess CES at sociocultural points of interest (Adamowicz et al. 1994). Human activity on waterbodies across time and space is frequently inferred from sparsely conducted visitor counts providing data with limited spatiotemporal scope (Davis and Darling 2017). Conventional approaches typically rely on direct in-person surveys or passive sensors for counting people or vehicles (often at boat launches), while other studies rely on mail-in questionnaires sent to registered anglers or boaters (Yi and Herriges 2017). All of these methods offer only a snapshot estimate of activity at particular locations and times (Rothlisberger et al. 2010, Anderson et al. 2014). Furthermore, such approaches are often biased toward older individuals and those who frequently visit sites of interest, and participants can typically only recall the locations they have visited most recently (Dolsen and Machlis 1991, Shonkwiler and Englin 2009).

Visitation data is valuable for understanding human preferences in leisure and recreational choice. High quality visitation estimates allow managers to identify hotspots of recreational activity and assess the drivers (e.g., environmental quality, built infrastructure) of revealed preferences in where humans engage in leisure and activities (Liu et al. 2022). In a lake context, these can be characterized as lake users who benefit from spending time on or adjacent to lakes and the supply of different types of lakes or lake access available within a given region they might choose to visit. From a resource planning perspective, revealed preference analyses enable managers to assess which attributes of sites attract visitors (Ewing and Kulka 1979, Ghermandi 2018) and prioritize enhancement of these features when upgrading existing or developing new points of access (Horne et al. 2005).

More recent work has modeled lake visitation and overland connectivity from volunteered geographic information (VGI) derived from mobile device applications developed specifically for anglers (Venturelli et al. 2017, Fricke et al. 2020, Weir et al. 2022). However, such methods narrowly target specific user groups and associated activities (e.g., anglers and boaters), precluding opportunities for more evaluating CES in locations with a diversity of activities. With increasing internet connectivity and mobile device use, researchers have begun testing whether mobile device applications and crowdsourced data generated by user posts can serve as proxies for empirical visitation at recreational sites of interest (Wood et al. 2013). For example, Keeler et al. (2015) and Nelson et al. (2023) observed the number of geotagged photographs on the image-sharing website Flickr had utility for estimating on-site lake visitation across regional scales. Although data from diverse mobile device applications are commonly all labeled VGI, and some are at times considered as substitutable, different mobile device applications have distinct user bases and community cultures (Boyd and Ellison 2007).

VGI is often strongly associated with ground-truthed visitation estimates for recreational points of interest. At US National Parks, for example, estimated visitation by the National Park Service each month corresponded highly with the number of photographs shared on Flickr of the same months (Sessions et al. 2016). Significant positive associations between estimates of actual visitation and those estimated from VGI have also been quantified at local city parks, regional state parks, and global recreational sites (Wilkins et al. 2021). Similar analyses have been conducted for water bodies, but thus far lake visitation has exclusively been evaluated with data from singular VGI sources, predominantly Flickr (Keeler et al. 2015, Nelson et al. 2023, Schirpke et al. 2021). Ideally, estimates of visitation incorporate multiple sources of mobile data, as data from different types of VGI sources (e.g., social media, citizen science, activity sharing) represent specific user groups and their coverages vary in temporal and spatial granularity (Heikinheimo et al. 2020). The value and accuracy of different VGI sources for estimating lake visitation has yet to be evaluated, despite emerging evidence for the benefit of such investigations (Tenkanen et al. 2017, Wood et al. 2020).

Here, we use data from five different sources of VGI – representing users with potentially different motivations to interface with nature – to model visitation at lakes in Western Washington, United States. These VGI are derived from mobile device applications that passively collect geo-referenced records from users who interact with the applications for different purposes that may broadly reflect different types of human-nature interactions (Havinga et al. 2020). Our study assesses the relative value of different sources of VGI for estimating visitation by comparing predictive visitation models informed by various combinations of different VGI data sources to empirical visitation counts. We also seek to better understand which built and environmental attributes (e.g., tree cover, water quality, built infrastructure facilitating lake access) may be responsible for differences in lake visitation to inform how urban planners might meet leisure and recreation preferences and enhance the delivery and durability of CES.

3.3 METHODS

3.3.1 *Study Area*

The study area encompasses 50 urban and suburban lakes in Western Washington, United States (Figure 3.1). The lakes range in surface area from 41 to 180 km^2. Water clarity of the lakes span from mesotrophic (moderate nutrients, moderate water clarity) to oligotrophic (low nutrients, high water clarity) (mean Secchi depth = 3.7 m, SD = 1.6 m). Every lake has at least one public access point (e.g., park, beach, boat launch), and provides recreational fishing opportunities typically involving stocked or established populations of rainbow trout, yellow perch, black basses, and sunfishes.

3.3.2 *Modeling Visitation at Lakes*

3.3.2.1 Volunteered Geographic Information

We evaluate the utility of geographic information from five VGI sources representing two nature-based citizen-science observations (eBird, iNaturalist), an image-sharing application (Flickr), a microblogging site (Twitter, now X), and a mapping application (Gaia GPS). eBird is a citizen science project with a mobile platform that allows users to share a variety of information about birds including observations and photographs. iNaturalist is a similar platform which encourages users to document all species of flora and fauna. Both eBird and iNaturalist users generally have active interest in the existence and conservation of living species (Jacobs and Zipf 2017). Flickr is an image-sharing application for amateur and professional photographers reflecting users' aesthetic appreciation of natural spaces, Twitter is a widely used micro-blogging site through which users can also share images and videos, and Gaia GPS is an activity tracking platform on which users track their runs, bike rides, and other forms of physical activity (Wood et al. 2013, Korpilo et al. 2017, Tenkanen et al. 2017). When selecting different VGI platforms we navigated tradeoffs between large, geographically dispersed data, publicly and easily available datasets, and potential platforms being used based on common lake activities. If we want to use VGI platforms as valid indicators of visitation they need to be easily and readily available – managers do not have the luxury of spending years acquiring data that is not publically available. These five platforms were selected largely because the data are accessible to researchers (e.g., through public acquisition interfaces or data sharing agreements, described below). Four of the platforms have also been the primary focus of previous studies of competing methods for estimating visitation (see reviews by Wilkins et al. 2021, Ghermandi et al. 2023).

The analyses involve a five-year period from 2015-2019 (inclusive) because this is the period of time for which on-site visitation data was available for the greatest number of lakes. This timeframe also falls well after the launch of all five VGI sources, and before the onset of the COVID-19 pandemic. Records from all of these sources include anonymous user identifiers and the geolocation (latitude and longitude) as metadata. We obtained posts for all VGI sources for the years 2015 through 2019 through various means. Flickr posts were obtained by spatially querying the Flickr application programming interface (API) with lake polygons. Twitter posts were acquired by querying the Twitter API v2 with lake centroid coordinates and the longest radius required to encapsulate the whole lake, then further spatially filtering acquired posts to lake polygons. All spatial processing of geotagged VGI included the lake and a 50-m buffer extending beyond the lake perimeter. This buffer distance was chosen because on-site counts only include visitors on the lake and shoreline; thus, a relatively small buffer excludes lake-adjacent park users who may not have been engaging with lake-specific benefits. This buffer distance is comparable to previous studies that spatially filtered geolocated social media records to lakes and their shorelines (Fricke et al. 2020, Keeler et al. 2015).

eBird and iNaturalist records were downloaded from their respective online data access portals for King and Snohomish counties (iNaturalist contributors 2021). Gaia tracks were provided as anonymous lake-level daily summaries of activity through a data sharing agreement with Outside, Inc. These daily counts were inferred from the overlap of breadcrumbs (the geospatial tracks created by Gaia users) with lake polygons. Next, we spatially filtered user posts from eBird, iNaturalist, Flickr, and Twitter to lake polygons from the USGS National Hydrography Dataset (USGS 2022). We then aggregated posts by VGI source, user ID, lake, and day to calculate the number of user-days – or distinct users who visit per day – per VGI source at each lake (Wood et al. 2013). In other words, if a user posted to the same platform from the same lake multiple times in one day this is considered a single lake user-day. This aggregation was done to prevent users who posted to a VGI source multiple times successively from a single location (i.e., high engagement) from dominating the analysis in comparison to users who post less frequently, but nevertheless are visiting lakes.

3.3.2.2 On-site Lake Visitation

On-site estimates of lake visitation come from counts carried out by trained volunteers for King County Department of Natural Resources and Parks and Snohomish County Conservation and Natural Resources. Volunteers (typically lakeside residents) counted the number of boaters, swimmers, and other recreationists on the lake water and shoreline at instantaneous points in time, bi-weekly from May through October, over the years 2015 to 2019. Counts were collected at various times of day between 8:00 and 18:00 and on random days of the week. Observations were made in addition to volunteers' primary purpose to measure water quality metrics (King County Water and Land Resources Division 2021, Snohomish County Surface Water Management 2021), so lakes were selected based on the counties' priority sites for water quality monitoring, as well as volunteer availability at each lake. Volunteers were instructed to collect counts at roughly the same time of day and day of week at the assigned lake, but upon analysis of the volunteer dataset we found that the dates and times of counts were inconsistent both within and between different lakes. To relate our on-site dataset to VGI counts, we temporally aggregated the on-site visitation estimates as annual mean measures of the instantaneous counts by lake. Given the sparsity and inconsistency of total counts between years and lakes, we averaged instantaneous counts on a yearly basis to dampen potential biases of individual outlying counts while still providing a meaningful representation of lake visitation.

3.3.2.3 Visitation Model

We compared the utility of different suites of VGI datasets for reflecting on-site lake visitation using linear mixed-effects models. The analyses modeled the annual average on-site visitation (from instantaneous volunteer counts) as a function of the fixed effects describing annual cumulative user-days for different combinations of VGI sources and a random lake effect to reflect variability among lakes. Previous work comparing VGI regression approaches found little difference between standard major axis (SMA) regression and ordinary least squares (OLS) algorithms (Ghermandi 2016). Furthermore, SMA regression cannot be done with more than one predictor variable, and thus we proceeded with OLS to predict on-site visitation rates. Model performance was assessed with Akaike's information criterion (AICc) and calculating the delta AICc for each candidate model. Next, we evaluated the top visitation models' ability to predict visitation at lakes lacking on-site data with out-of-sample testing. For each top model, we trained the model on all observations from two-thirds of the lakes in our dataset and tested it over all observations for the remaining one-third of lakes, repeated for 1,000 estimates. Given discrepancies in the number of total years each lake was sampled over the five years of our study (e.g., some lakes were only sampled for two or three years while others were sampled for all five), we grouped cross-validation by lake to ensure accurate representation. In other words, all years of data from a single lake were included in either the training or test dataset. This approach also allowed us to assess how effective a model trained on one set of lakes was at predicting visitation on an entirely different set of lakes. We calculated the average root mean squared error (RMSE) and R-squared of the out-of-sample tests to assess the models.

3.3.3 *Environmental and Built Infrastructure Influences on Visitation*

3.3.3.1 Measures of Lake Attractiveness

To assess the attractiveness of lakes to visitors, we collated information on public amenities, lake water quality, and tree cover in the public park and along the shoreline. We tabulated the presence or absence of amenities on lake shorelines and in adjacent lake-parks (including parks, bathrooms, shelters, playgrounds, swimming beaches, docks, and boat ramps) from lake-park descriptions on King and Snohomish counties' websites. We define parks as city, county, or state-managed parks and open green spaces, while swimming beaches are sandy shorelines with wading areas (these may or may not be roped off and have lifeguard supervision). Our water quality estimates are annual average Secchi depth (m), which was measured at the deepest point of lakes by county volunteers at the same time visitor counts were taken for the years 2015–2019. Secchi depth measures the transparency of water, where higher depth values correspond with clearer (and perceived "cleaner") water. Lastly, tree cover for the 50 m shoreline buffer and lake-park areas was calculated by overlaying polygons of lake shorelines and lake-adjacent parks with the National Land Cover Dataset Tree Cover raster from 2019 in ArcGIS and calculating the percent lakeside area with 50% or greater canopy cover (Dewitz 2021). These predictors were selected because they can reasonably be influenced by natural resource managers, and previous studies have demonstrated visitors are willing to travel further to lakes and parks which offer superior water quality and built and natural amenities (Keeler et al. 2015, Nelson et al. 2023).

3.3.3.2 Revealed Preference Model

We modeled our visitation estimates as a function of lake amenities, water quality, and shoreline tree cover to assess the associations between measures of lake attractiveness and degree of human use. We used our visitation model to estimate visitation at all 50 lakes for the five years of our study, including years during which we lacked on-site data at certain lakes. Then, we modeled these estimates as a function of the lake attributes described previously in a linear mixed-effects model which also included the lake as a random effect. Correlated lake attributes related to the presence of amenities (parks, bathrooms, shelters, public docks, playgrounds, and swimming beaches) were aggregated into a single lakeside amenity variable based on variance inflation factor (VIF) of each predictor. Six significantly correlated general amenities were combined into a lake amenity score metric with a range from one to six, and boat ramps were included as a separate presence/absence variable to reflect recreation specifically for boating and fishing. All statistical analyses were completed using the lme4 package (Bates et al. 2015) in R (version 4.3.1, R Core Team 2023).

3.4 RESULTS

Across all 50 lakes, the number of total VGI user-days were as follows for the five years of our study: eBird (n = 1779); iNaturalist (n = 224); Flickr (n = 389); Twitter (n = 1274); and Gaia GPS (n = 604). The mean number of total user days per lake across all VGI sources and years was 83.6, with a range from 1 to 1096. Green Lake – the most urban lake of our dataset in the city of Seattle, with a park spanning its entire shoreline – had the highest number of total user-days for all VGI sources except eBird (Figure 3.2). Many lakes had years in which there were zero records for one or more VGI datasets. User-days across most of the different VGI sources exhibited marginal to low cross-correlation with one another, but to varying degrees, with eBird and iNaturalist exhibiting the weakest correlation with other sources. The pairings of Flickr ~ Twitter ($r = 0.53$), iNaturalist ~ Gaia ($r = 0.50$), Gaia ~ Flickr ($r = 0.42$), Twitter ~ Gaia ($r = 0.31$), iNaturalist ~ Flickr ($r = 0.28$), iNaturalist ~ Twitter ($r = 0.26$), and iNaturalist ~ eBird ($r = 0.26$) were significantly correlated ($p < 0.001$) while Twitter ~ eBird ($r = 0.18$), and Gaia ~ eBird ($r = 0.15$) were also correlated ($p < 0.01$ and $p < 0.1$, respectively) (Figure 3.3). Flickr ~ eBird was the only VGI source pairing that was not correlated ($r = 0.04$).

Associations between annual cumulative VGI user-days and on-site estimates of visitation were moderate. iNaturalist ($r = 0.32$), Flickr ($r = 0.28$), Twitter ($r = 0.35$), and Gaia GPS ($r = 0.32$) all positively correlated with on-site visitation, while eBird ($r = 0.04$) showed little correlation (Figure 3.4).

In our comparison of alternative models using VGI sources to estimate on-site visitation, the model informed by Twitter and Gaia performed the best ($n = 231$, *combined* $R^2 = 0.845$) with the VGI sources as fixed effects and lake identification as a random effect (Table 3.1). Both Twitter ($p = 0.012$) and Gaia ($p = 0.001$) significantly predicted on-site visitation in this model. The top-supported models are those with a delta AICc < 2 and all VGI data sources were included, in different combinations, in the top-ranked performing models.

We used the model informed by all five VGI datasets ($n = 231$, *combined* $R^2 = 0.85$, in-sample testing) to predict empirical visitation across all sites (and for years in which we lacked empirical data for certain lakes). Predicted mean annual visitation positively correlated with on-site visitation, though this model and the others we tested explained only a modest percentage of the data's variance in out-of-sample testing (Delta AICc = 4.62, RMSE = 1.06, $R^2 = 0.12$) (Figure 3.5).

The lake attributes we tested in our revealed preference model explained a significant proportion of variance in estimated visitation between lakes (n = 250, *conditional* R^2 = 0.96, *marginal* R^2 = 0.28) (Figure 3.6). The only significant coefficient in the model was the lake amenity metric, which tallied the presence/absence of parks, bathrooms, shelters, public docks, playgrounds, and swimming beaches. Water quality (Secchi depth), presence of boat ramps, and tree cover demonstrated no significant contribution to lake preference.

3.5 DISCUSSION

Our models incorporating data from multiple VGI sources are found to produce more accurate estimates of human visitation than models with any single VGI source alone. This is likely because different mobile device applications are used by different groups of people and therefore better capture the full range of lake users and activity types, and would therefore be a better reflection of the associated CES value. Our second analysis of preference for lake attributes indicates that built infrastructure supporting public amenities – such as playgrounds, parks, shelters, bathrooms, and swimming beaches – strongly promote lake use, whereas water clarity, boat ramps, and tree cover contribute less to visitation rates. These findings can aid resource managers in understanding lake visitation across urban-rural landscapes, help anticipate hotspots for lake degradation associated with human activities, and assist planners to ensure equitable access to lakes for different intended uses and associated ecosystem services.

3.5.1 *Benefits of Diversifying Volunteered Geographic Information Sources in Visitation Models*

The visitation model informed by Twitter and Gaia was best at predicting on-site lake visitation in Western Washington, based on model fit and cross-validation, followed closely by models that included at least one additional data source. All VGI sources in our analyses were included among the top-performing models. Previous studies of public lands across the United States have similarly found that no single VGI data source outperforms others when modeling on-site visitation (Winder et al. 2025). Wood et al. (2020) found that visitation models with multiple VGI data sources are better at estimating visitation in cross-validation, and suggested that weak correlation of posting frequencies among VGI sources may indicate that each platform represents distinct user-groups participating in distinct recreational activities. Our results support this suggestion by highlighting generally weak associations between user-days estimated from different VGI sources for lakes, particularly those expected to have very different user-bases (e.g., eBird and Twitter).

Our analysis suggests that including a diversity of VGI datasets rather than singular sources can benefit predictions of on-site lake visitation. What remains a persistent challenge is understanding how the use of different mobile device applications, and therefore the volumes of VGI data from different platforms, are related to specific CES for people. Havinga et al. (2020) proposed a framework of CES service categories (e.g., activity, aesthetic, artistic, knowledge) and how each is associated with specific types of VGI. According to the framework, Gaia GPS is an indicator of activity services because its users are physically interacting with the environment, whereas Flickr is an indicator of aesthetic appreciation or artistic inspiration, and eBird an indicator of connection to nature. However, there is also growing recognition that CES benefits may vary considerably within the user-group of a single VGI source (Song et al. 2020). VGI sources probably represent more than just one CES, and some CES are easier to recognize and classify through VGI analysis than others. Understanding representation of specific types of CES, or lack thereof, in selected data sources and across different ecosystems is critical for considering how ecosystem valuation using VGI analyses can support natural resource management and planning.

3.5.2 *Amenities Drive Lake Visitation*

Our analysis of visitation as a function of lake attributes indicates that built lakeside amenities are the strongest driver of lake visits. This confirms previous findings that lakeside structures are a more powerful predictor of visitation than attributes such as water quality (Nelson et al. 2023). Though studies in the midwestern U.S. have associated improved water quality with increased lake visitation (Keeler et al. 2015), the suite of lakes studied here do not vary substantially with respect to water clarity. Some lakes in our analysis have a history of infrequent algae blooms, however such events are rare and typically occur over only a few weeks and thus were not captured in annual average clarity that was calculated specifically to align with our empirical and VGI visitation data. Previous lake recreation studies have also recognized boat ramps as a driver of lake use (Keeler et al. 2015), but our revealed preference model did not identify boat ramps as a significant variable predicting lake visitation. This is likely because the vast majority of lakes in our study have boat ramps and fishing docks, so angler and boater access is less of a limiting factor across lakes.

Tree cover has variable effects on visitation in the revealed preference model, highlighting the fact that some people may be attracted to undeveloped natural lakes to connect to nature while others may be attracted to developed lakes given the host of amenities they offer. For example, lakes can help alleviate the negative impacts humans experience from urban heat and noise (Völker et al. 2015), and the addition of canopy cover to existing green and blue spaces enhances evapotranspiration-based cooling influences of urban waterbodies (Gunawardena et al. 2017). At the same time, many people are drawn to recreational areas that support opportunities for children to play, picnic benches for socializing, and well-maintained access points for swimming and other activities (Stankey 1979). Previous research has reported a similarly complex relationship between tree cover and visitation of urban parks inferred from VGI, suggesting that differences in behavior between users may play a role (Donahue et al. 2018).

Managers face a challenge in determining how to balance demands for competing CES through lakeside development or restoration. While water-based activities contribute to human well-being, they can simultaneously impose stressors on aquatic systems such as depleting aquatic and riparian habitat quality, altering species' behaviors, and changing the biogeochemical cycles of aquatic ecosystems (Venohr et al. 2018, Schafft et al. 2021). Negative impacts to the natural environment subsequently adversely affect nature-based activities such as birdwatching and aesthetic appreciation. These competing demands are somewhat addressed by the heterogeneous spatial distribution of public activity-specific infrastructure (e.g., boat ramps, fishing docks, swimming beaches, natural preserves) at lakes, but access to lakeside environments supporting different lake-based CES is not equitable across the landscape. When allocating funds and resources to lakeside enhancement projects, managers should carefully consider tradeoffs between enriching built environments and introducing environmental stressors related to lake use hotspots (e.g., garbage, deteriorating riparian quality) which may impair CES derived from more natural lake environments (Allan et al. 2015). Furthermore, intentional spatial zoning of public lake shorelines can help facilitate multiple types of CES that may directly conflict with one another, such as swimming and fishing (Meyerhoff et al. 2019).

3.5.3 *Limitations and Future Directions*

Our study would have benefited from more accurate and abundant on-site visitor count data. Improved on-site data would not only increase confidence in the performance of our visitation models, but could also facilitate an analysis of absolute, rather than relative, visitation. Lake visitation is also highly seasonal, and a robust, year-round on-site dataset would have allowed us to assess the ability of VGI to estimate temporal patterns in human activities at lakes.

Utilizing instantaneous empirical data for our validation dataset presented a challenge. Given the sparse nature of our on-site and VGI data we needed to temporally aggregate both datasets to an annual basis, which reduced the already relatively small number of observations in our dataset. Typically, studies leveraging VGI to estimate visitation have relied on census counts of visitors collected with pedestrian or vehicle counters or other types of sensors at sites with controlled access points (Fisher et al. 2018). While this could be achieved at some lakes, by counting traffic at boat launches or other singular access points, it would be difficult to count every visitor to lakes which have numerous access points and can be reached via many modes of transportation. A study focused on the subset of lakes that do have controlled access would be biased towards locations that are primarily accessed by vehicles and designed to serve primarily boaters and anglers. Previous studies have converted instantaneous counts into raw total visits or visitors per day to approximate the count estimates that would be produced by a passive sensor (Mulvaney et al. 2020). Unfortunately, we lacked the in-person survey or passively collected data to do so, and our study is more limited than previous work in this regard because we do not know how our estimates of relative visitation relate to the actual total number of people visiting a lake.

The VGI data sources used in this study are all convenience samples that are not representative of the population of lake users (Wood et al. 2013, Heikinheimo et al. 2020, Tenanen et al. 2017). Visitors represented by some VGI sources, for example, are known to be younger (Tenkanen et al. 2017) or biased toward a particular gender (Heikinheimo et al. 2020) compared with actual visitors. Furthermore, there are reasons why lake visitation may be challenging to measure using VGI, compared with studies investigating potential of VGI for terrestrial parks and protected areas. Individuals participating in water-based activities – such as fishing, boating, and swimming – may be less likely to engage with their mobile device while visiting a waterbody (Wood et al. 2013). This may result in lower amounts of available VGI and, since VGI patterns tend to more accurately represent empirical visitation at sites with greater volumes of VGI (Tenkanen et al. 2017), the need to aggregate data to annual or monthly scales, as in this study. It remains unclear what the utility of VGI will be for estimating lake visitation over shorter timescales (Wilkins et al. 2021). Future research should explicitly show how specific sources of VGI are associated with CES through on-site surveys that categorize lake visitors by activity type and the value they receive from the visit.

Previous work has demonstrated discrepancies between the CES described in visitor use survey responses and CES inferred from automated analysis of text and images included in VGI, suggesting that further research is needed to understand how well VGI reflects visitors' perceived benefits at recreational sites of interest (Moreno-Llorca et al. 2020). Here we argue that multiple sources of VGI better estimate visitation because more diverse user-groups are represented, but this is likely an oversimplification of the true CES the individuals that posted to mobile device applications are experiencing. Urban and suburban lakes offer numerous benefits to humans that may not be fully reflected in any source of VGI, such as improving health, reducing stress, providing social and place-based belonging, and mediating negative impacts of urban heat and noise (Gascon et al. 2017, Pasanen et al. 2019). A comprehensive in-person survey asking lake users which CES they relate to through their VGI posts and which benefits they feel are not captured by their mobile device application activity would further refine the capabilities and limitations of VGI for estimating lake-based CES. Moreover, given that VGI based approaches may poorly represent specific socio-demographic groups of people, holistic representation of lake users in CES assessments may be best achieved through a combination of measurement techniques including VGI, surveys, and in-person workshops (Ebner et al. 2022).

3.5.4 *Practical Implications*

Managers responsible for open-space planning would ideally have access to data from a wide range of VGI sources that holistically represent potential CES associated with recreation over time. However, there are practical and ever-evolving limitations to VGI acquisition. Notably, access to VGI is constantly evolving (Wood et al. 2020). For example, geolocated Instagram posts are no longer available through an API, and since the completion of our analyses Twitter has changed ownership and the new company (X) has placed burdensome costs and rate limits on its API. Furthermore, mobile device application use and the popularity of individual applications changes over time, so VGI sources may not consistently reflect on-site activities (Wood et al. 2020, Leppämäki et al. 2025). Given the increasing hurdles raised by VGI companies to access these data and the temporary nature of use trends in mobile device application activity (Ghermandi et al. 2023), practitioners should consider the relative return on investment of acquiring many different VGI sources. Future research could explicitly calculate the cost (i.e., necessary personnel and monetary investment) of collecting different VGI sources relative to empirical data collection methods. In light of the uncertainty surrounding long-term research access to some platforms (e.g., Twitter) and VGI's ability to simply enhance but not replace on-site estimates (Wood et al. 2020), collection of on-site visitation and survey data will likely remain critical for recreational site management (Wilkins et al. 2021).

Broadly, the importance of amenities in driving lake visitation suggests that if managers and policymakers seek to enhance lake access and use then they should invest in improvement of and additional lakeside facilities. Notably, the allocation of urban waters and parks is notoriously spatially inequitable (Venter et al. 2023), and this inequity is further compounded by limited water access and amenities at some lakes. In Western Washington, for example, lakes in wealthier suburban neighborhoods typically enjoy superior amenities and access compared to lakes in urban regions of lower socioeconomic status. Equitable enhancement of lake access will be best supported through investing in the built lakeside environment, but this should not be prioritized at the expense of retaining some natural lakeside habitats, as lakes are also valued as settings to connect with nature (White et al. 2020). Practitioners face tradeoffs between enhancing built infrastructure that supports some forms of recreation while potentially diminishing nature-based recreation at the same time (Echeverri et al. 2022). Plans to increase access to or enhance visitor infrastructure at blue spaces should acknowledge that different cultural values and worldviews may lead to differing preferences and seek ways to address existing inequities in access to different types of lake environments (Haeffner et al. 2017).

3.6 Conclusion

VGI reflect relative differences in visitation between lakes and can be used to help estimate visitation at sites lacking detailed on-site visitor count data. Widely used VGI sources such as Twitter and Gaia GPS appear to be moderate predictors of lake visitation in Western Washington, where VGI tailored toward niche activities such as eBird and iNaturalist provide additional, albeit minor, contributions in a visitation model. While this may be viewed as a limited return on investment for adding additional VGI datasets to visitation models, we caution researchers to consider the inherent biases of different mobile device applications and how each VGI source may reflect only portions of the suite of CES that are provided by a location. Simply put, diverse VGI sources are likely to characterize the diversity of reasons motivating people to interact with nature. Ultimately, our analysis reinforces the need for quality empirical data which data from mobile devices can complement. VGI cannot fully substitute for on-site data but can enhance visitation models informed by both VGI and on-site data to guide lake and visitor management.

3.7 Acknowledgment

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3.8 TABLES & FIGURES

Table 3.1 The top ten candidate visitation models relating mobile platform use and on-site visitation estimates. K is the number of parameters in the model, Delta AICc is the difference between AICc of the best fitting model and that of the top model, Model Likelihood is the relative likelihood, AICc Weight is the Akaike weight, and the R^2 and root mean square error (RMSE) values are from out-of-sample testing. All models with Delta AICc < 5 are listed.

Model	**K**	**AICc**	**Delta AICc**	**Model Likelihood**	**AICc Weight**	**R^2**	**RMSE**
Twitter + Gaia	6	393.4	0.00	1.00	0.17	0.14	1.09
iNat + Twitter + Gaia	7	394.8	1.35	0.51	0.08	0.13	1.08
eBird + Twitter + Gaia	7	394.8	1.37	0.50	0.08	0.13	1.07
Flickr + Twitter + Gaia	7	394.9	1.47	0.48	0.08	0.11	1.09
iNat + Twitter	6	394.9	1.50	0.47	0.08	0.12	1.02
Gaia	5	395.7	2.30	0.32	0.05	0.07	1.08
eBird + Flickr + Twitter + Gaia	8	396.3	2.93	0.23	0.04	0.10	1.08
eBird + iNat + Twitter + Gaia	8	396.3	2.93	0.23	0.04	0.12	1.08
Flickr + Gaia	6	396.3	2.94	0.23	0.04	0.04	1.07
iNat + Flickr + Twitter + Gaia	8	396.4	2.99	0.22	0.04	0.11	1.10

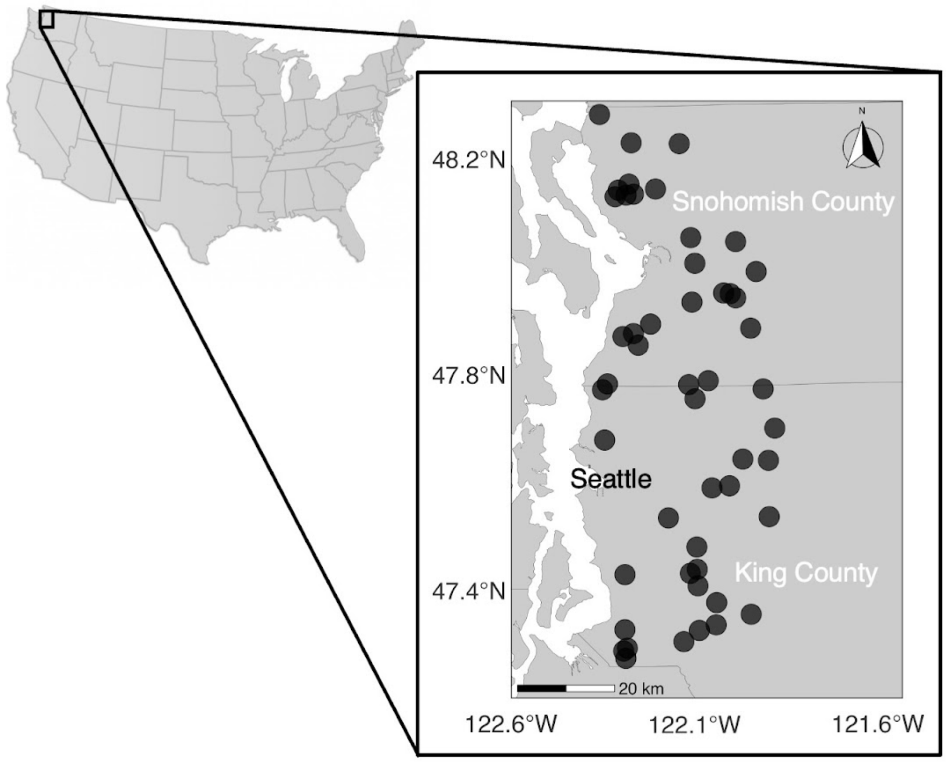

Figure 3.1 Locations of 50 lakes in Western Washington, United States.

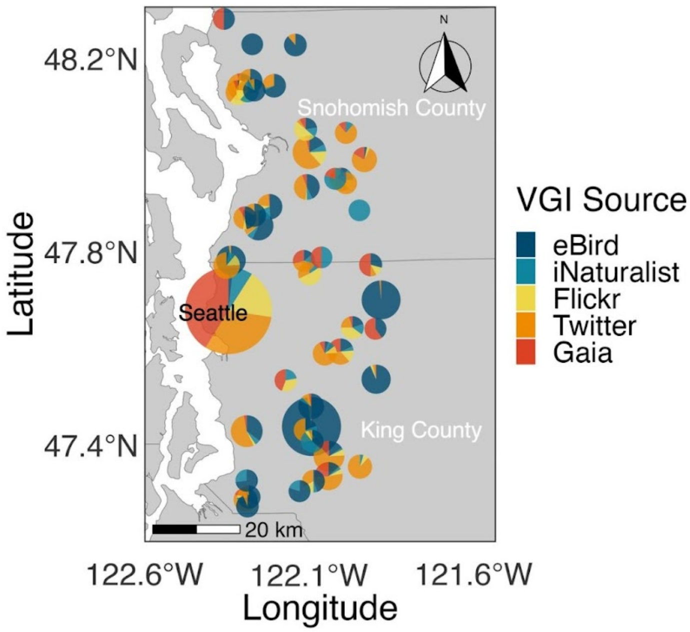

Figure 3.2 Map of cumulative VGI user-days at 50 lakes in Western Washington for 2015-2019 on eBird (dark blue), iNaturalist (teal), Flickr (yellow), Twitter (orange), and Gaia (red). Point size corresponds to the number of user-days and point locations are jittered to ease interpretation.

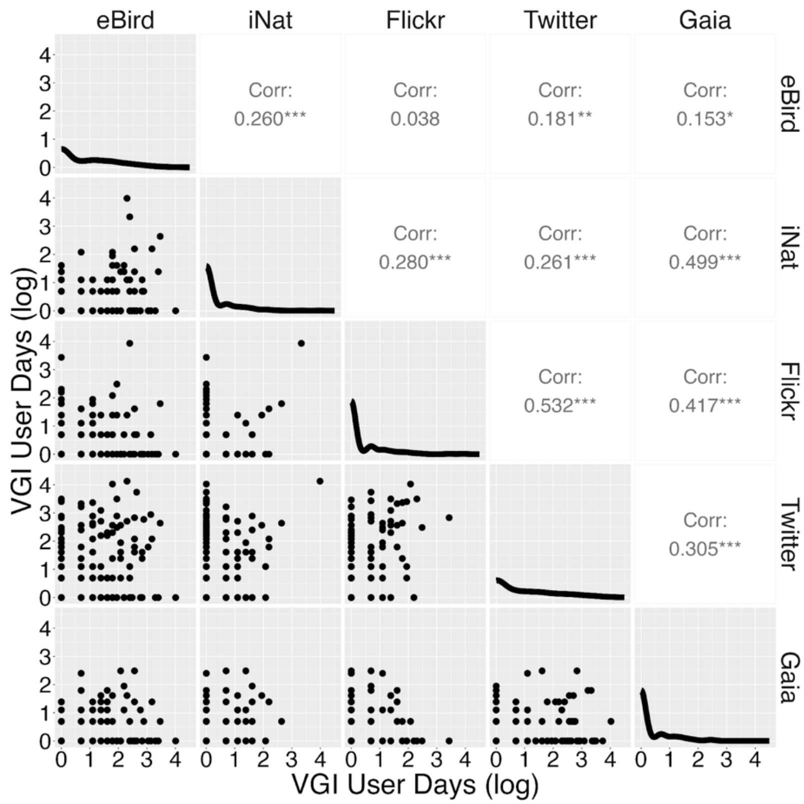

Figure 3.3 Scatterplots (lower-left), density plots (diagonal), and Pearson's correlation coefficients (upper-right) comparing VGI datasets. Statistical significance is indicated by *(<0.1), **(<0.01), and ***(<0.001).

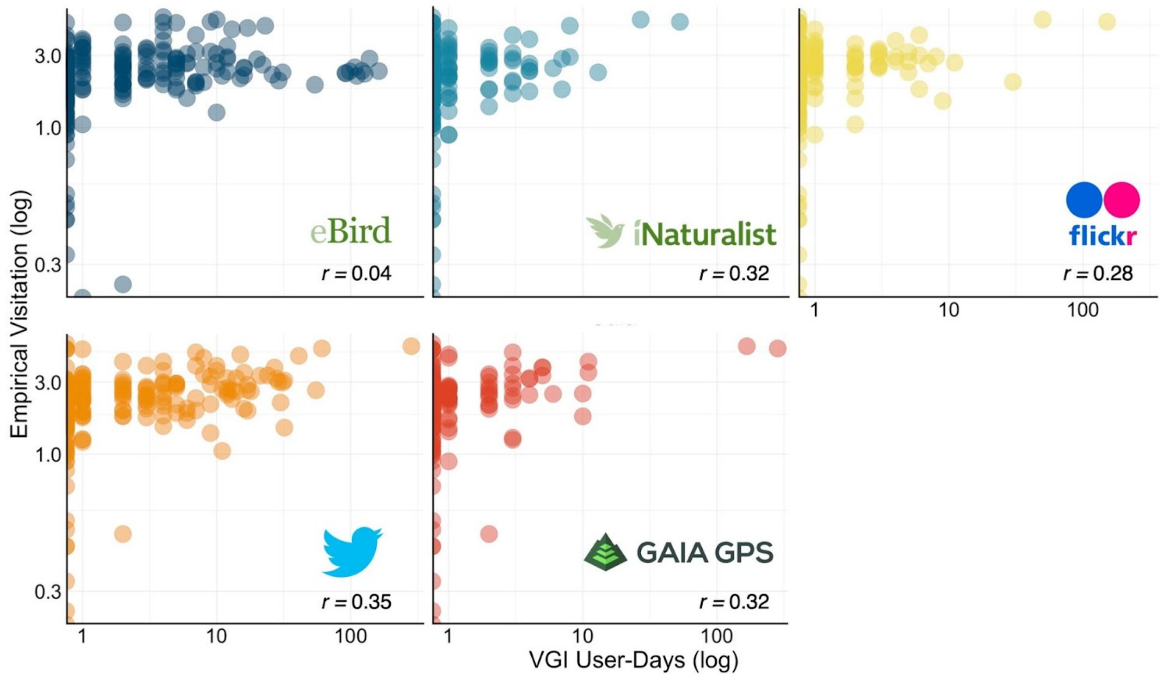

Figure 3.4 Scatterplots of annual cumulative VGI user-days from eBird, iNaturalist, Flickr, Twitter, and Gaia GPS versus annual mean on-site visitation estimates.

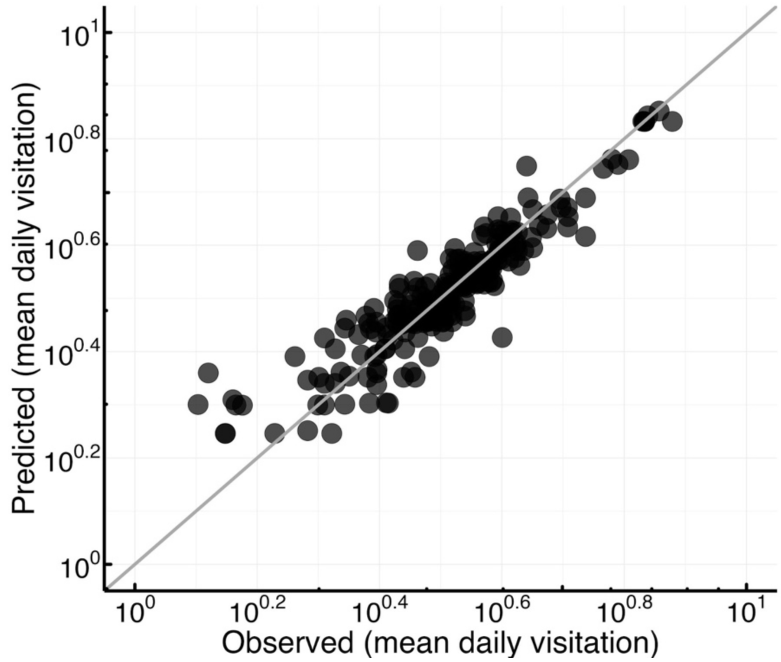

Figure 3.5 Observed and predicted in-sample annual mean daily visitation at lakes, predicted as a function of annual VGI user-days from eBird, iNaturalist, Flickr, Twitter, and Gaia. Predicted values are plotted relative to observed empirical visitation (R^2 = 0.89), and the slope line indicates a 1:1 relationship.

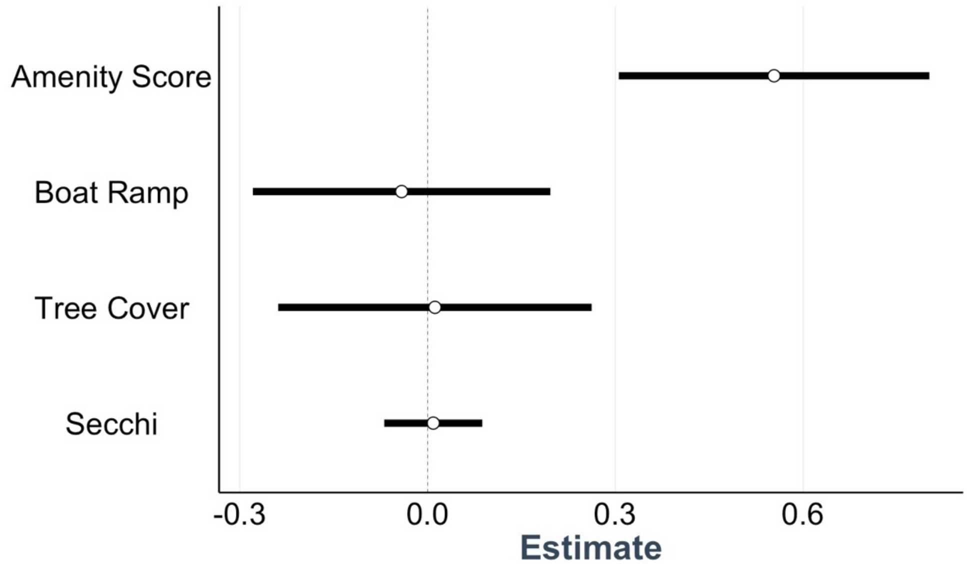

Figure 3.6 Coefficient estimates from the revealed preference model relating lake visitation to lake attributes. White circles represent means and bars are 95% confidence intervals of the estimates.

3.9 References

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Chapter 4. MOTIVATIONS TO VISIT AND PERCEIVED BARRIERS TO ACCESSING THE CULTURAL ECOSYSTEM SERVICES OFFERED BY BLUE-GREEN PUBLIC SPACES ON URBAN LAKES

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4.1 ABSTRACT

Urban blue-green spaces provide numerous cultural ecosystem services to human populations, yet these contributions are commonly poorly documented and underappreciated. Here, we surveyed visitors at public urban blue-green spaces in western Washington, USA, in summer 2021 to quantify what activities and amenities motivate users to visit blue-green spaces, and how differing sociodemographic identities influence users' perceived barriers to visiting blue-green spaces. Our findings show that blue-green space users' behaviors and use of amenities can broadly be characterized by whether or not they participate in activities, the ecosystem where these activities occur (lake versus park), and whether these activities are more social or solitary. In addition, survey responses suggest that barriers such as limited public transportation availability and water safety disproportionately impact underrepresented sociodemographic groups. Cumulatively, these findings will support lake-specific improvements in communication and accessibility by county water resource management partners.

4.2 INTRODUCTION

Urban and suburban blue-green spaces – referring to lakes, rivers, wetlands, and ponds adjacent to public parks – can offer a broad suite of ecosystem services and health benefits to society. Among these are numerous cultural ecosystem services (CES), such as diverse opportunities for recreation (e.g., swimming, boating, fishing, exercising, photography, relaxation, socializing) (Reynaud and Lanzanova 2017, IPBES 2019, Vári et al. 2022). Time spent in blue spaces has been linked to lower perceived stress, improved mental health and well-being, and increased physical activity (Gascon et al. 2017, Garrett et al. 2019, Pasanen et al. 2019). Blue spaces and adjacent green spaces also serve as hotspots of connections to nature and offer heat stress relief from urban heat island effects and during heatwaves (Burkart et al. 2016, Gunawardena et al. 2017). Despite the many benefits of urban blue spaces, however, visitor use of these spaces, and how blue space may be utilized differently from adjoining green space, is relatively less understood.

Humans simultaneously benefit from and can be a detriment to lake ecosystems (Venohr et al. 2018). Studies across the globe have shown that boating and shoreline use consistently degrade freshwater ecosystem integrity (Schafft et al. 2021a). Recreational impacts on aquatic and riparian biodiversity at lakes vary depending on the activity and species of interest. For example, walking trails and dog walking can damage riparian vegetation (Schafft et al. 2024), and the clearing of aquatic macrophytes in swimming and boat launch areas can compromise fish habitat and negatively influence water quality (Meyer et al. 2021, Schafft et al. 2021a). The potential for damage to aquatic ecosystems varies by the kind of infrastructure present and activities undertaken on lake shorelines. For example, boating can negatively impact biodiversity while activities such as swimming and fishing have demonstrated more variable effects (Schafft et al. 2021b). Thus, understanding human use of blue-green spaces is critical not only for lake conservation but also has relevance to ensuring the continuation of derived ecosystem services for societies that depend on healthy, intact lake ecosystems (Meyerhoff et al. 2022).

Understanding the distribution of lake-associated ecosystem services across the landscape can inform management of built and natural environments to facilitate diverse lake experiences for visitors (Hossu et al. 2019). For example, a study of urban green and blue spaces in Guyana found that blue spaces were generally considered non-restorative because they were all inundated with anthropogenic noise pollution and perceived as artificial, rather than natural (Fisher et al. 2021). Other work has shown that integration of urban blue and green space can promote participation in different types of physical activities which can further improve public health outcomes. Specifically, in a survey of urban Singaporean residents individual-based exercise rates increased in regions with a mix of blue and treed green space cover within 250 m from respondents' homes (Tan et al. 2021).

Strategic design and management of urban blue-green spaces should aim to alleviate publicly perceived barriers through co-design of public natural spaces (Astell-Burt et al. 2023). Public lake spaces may not be universally accessible across sociodemographic groups, with people of color and low-income communities being the least able to benefit from them. Previous studies in urban settings have associated lower socioeconomic status with fewer visits to and less time spent in blue spaces (Astell-Burt and Feng 2021). Even when high socioeconomic status and white households are located further from access points to urban waterways these individuals are still more likely to spend time on urban waterways than low socioeconomic status and nonwhite households (Haeffner et al. 2017). Socioeconomic status can also influence the benefits users most strongly associate with time spent in blue spaces – less educated users identified social benefits of visiting blue spaces more often than well-educated, economically advantaged users in a recent survey (de Bell et al. 2017). Previous studies spanning the United States have further revealed ethnic minorities and marginalized groups identify personal safety, language barriers, and transport as obstacles constraining their ability to access the outdoors broadly (Ghimire et al. 2014).

Greater understanding of the CES offered by blue-green spaces is needed to prioritize improvements in infrastructure and accessibility by water resource management partners. Knowledge of use trends can also aid with messaging and management of personal safety, water quality, and environmental issues – specifically by quantifying where blue-green space users face these challenges and seeking public feedback on communication preferences. To this end, the present study sought to quantify and survey users of blue-green spaces across urban and suburban lakes in western Washington with adjacent public park spaces. Specific goals were to 1) evaluate spatial trends in lake use, 2) understand how racial and ethnic identities influence individuals' motivation to visit lakes and typical patterns of use, and 3) assess how these identities relate to perceived barriers to lake access. Surveys were developed in collaboration with management partners employed by King and Snohomish Counties, Washington, and results will inform future public lake access planning, management, and communication strategies.

4.3 Methods

4.3.1 *Study Area & Visitation Data Collection*

Lake visitation was quantified at 18 popular urban and suburban blue-green spaces in King and Snohomish Counties in Western Washington, US (Figure 4.1, Table S4.1). Blue-green spaces were chosen based on the presence of public green space on a lake shoreline, lake and park size (prioritizing smaller lakes and parks where paper surveys could be distributed by a limited number of personnel), and in consultation with colleagues at King and Snohomish Counties who coordinate water quality surveys by community scientists at area lakes. The authors sought to estimate blue-green space visitation in warm summer months, when these spaces are most used, via monthly count replicates. Counts of visitation were taken by the authors at each lake on 4 weekdays and 4 weekend days during summer (June-September) 2021 – or one weekday and weekend day each month for the duration of the study. Instantaneous visitation counts were taken every two hours from 9:00 am to 5:00 pm each day a lake was surveyed, and mean noon visitation was calculated by averaging all 11:00 am and 1:00 pm count values.

At every lake, instantaneous visitation counts were conducted by the authors who navigated the entire park and public lakeshore access and tallied lake and park users by activity. Activity types associated with the lake included boating (separated by non-motorized and motorized watercraft), fishing, swimming, and other shore-based activity in contact with the water. Park-associated activities included walking (including standing), resting (sitting), and exercising (jogging or participating in a sport). Surveyors also noted the number of unhoused individuals based on temporary dwellings and counted the number of dogs present and number of vehicles in the parking lot.

4.3.2 *Survey Distribution*

Paper surveys and QR codes linking to an online version of the survey in Google Forms were distributed to visitors over the age of 18 that authors encountered while counting visitation at lake parks (hereafter referred to as 2021 survey). The authors navigated the entire park and lake shoreline (plus docks, if applicable) between their instantaneous counts to maximize the number of potential respondents and limit any bias in survey distribution. Electronic versions of the survey were also distributed across western Washington in summer 2021 via NextDoor forums, King and Snohomish County Parks' social media pages, and the Washington Lake Protection Association volunteer email list. Electronically dispersed versions of the survey asked respondents to identify which lake they had visited last and reference their responses to the questions on that visit. Only survey responses for lakes in King and Snohomish counties were included.

4.3.3 *Blue-Green Spaces Activities and Amenities*

Surveys were provided in English and asked respondents to identify the CES they associate with lakes and lakeside parks over a series of questions about specific activities and amenities they might engage in or use while visiting lakes. Respondents indicated how often they use lakes and adjoining lands for specific activities on a three-point Likert scale (Often, Sometimes, or Never). The activities (blue-space related in italics) they were asked to provide ratings for included *fishing (catch and release)*, *fishing (to eat), swimming/wading, boating (motorized), boating (non-motorized)*, bird watching, socializing with family and friends, exercising (hiking, playing sports), playing with kids (playground), walking pet, and relaxing, with an option to list additional activities. The survey asked respondents how likely they were to use specific amenities when visiting lakes on a four-point Likert scale (Never, Unlikely, Somewhat likely, or Very likely). Amenities (blue-space related in italics) included *swimming beaches, boat ramps, fishing docks, kayak launches*, bathrooms, sports playfields, kids' playgrounds, shelters or picnic tables, shade from trees, open greenspace, hiking trails, dog parks, and an option to list additional (other) amenities.

4.3.4 *Barriers to Blue-Green Space Use*

The survey also asked respondents to identify any problems they would like to see addressed in order to increase their use of lake and adjoining lands. Respondents were asked to select up to four of the following potential problems: lack of public transportation, lack of parking, safety of water (e.g., algae blooms, bacteria), excess garbage or other waste, nuisance animals (birds, rodents), too many dogs (including off-leash), risk of drowning (lack of lifeguards), personal safety, improvised shelters and homeless people, lack of amenities (dock/fishing pier, bathrooms, playgrounds, playfields, picnic shelters), lack of shade from trees, and an option to list additional barriers. Lastly, respondents had the option to self-report sociodemographic information including gender, age, racial and ethnic group(s) with which they identify, ethnicity, annual household income, and home zip code. All survey questions were optional.

Because some barriers could completely exclude users from accessing blue-green spaces and therefore prevent their representation in our surveys, a subset of data from a secondary survey was utilized to include responses from individuals who had never visited a blue-green space. These survey respondents experienced barriers across the full range of impacts – from reducing visitation to eliminating it. The additional barrier data was collated from a 2023 survey with 778 responses which asked the same question above about problems respondents would like to see addressed to increase their blue-green space use (Delie and Hardy 2023; hereafter referred to as 2023 survey). This study was disseminated by Qualtrics via email to a sociodemographically representative subset of King County residents, some of whom had never visited a lake.

Lake water quality status was assessed from total phosphorus (µg/L) concentration measurements taken bi-weekly at a depth of one meter in the deepest part of each lake during June through September. These measurements were collected by volunteer lake surveyors in King and Snohomish counties as a part of ongoing community monitoring (King County 2024, Snohomish County 2024). Given discrepancies in the duration of phosphorus concentration time series available for each lake, we calculated the average concentration from all available measurements (ranging from 5 to 30 years of data) by lake. Blue-green space shade extent was quantified by calculating the average percent canopy cover for a 50 m buffer of each lake shoreline, plus any lake-adjacent parks, from the 2021 National Land Cover Database's Tree Canopy Cover layer – a 30 m raster geospatial dataset containing continuous percent tree canopy estimates for each pixel (USDA Forest Service 2023). Geospatial analyses were completed in ArcGIS Pro version 3.4.

4.3.5 *Statistical Analyses*

When analyzing Likert scaled responses to survey respondents' activity and amenity preferences, we excluded participants that responded to two or fewer activity or amenity options as incomplete responses. To understand how survey participants were grouped based on their activity and amenity preferences, we used polychoric factor analysis of ordinal data with the psych package (Revelle 2024) in R (version 4.4.1, R Core Team 2024) to project activity and amenity variables into a lower dimensional space. Polychoric correlations estimate the correlation between underlying continuous traits assumed to be normally distributed and are used in place of traditional Pearson correlations, which can produce biased results when used on ordinal data. Lastly, to assess relationships between race and identified barriers we calculated the percentage of respondents by racial identity across both surveys who selected a given barrier as impeding their use or access of lakes. Individuals who identified as multiple races were included in percent totals for each racial identity group they selected.

4.4 RESULTS

A total of 667 individuals responded to the 2021 survey (Table S4.2). 486 responses came from the core 18 lakes where surveys were distributed in person, including both surveys distributed in-person and online responses based on recent visits to core lakes. Of the in person surveys, 19% were from respondents visiting a lake in the same zip code as their residence. The number of survey responses was positively correlated with mean noon visitation at core lakes ($r = 0.56$, $p = 0.02$, $df = 16$), but response frequency was variable across lakes. Furthermore, visitation did not correlate with the weighted mean population density of census tracts in which lakes were located ($r = 0.01$, $p = 0.97$, $df = 16$), though population density had limited variability given that all lakes are in suburban or urban settings (Figure 4.2).

Across all lakes, survey respondents indicated they were likely to engage in relaxing, socializing, and exercising most often (Figure 4.3A). More niche activities requiring equipment such as boating, bird watching, and fishing elicited the highest frequency of "Never" responses. Similarly, respondents indicated they were very or somewhat likely to use common and generalized amenities such as bathrooms, trees, greenspace and shelters at the highest frequencies (Figure 4.3B). Amenities intended for more specific activities such as docks, dog parks, and boat ramps had the greatest number of never or unlikely responses.

Based on activities' eigenvectors in our factor analysis of respondents' rating of their likeliness to participate in different activities while visiting blue-green space parks (Figure 4.4), we broadly interpreted three significant factors – Axis I (Activity), Axis II (Ecosystem), and Axis III (Socialness). Activity differentiates between the types of activities visitors participate in at lakes, ecosystem separates between participation in lake-based (e.g., fishing, boating) versus park-based (e.g., exercising, relaxing) activities, and socialness distinguishes participation in more social (e.g., socializing, playing with kids) versus more solitary (e.g., bird watching, walking pets) activities (Figure 4.4). Activity (24%) explained the highest proportion of variation in activity responses, followed by ecosystem (12%) and socialness (8%). Activity rankings were variable across age brackets (Figure S4.1). No observable differences were seen in activity participation based on race. Survey respondents at larger lakes were more likely to participate in different activities than those visiting smaller lakes ($F_{1,582} = 6.92$, $p < 0.001$).

Factor analysis of amenities reflected the same second and third factors as activities, with respondents parsing into lake visitors that used amenities and those that did not along Axis I (Use) (Figure 4.5A). Amenities also generally sorted into lake-related (e.g., boat ramp, kayak launch, dock) and park-related ecosystems (e.g., greenspace, playground, shelters), and could be further grouped by their facilitation of more and less social-oriented activities (Figure 4.5A and 4.5B). Use (35%) explained the highest proportion of variation in amenity responses, followed by ecosystem (12%) and socialness (5%). Notably, trees are associated with amenities that tend to facilitate less social activities (e.g., hiking trails, dog parks) (Figure 4.5B).

The most commonly identified barriers to lake use across all respondents were poor water quality (36%) and limited parking at lake access locations (34%) (Figure 4.6). Excessive waste (25%), lack of amenities (20%), lack of shade (19%) and concern for personal safety (17%) were also highly selected. Lake accessibility was more frequently identified as a barrier among Black or African American and White respondents compared to other racial identities (Figure 4.6). Asian respondents identified dogs, risk of drowning, personal safety, lack of shade, and limited parking as barriers more than other racial identities, while Hispanic, Latino, or Spanish respondents identified garbage and water quality as barriers more than other racial identities.

Across different lakes, water quality was more frequently identified as a barrier at Steel, Wilderness, and Killarney than other lakes of significant sample size, and limited parking was the most commonly identified barrier at Pine and Meridian (Figure 4.7). The presence of unhoused individuals was more often identified as a barrier at Echo, Haller, and Killarney than other lakes in the region, while Cottage lake had a particularly high proportion of respondents that identified lack of shade as a barrier. Lake water quality (total phosphorus) was not correlated with the proportion of respondents identifying water quality as a barrier at the 18 lakes with in-person survey distribution ($r = 0.17$, $p = 0.5$, $df = 16$), but shoreline and park tree cover was strongly correlated with the proportion of respondents identifying shade as a barrier ($r = 0.75$, $p < 0.001$, $df = 16$).

4.5 DISCUSSION

Understanding the dynamics of urban blue-green space use – with respect to who is visiting which lake-parks and engaging in which activities – facilitates proactive management approaches to enhance public participation, communication, and safety. The present study quantifies public participation in activities and use of amenities associated with blue-green spaces in western Washington lakes, in addition to identifying potential access barriers affecting individuals from multiple sociodemographic groups.

One possible but imperfect interpretation of survey results is that lake users generally comprise those engaging in activities on the lake or shoreline (e.g., swimming, fishing) versus those spending time in the park (e.g., playing sports, socializing). This dichotomy is also reflected in survey respondents' selection of amenities they are likely to use at lakeside parks, where responses fell into visitors predominantly using lake-based amenities (e.g. docks, swimming beach) versus park-based (e.g. open greenspace, playgrounds) amenities. In addition, the preferred activities and associated amenities of the respondents fell along a gradient of socialness – some users visit lakeside parks to engage in solitary activities, while others use them as social gathering spaces. These findings suggest that urban blue-green spaces are used by visitors seeking different CES across both lakes and parks, and should be managed to support diverse types of activities.

Water quality and parking were the most prevalent barriers to lake access selected across all racial and ethnic groups. Survey respondents also frequently attributed lack of amenities, insufficient shade from the sun, and concern for personal safety as barriers that preclude greater use of urban blue-green spaces. Quantitative metrics suggest that respondents' perceptions of shade are accurate, because tree cover is negatively correlated with the proportion of respondents identifying shade as a barrier. Water quality perceptions, on the other hand, appear to be less accurate given that lake water quality (total phosphorus) was not correlated with the proportion of respondents identifying it as a barrier. Nevertheless, water quality is annually impaired at some study lakes to the extent that county officials deploy fencing and signage around water access points to deter visitors from entering the water.

Previous work in Europe has shown that improved water quality in waterbodies close to home would increase individuals' likelihood to participate in swimming and fishing (Vesterinen et al. 2010). Encouraging public participation in swimming by improving lake water quality may promote positive health outcomes associated with outdoor swimming such as enhanced mindfulness and resilience (McDougall et al. 2022). This finding also points to an opportunity to engage the public in outreach about how to identify water quality or where to locate publicly available information. In addition, urban blue-green spaces are often viewed as heat refuges in summer months and strategic planning can help maintain or enhance the cooling features of lake-parks – including clean water, natural shade, and built shelters – as climate adaptation strategies (Yang et al. 2020). Importantly, our study included data from a 2023 Qualtrics survey which queried a socodemographically representative subsample of King County residents and included individuals who had never visited a lake, thus capturing responses from rare visitors to public lakes whose perspectives are unlikely to represented in paper surveys disseminated on-site.

Furthermore, limited use of specific lakes may be attributed to deterring factors. Lakes Echo, Haller, and Killarney had some of the lowest visitation rates, and a relatively high proportion of survey respondents at these lakes identified the presence of improvised shelters and homeless people as a significant barrier to their lake use. Notably, Echo and Haller are located along a major thoroughfare and public transit corridor in North Seattle. Killarney has a heavily vegetated shoreline with limited public access points and poor visibility, which may explain why personal safety was also a highly identified barrier at that lake. A previous survey of professionals supporting unsheltered homeless populations in the Seattle metropolitan area suggests that urban blue-green spaces can offer therapeutic CES to unhoused populations, but given homeless individuals' limited ability to adapt to changing seasons or poor weather CES benefits can be overshadowed by the drawbacks of being unhoused (Derrien et al. 2024).

Additional barriers to urban blue-green spaces use, including accessibility, dogs, and risk of drowning, were highlighted to varying degrees across races and ethnicities. County-, city- and park-level management decisions regarding transit, parking, lighting, public signage and other safety features can have a significant impact on access, especially for minority demographic groups. While tangible limitations such as distance to blue-green spaces and available transit lines can physically impede accessibility, these barriers can also be reinforced by psychological perceptions of park safety and quality (Park 2017). Directly involving local community members in public blue-green space planning can aid in identifying and alleviating both tangible and perceived accessibility challenges. In addition, previous studies have shown that African Americans are more likely to die due to drowning, but outreach campaigns through brochures and social media can positively influence water safety perceptions and save lives (Glassman et al. 2017).

Accurate estimates of visitor use are particularly challenging to obtain for urban blue-green spaces given their multiple points of access (Donahue et al. 2018). We holistically quantified visitors using blue-green spaces for different purposes with instantaneous counts of people visiting the lake, lakeshore, and park taken at the same time of the day across lakes, although we recognize that instantaneous counts may not always correlate with total visitation (Leggett 2017). We also maximized returns on survey effort by conducting surveys over the peak summer season during daytime, but this seasonal focus of sampling may have relatively under sampled activities that occur year-round and in the early morning and evening, such as bird watching and fishing, in comparison to seasonal daytime activities such as swimming (Vierriko and Yli-Pelkonen 2019). Furthermore, fishing at lowland urban lakes may be particularly concentrated in the weeks after fish stocking events which tend to occur in March and April – well before the commencement of our survey distribution. Survey respondents were also likely biased toward individuals walking, resting, or playing with kids who were easier to interrupt and approach with the survey than those swimming, boating, or exercising. Additionally, the survey was only offered in English and thus language may have been a participation barrier for some potential respondents.

The value of urban waterways are often overlooked, thus qualifying human benefits from water resources offers additional metrics to support restoration and maintenance of these ecosystems (Bell et al. 2021). Our study found water quality to be the most identified barrier to blue space access. Previous studies have shown that even marginal gains in freshwater health as a result of restoration efforts can promote significant social and economic benefits (de Bell et al.

2020). For example, lake users in the Midwestern US were willing to travel almost an hour's driving time further for every one-meter increase in lake water clarity (Keeler et al. 2015). Furthermore, management of urban waterbodies is often reactive and centered on closure of access in response to degraded water quality, such as the result of harmful algal blooms, rather than attempting to proactively alleviate barriers to lake access and use (Wiegand et al. 2013).

Urban lakes are also often monitored and managed without significant direct input from adjacent communities, which contributes to little custodianship among local user populations for lake health and integrity (Walker et al. 2013). Most of the lakes surveyed in our study undergo county-led monitoring using community volunteers, but these efforts often focus on lakeshore residents rather than community residents living outside of the lake shoreline radius (i.e., individuals dependent on public lake access points). Furthermore, studies on urban blue spaces have historically prioritized rivers and ocean coastlines, even though urban lakes are more spatially dispersed and relatively accessible to resident populations (Peng et al. 2024).

Assessing how and where users engage with lakes – or conversely choose not to engage – in urban blue-green spaces can inform outreach on safety, conservation, and funding priorities. Lakeside parks are just parks unless visitors are proactively invited to engage with lakes through waterfront access, infrastructure, and safety considerations – though even the sight of water alone can convey spiritual and other well-being benefits (Parsons 1991). A survey of citizens in Leipzig, Germany, found public blue green space users visit public spaces to fulfill incongruous demands (Palliwoda et al. 2022). This is reflected in our findings, where blue-green space users could broadly be classified by primary use of the park or lake and participation in more social versus more solitary activities. Thus, management of these public spaces should aim to provide diverse types of lake access across the landscape, including natural shorelines for wildlife viewing and more developed beaches designated for swimming.

Urban lake-parks serve large and diverse user populations, and results from this study can help inform public lake access enhancement and communications strategies tailored to lake-specific user bases. For example, our findings showed that lake users could generally be grouped into individuals engaging in social versus solitary activities. These results reflect a previous urban lake survey which found that the spatially confined layout of public lake shorelines promoted users' social interaction, whereas solitary and intensive physical activities were more associated with open greenspaces away from the lakeshore (Zhou et al. 2022). Results from our study also suggest that physical activity association with open greenspace, specifically in summertime, was encouraged by the availability of shade – which lake shorelines often lack.

In conclusion, this study demonstrates the value of intentional surveying of lake visitors to identify the diversity of activities and desired amenities in support of these activities across urban blue-green spaces. Lake use types are heterogenous, and thus development of lake access should facilitate diverse activities. Based on our analysis of activity preferences, county water resource management partners should emphasize enhancing blue-green spaces to facilitate both highly social (e.g., kids playing, swimming) and less social (e.g., fishing, bird watching) types of lake use. In addition, our results can inform the targeted alleviation of barriers to lake use on a lake-specific basis to improve equity in lake access across the landscape. Improved access to blue-green spaces remains fundamental to helping close the nature gap in urban environments where people of color, families with children, and low-income communities are most likely to be deprived of the benefits that nature provides.

4.6 ACKNOWLEDGMENT

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4.7 FIGURES

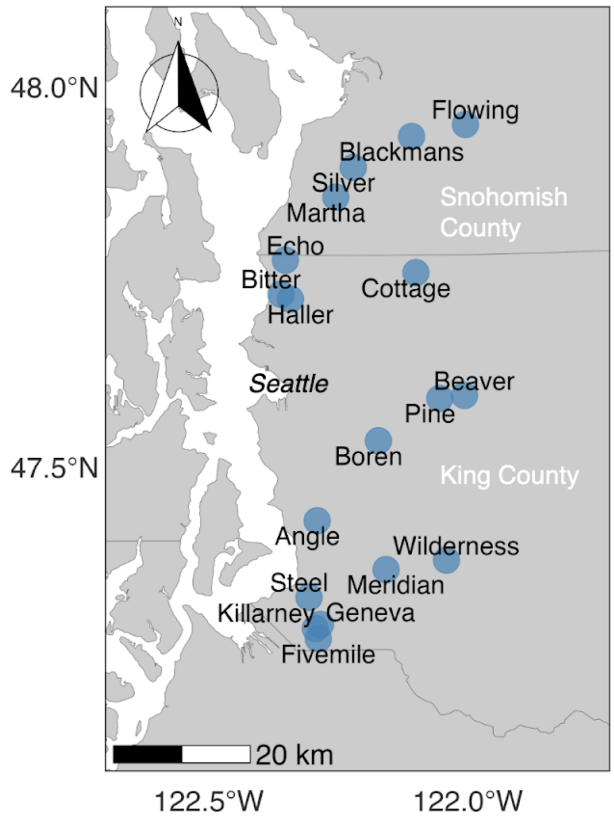

Figure 4.1 Map of 18 core lakes where visitation counts were collected and surveys were distributed in-person in Western Washington (King and Snohomish Counties).

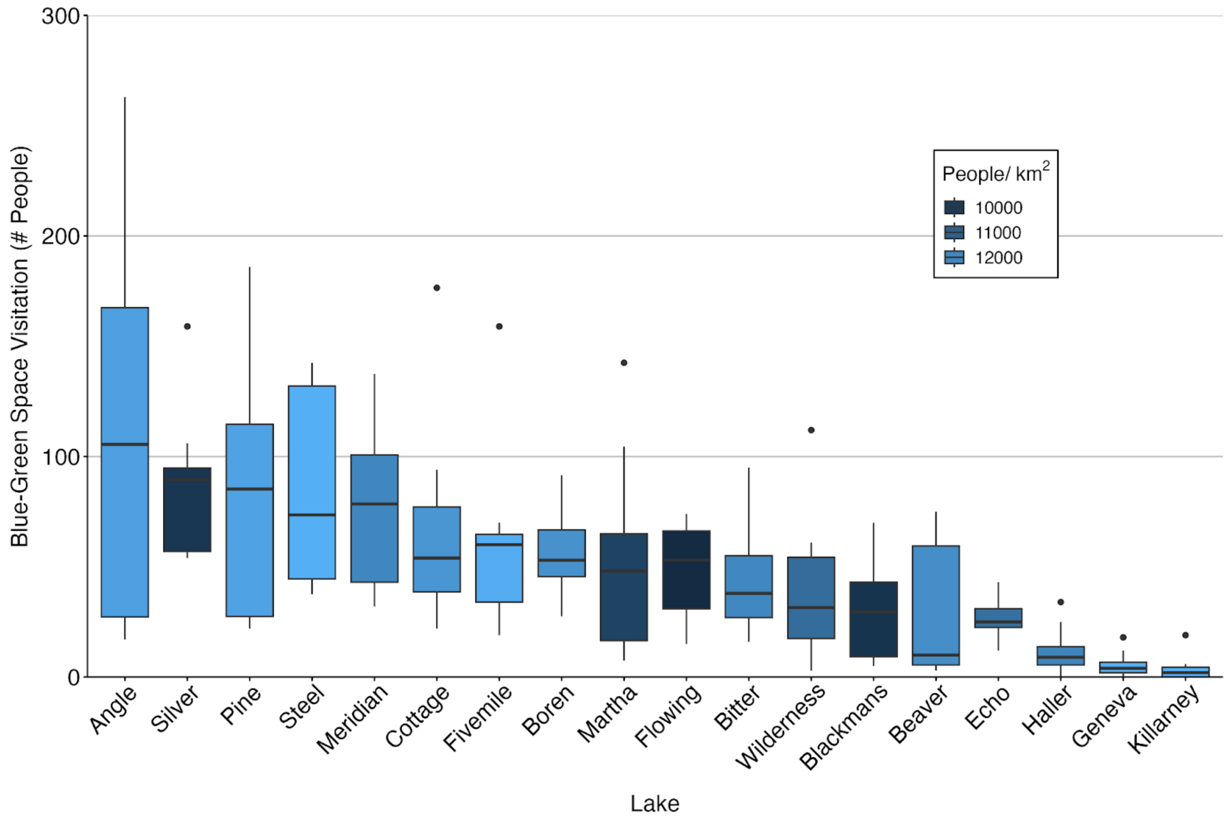

Figure 4.2 Blue-green space visitation (number of people observed at 12 pm) at 18 core lakes where surveys were distributed in-person. Boxes are colored by the mean population density (people/km^2) of the census tracts in which the lake is located.

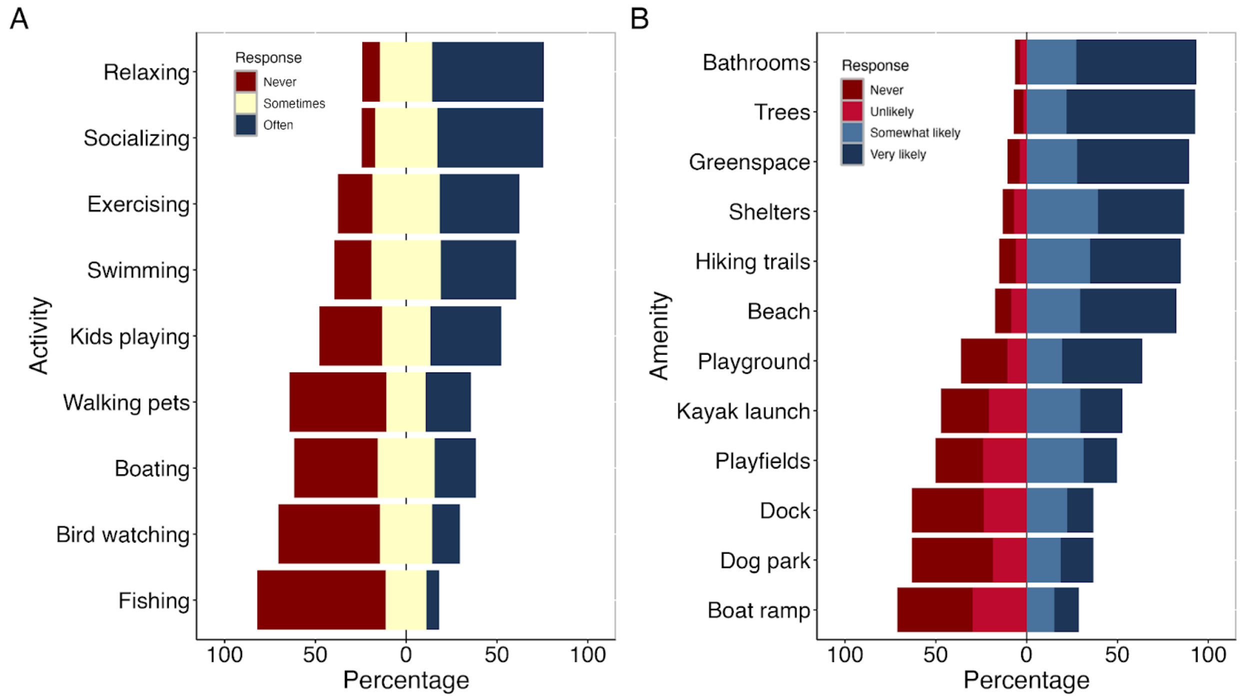

Figure 4.3 (A) Lake visitors' likelihood (% responses) of participating in blue-green space activities (N = 584) ranked never (red) sometimes (yellow) or often (blue) for each activity, based on 2021 survey responses. **(B)** Lake visitors' likelihood (% responses) of using lake and park-based amenities (N = 594) ranked never (dark red), unlikely (light red), somewhat likely (light blue), or very likely (dark blue) for each amenity.

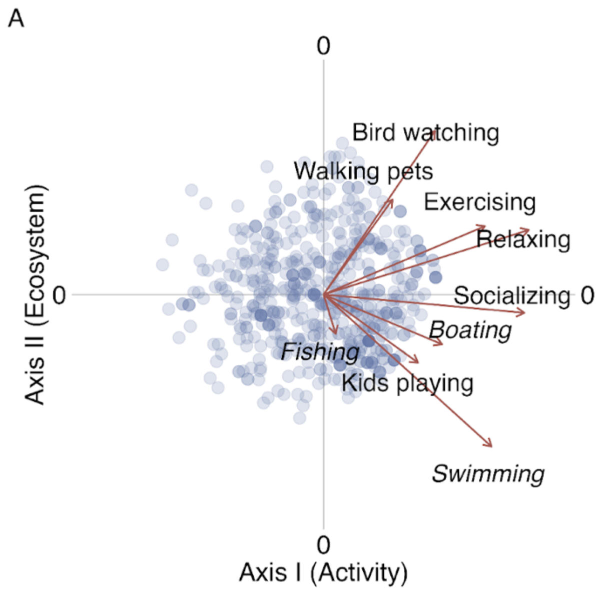

Figure 4.4 Factor analysis of survey respondents' rankings of activity participation at lake parks, showing activity loadings (red arrows) and individual respondents' scores (blue points). **(A)** Axis I (Activity) reflects the typical activities users engage in when visiting lakes, and Axis II (Ecosystem) reflects park versus water-based activities. **(B)** Axis III (Socialness) reflects more versus less social activities, and Axis II (Ecosystem) again reflects park versus water-based activities. Lake-related activities are denoted in italics while park-related activities are not.

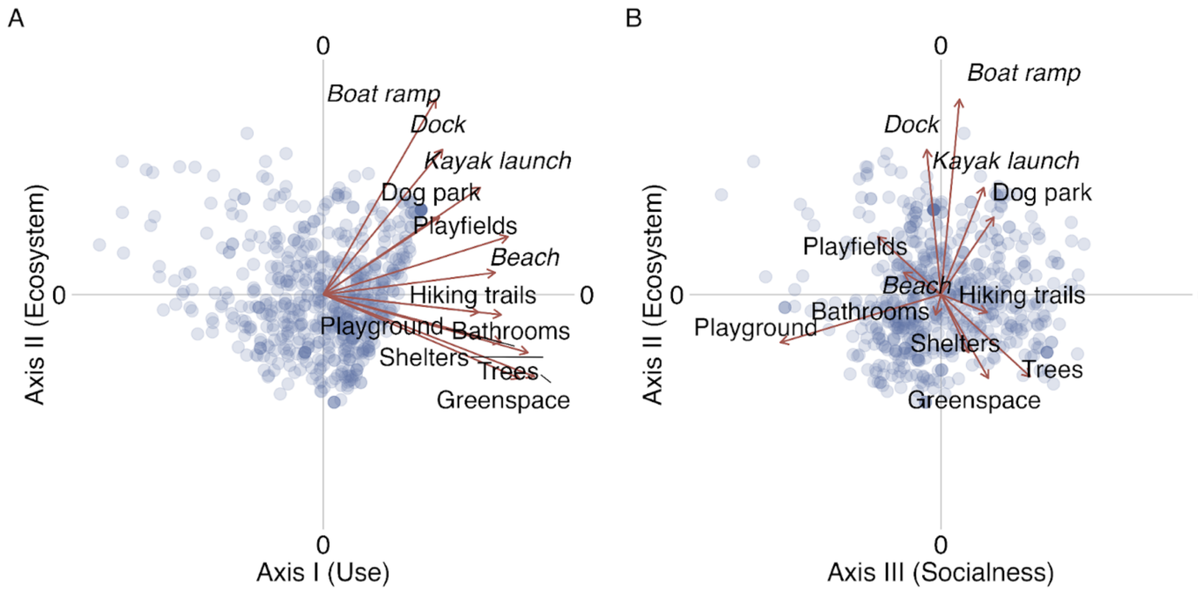

Figure 4.5 Factor analysis of survey respondents' rankings of amenity use at blue-green spaces, showing amenity loadings (red arrows) and individual respondents' scores (blue points). (A) Axis I (Use) reflects use of amenities versus no use, and Axis II (Ecosystem) reflects park versus water-based amenities. (B) Axis III (Socialness) reflects use of social versus individual activity-based amenities, and Axis II (Ecosystem) again reflects park versus water-based amenities. Lake-related amenities are denoted in italics while park-related activities are not.

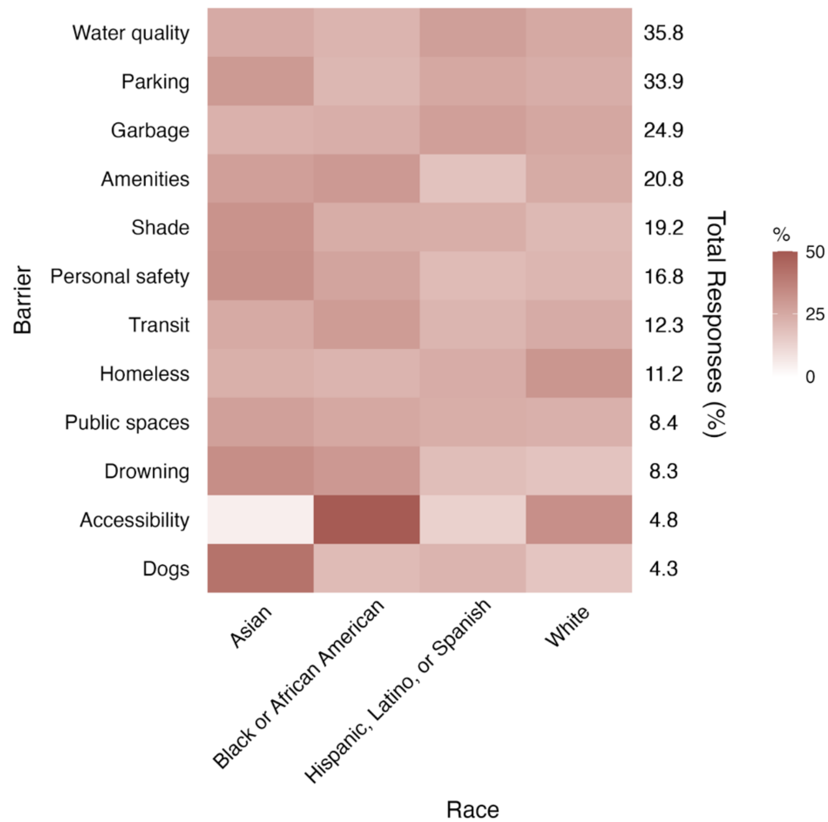

Figure 4.6 Heatmap of lake use and access barriers selected by 2021 and 2023 survey respondents (n = 1,432), colored by the percentage of individuals by race who selected each barrier as limiting their ability to visit lakes. Numbers on the right side are the percentage of total respondents across all races (%) who identified that barrier. Respondents could select one or multiple of White (n = 1,020), Hispanic, Latino, or Spanish (n = 102), Asian (n = 145), Black or African American (n = 96), Middle Eastern or North African, Native Hawaiian or Pacific Islander, and American Indian or Alaska Native, with an additional option to self-identify. Only results for racial identities with N > 30 are displayed here.

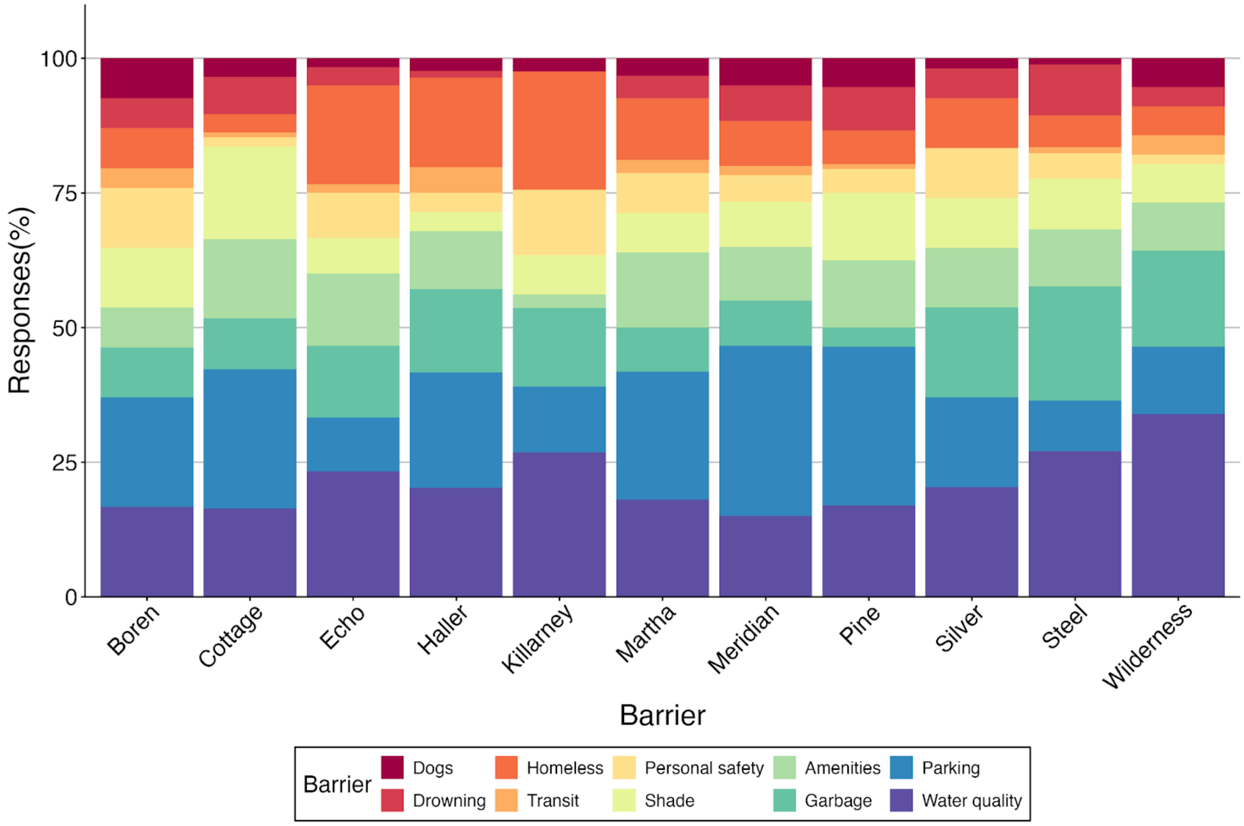

Figure 4.7 Scaled percentage of survey respondents who selected potential barriers to lake access as impeding their ability to use lakes at lakes with N > 20 survey responses. Respondents often selected more than one barrier, so the sum of percentages was scaled to 100% for each lake.

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4.9 APPENDIX 4

Table S4.1 Survey responses and locations of lakes where 2021 surveys were distributed in-person.

Lake	**Latitude**	**Longitude**	**Surveys (n)**
Pine	47.58737	-122.0447	57
Cottage	47.77144	-122.3431	51
Martha	47.3631	-122.153	45
Angle	47.42824	-122.2858	38
Steel	47.32756	-122.3029	38
Meridian	47.85363	-122.2434	34
Wilderness	47.37453	-122.0357	33
Haller	47.29177	-122.2812	32
Boren	47.75318	-122.0884	23
Echo	47.2729	-122.2856	23
Silver	47.89244	-122.2088	23
Killarney	47.28656	-122.2912	20
Blackmans	47.9324	-122.0938	17
Bitter	47.72665	-122.3524	16
Flowing	47.71991	-122.3339	14
Fivemile	47.94725	-121.9878	13
Beaver	47.59085	-121.9966	9
Geneva	47.53266	-122.1652	4

Table S4.2 Survey respondents' sociodemographic makeup (gender, age, race or ethnicity, income) as sample size and percent (%) of total respondents for 2021 and 2023 surveys. County population percentages are also provided for gender and racial identity in King and Snohomish counties (U.S. Census Bureau 2024).

Demographic Variable	2021 Survey (N = 667)	2023 Survey (N = 756)	King County	Snohomish County
Gender				
Female	406 (6.0%)	410 (54.2%)	49.3%	49.5%
Male	224 (35.0%)	338 (44.7%)	50.7%	50.5%
Non-binary	10 (1.6%)	5 (0.7%)		
Other	2 (0.4%)	3 (0.4%)		
No Response	25	0		
Age				
18-25	69 (11%)	105 (14%)		
26-35	124 (19%)	148 (20%)		
36-45	207 (32%)	173 (23%)		
46-55	87 (14%)	97 (13%)		
56-65	69 (11%)	97 (13%)		
Over 65	85 (13%)	136 (18%)		
No Response	26	0		
Race or Ethnicity				
American Indian or Alaska Native	0	9 (1.2%)	1.1%	1.6%
Asian	58 (9.5%)	60 (8.2%)	22.1%	15.1%
Black or African American	15 (2.5%)	72 (9.8%)	7.4%	4.4%
Hispanic, Latino, or Spanish	21 (3.4%)	32 (4.3%)	9%	10.1%
Middle Eastern or North African	8 (1.3%)	5 (0.7%)		

Native Hawaiian or Pacific Islander	6 (1.0%)	9 (1.2%)	0.9%	0.7%
White	467 (77.0%)	488 (65.0%)	53.7%	62.7%
Multiple Races	*54 (8%)*	*50 (6.6%)*	*5.7%*	*5.4%*
American Indian or Alaska Native	6	12		
Asian	16	12		
Black or African American	11	13		
Hispanic, Latino, or Spanish	28	20		
Middle Eastern or North African	5	0		
Native Hawaiian or Pacific Islander	8	6		
White	44	40		
No Response	58	31		
Household Income				
Less than $10,000	19 (3.7%)	65 (8.8%)		
$10,000 to $24,999	16 (3.1%)	67 (9.1%)		
$25,000 to $49,999	62 (12.0%)	137 (18.1%)		
$50,000 to $74,999	65 (13.0%)	141 (19.0%)		
$75,000 to $99,999	72 (14.0%)	110 (15.0%)		
$100,000 to $149,999	126 (24.0%)	117 (16.0%)		
$150,000 or more	157 (30.0%)	101 (13.4%)		
No Response	150	18		

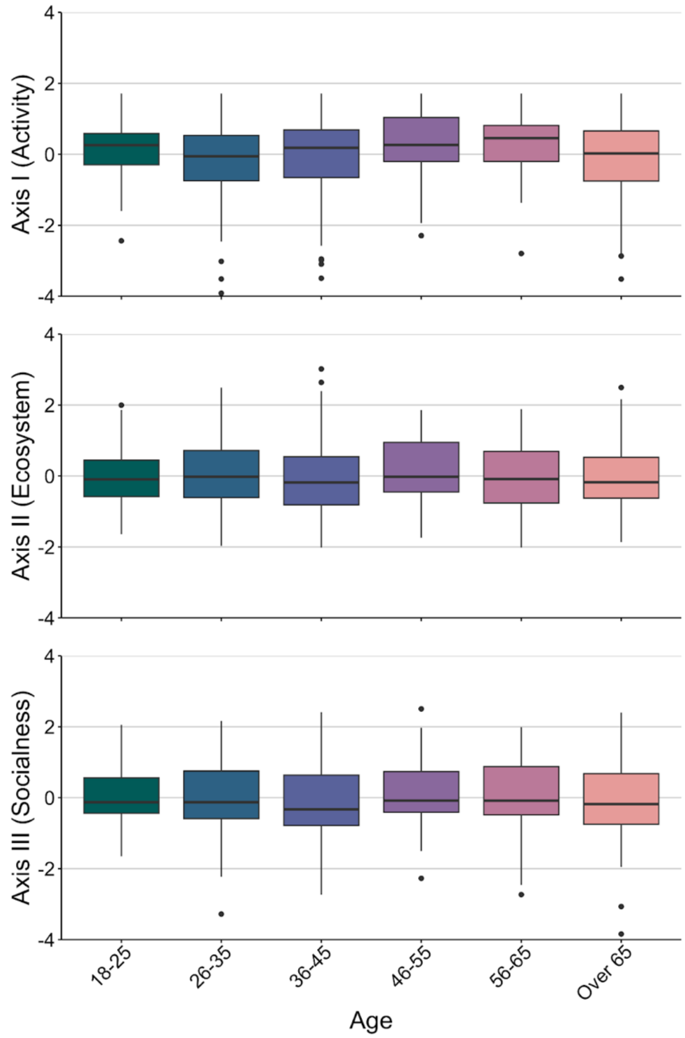

Figure S4.1 Means and distributions of individual factor scores for activities by Axis I (Activity), Axis II (Ecosystem), and Axis III (Socialness) binned by respondents' age group.

Chapter 5. REVEALING HUMAN-MEDIATED PATHWAYS FOR AQUATIC INVASIVE SPECIES FROM VOLUNTEERED GEOGRAPHIC INFORMATION

Publication history: This study was co-authored with Andrew Berdahl, Spencer Wood, and Julian Olden. At the time this dissertation was published, this chapter was not in review with a journal.

5.1 Abstract

Human-mediated pathways represent a significant and growing driver of species invasions in freshwater ecosystems. Angling and boating activities that entangle invasive organisms on fishing gear, boat hulls, and outboard engines, or use non-native species as live bait, serve as modes of introduction. Shifting scientific inquiry towards a better understanding of human movement may promote effective implementation of vector prevention strategies for suites of invaders. Human behavior is currently inferred from sparsely conducted in-person or mail-in surveys, thus generating data with limited spatiotemporal scope. Volunteered geographic information (VGI) – including geotagged social media uploaded by mobile phone applications – offers an opportunity to improve our understanding of human behavior. Here, we leverage VGI from the photo-sharing application Flickr to quantify the magnitude, direction and timing of overland connections between waterbodies in the Western US Then, we use network-based methods to infer risk of invasive species spread across the network. In our network waterbodies are nodes and edges are based on directed movements inferred from consecutive trips to waterbodies inferred from geolocated Flickr images. The network comprises a single, large, and connected subgraph spanning over 6,000 waterbodies in the western two-thirds of the United States. Compared to random networks with the same number of nodes and edges the Flickr-based network has more components and significantly higher mean node betweenness centrality

and Katz centrality, suggesting that human movement networks have more singularly influential and connective nodes than randomly distributed networks. These data and approaches could be leveraged at the state and county scales to identify specific waterbodies at the highest risk of invasive species introductions based on their relative frequency of incoming visitor movements. By identifying potential invasion hubs, management agencies can prioritize waterbody locations for preventative measures such as educational signage, boat inspection stations, and gear cleaning services.

5.2 INTRODUCTION

Invasive species pose a significant threat to biodiversity, ecosystem services, economic stability, and human health worldwide (Pyšek and Richardson 2010, Early et al. 2016). This is especially true in freshwater systems, where human transport of non-native organisms has facilitated and expedited the dispersal of species across watersheds and continents (Johnson et al. 2001, Havel et al. 2015). As the pace of non-native species introductions continues to grow rapidly at an international scale, there is unanimous evidence pointing to the importance of propagule pressure – the number of non-native organisms introduced – as the primary determinant of successful species invasions (Lockwood et al. 2005, Seebens et al. 2017). Human-mediated pathways, including entanglement of organisms on fishing gear, boat hulls, and outboard engines, as well as the release of non-native species used as live bait, represent a significant and growing source of aquatic invader propagules (Rothlisberger et al. 2010, Drake and Mandrak 2014, Smith et al. 2020). Consequently, new scientific insights that shed light on human movement patterns between waterbodies are needed to inform targeted management and policy actions aimed at reducing invasions (Lockwood et al. 2005).

Rather than attempting to predict the identity of individual plant and animal invaders, understanding human behavior may offer critical insight into the effective implementation of vector prevention strategies for suites of invaders (Schwoerer et al. 2024). One way past studies have tried to estimate potential propagule pressure at lakes is by developing gravity models from angler and boater surveys (Padilla et al. 1996). These models measure the attraction between origin and destination lakes based on human movement between them (MacIsaac et al. 2004). Past studies have also identified two main types of movements that disperse invasive species between lakes. These include localized movements connecting lakes over short distances and long-distance movements, referred to as jump dispersal, which connects waterbodies across significant distances (Havel and Medley 2006). More recent work has conceptualized waterbody connectivity as networks to facilitate landscape-scale management for aquatic invasive species. Within networks, destination and origin waterbodies are nodes, and edges are lakes that are visited by shared individuals, representing potential human-mediated pathways of spread between locales (Schwoerer et al. 2024, Ashander et al. 2022). Network metrics such as degree centrality and betweenness centrality – which measure the number of other nodes a node is either directly or indirectly connected with – are reflective of individual waterbodies' roles in interlinking human movement (Kvistad et al. 2019). Nodes with high centrality measures may be good locations to target intervention measures such as boat inspection or gear cleaning stations (Perry et al. 2017, Fischer et al. 2021).

Human activity on and movement between lakes is often inferred from in-person surveys or mail-in questionnaires (Davis and Darling 2017, Anderson et al. 2014), which are effective but logistically burdensome. Given the increasing scales and volume at which invasive species are being transported overland volunteered geographic information (VGI), in the form of geotagged posts, tracks, and photographs uploaded to digital platforms (e.g., Flickr, Twitter) offer an opportunity to understand human behavior as it relates to the potential for transport of aquatic invasive species over larger scales (Papenfuss et al. 2015, Venturelli et al. 2017). In recent years, computational methods have leveraged publicly available VGI to estimate human visitation to natural areas across time and space (Wood et al. 2013). Previous work has established that VGI sources – particularly the photo-sharing platform Flickr – are reflective of relative differences in visitation across lakes in the US (Keeler et al. 2015, Nelson et al. 2023). In addition to offering visitation estimates, VGI about users' activity also provides a time-series of sequential activity across vast distances and can log movement across the landscape among points of interest. When these movements are represented as a network, VGI can be further utilized to quantify inter-waterbody connectivity through overland travel (Frost et al. 2019, Weir et al. 2022).

In the United States (US), management entities are particularly concerned about the transport of impactful aquatic invasive species (AIS) that are known to easily establish in new waterbodies, such as zebra or quagga mussels (*Dreissena* spp.) (Johnson and Padilla 1996). The current invasion front moving westward for zebra mussel and many other consequential AIS is commonly seen as the midwestern US, specifically the Missouri River basin. The Continental Divide serves as a natural watershed barrier, preventing aquatic species from dispersing from east to west. Zebra mussels have already been detected west of the Divide in closed basins or isolated occurrences in California, Nevada, and Idaho. If the species were to establish in the Columbia River basin, for example, habitat suitability models predict the species will thrive and render considerable damage to local ecosystems, hydropower infrastructure, and fisheries

(Bossenbroek et al. 2007). Therefore, managers are consistently seeking new and affordable data sources to inform and optimize AIS prevention strategies.

Waterbody characteristics and the surrounding environment can influence the roles of lakes in the dispersal and spread of aquatic invasive species. For example, previous studies have found that reservoirs, more so than natural lakes, are likely to act as invasion hubs – or centers for the dispersal of invasive species to additional waterbodies (Havel et al. 2005, Stewart-Koster et al 2015). Previous work has also shown that environmental characteristics such as higher local population density and larger lake surface area correlate positively with lake visitation (Keeler et al. 2015). Understanding the variables that drive lake centrality within the network could assist in identifying target lakes for prevention measures in regions where human movement data are insufficient.

This study leverages VGI from Flickr to conceptualize human movement over time as a network linking waterbodies in the US. To our knowledge, this is the first effort to quantify human movement inferred from a general-interest VGI source representing locations of multiple user-groups (e.g., boaters, swimmers, and anglers), with the goal of informing AIS prevention and management. We aim to (i) measure large-scale human mobility data from Flickr to create an inter-lake movement network for the western US, (ii) characterize geographic trends in Flickr user movement among waterbodies by calculating multiple network properties, (iii) understand if the empirical network emerging from human visitation patterns is structured in a way that is more or less prone to spread of AIS than any other network of the same size using comparisons with similarly sized random networks, and (iv) assess the influence of environmental attributes on waterbodies' roles within the network. We discuss how our findings could support prioritization of locations for preventive measures such as educational signage, boat inspection stations, and gear cleaning services.

5.3 METHODS

5.3.1 *Study Area*

Our study encompasses lakes and reservoirs in the western two-thirds of the continental United States, delineated by two-digit Hydrologic Unit Codes (major river basins) 10 through 18 in the National Hydrography Dataset (NHD) (USGS 2024). We chose this geography because it represents the current leading edge of AIS spread from east to west across the United States for species of high concern such as zebra mussel (Drake and Bossenbroek 2004). Basins within this region, east of the Continental Divide, include the Missouri, Arkansas-Red-White, Texas, and Rio Grande basins. Basins west of the Continental Divide are the Upper and Lower Colorado, Great Basin, Pacific Northwest, and California basins.

5.3.2 *Data Acquisition and Filtering*

We acquired metadata for every publicly available Flickr photograph shared from 2006 through 2024 by querying the Flickr application programming interface with lake bounding box coordinates via the photosearcheR package (Fox et al. 2020) for R (version 4.4.2, R Core Team 2024). Waterbody bounding boxes were derived from lake polygons in the NHD v2, which were identified by filtering the NHD Waterbody Boundary Dataset to lake and reservoir type waterbodies. After acquiring Flickr metadata, we spatially filtered records by their geocoordinates to only include metadata from photographs taken within a 50 m buffer of waterbody polygons (to include waterbody shorelines). We then aggregated Flickr posts to user-days – distinct combinations of user ID, lake, and day – to remove repetitive Flickr posts from users who posted multiple photographs during a single trip to a waterbody (Wood et al. 2013).

5.3.3 *Network Conceptualization and Metrics*

In our empirically derived network, waterbodies are nodes, and edges are inter-lake movements created by consecutive trips to two different waterbodies by the same Flickr user. Our network does not include other trips to locations besides waterbodies that users may have visited and shared geolocated photographs between trips to consecutive waterbodies. The empirical network is useful for understanding general movement patterns over the landscape, rather than specific links. We employed a liberal temporal threshold and included inter-lake movements with a timespan of one year or less between trips to different lakes as connections in the network. Additionally, we excluded waterbodies that were only connected to the larger network through a single user movement over the entire study period. We also excluded repetitive movements across the same edge by a single Flickr user to ensure that edges were not overweighted by individual Flickr users repetitively moving among the same lakes. Each edge is directional and was assigned a weight equivalent to the total number of Flickr user movements that crossed it.

We identified network properties that offer insight into human movement patterns, which can promote AIS introduction and spread. We used the igraph package (Csardi and Neputz 2006) for R (version 4.4.2, R Core Team 2024) to calculate network statistics. We computed two network-level metrics and five statistics describing the nodes in the network.

The network metrics were: (i) Component: a distinct connected sub-network within the larger network (Clark and Holton 1991). Networks with fewer components are more connected, indicating AIS may more readily spread throughout them because more waterbodies are connected to one another via human movement. (ii) Mean shortest path length: the directed, unweighted mean pairwise distance between any two connected nodes in the network, expressed as the minimum number of edges needed to move from one node to another (Freeman 1977). This provides another measure of how connected the network is – more connected lake networks will have a shorter mean path length and can disseminate AIS further across fewer edges.

The node metrics were: (i) Degree centrality: the total number of other nodes directly connected to a given node, regardless of direction (Newman 2010). Waterbodies with high degree centrality act as hubs within the network and can spread AIS between many interconnected waterbodies. (ii) Out-degree centrality: the number of other nodes directly connected to a given node in the outward direction (Freeman 1979). High out-degree centrality indicates a waterbody is commonly a potential sender of AIS via human movement directed toward other lakes in the network. (iii) In-degree centrality: the number of other nodes directly connected to a given node in the inward direction (Freeman 1979). High in-degree centrality indicates a waterbody is commonly receives human movements that could bring AIS from other lakes in the network. (iv) Betweenness centrality: the number of pairwise shortest paths that pass through a given node – not where the node is an end point (Freeman 1977). Waterbodies with high betweenness centrality concentrate many pairwise pathways between other lakes, and could be prime locations to intercept invasive species flow between different lake clusters. (v) Katz centrality: node influence within the network as a sum of node closeness to all connected nodes weighted by interconnecting edge weight, where shorter path connections (e.g., first degree) are weighted greater than longer (crossing more nodes) paths (Katz 1953). Waterbodies with high Katz centrality have both high degree centrality across multiple adjacent degrees as well as high adjacent edge weights, and can disseminate AIS by human movement across many highly trafficked and intersecting paths.

5.3.4 *Null Network Simulations*

To assess the statistical significance of the network metrics described above, we simulated 1,000 null networks by randomly rewiring the empirically derived network. In other words, we maintained the same number of nodes and edges as well as the same edge weight distribution, but randomly redispersed edges and edge weights across nodes in each null iteration. We also calculated all previously mentioned node and network metrics for every null simulation to create expected distributions of each network and node metric. Next, we compared the null and empirical distributions with two-sample Kolmogorov-Smirnov tests and calculated the percentile of empirical network metric values relative to the null distributions.

5.3.5 *Node Metric Models*

We modeled node degree centrality, out degree centrality, in degree centrality, betweenness centrality and Katz centrality in linear mixed-effect models as a function of each waterbody's catchment population density, lake surface area, and lake elevation to assess the influence of environmental attributes on waterbody relevance in the movement network. We expected population density and surface area to positively influence these metrics because they are generally associated with increased lake visitation (Keeler et al. 2015), and we expected elevation to exhibit a negative relationship with centrality measures because lakes at lower elevations tend to have higher accessibility via roads (Schirpke and Ebner 2022). We completed all statistical analyses with the lme4 package (Bates et al. 2015) in R (version 4.4.2, R Core Team 2024). Environmental attribute measures were provided by the US Environmental Protection Agency's LakeCat dataset (Hill et al. 2018).

5.4 RESULTS

The VGI dataset includes 135,124 photo user-days across 8,552 lakes. Within the empirical network, there are 65,326 photo user-days and 46,921 movements representing trips to two consecutive waterbodies. The empirical network has 34,526 edges by 10,000 different Flickr users connecting 6,325 waterbodies (Figure 5.1). The median time between consecutive trips to different waterbodies was 29 days, with median distance between waterbodies of 72 km. Visited waterbodies are generally near metropolitan areas, though many users also visited alpine lakes in the Cascade, Sierra, and Rocky mountain ranges.

Distance between consecutively visited lakes in the network has a left-skewed distribution, with a mean Euclidean distance between waterbodies of 72 km (Figure 5.2A). Trips often occurred within less than a month of one another, with a median time between trips of 19 days (Figure 5.2B). Forty percent of movements were by users visiting two different waterbodies within one week.However, some edges span a significant distance – up to 3180 km. Most Flickr users (60%) contributed few inter-lake movements (two or less) to the network, and the mean number of movements per user is five (Figure 5.2C). Generally, Flickr users who contributed more edges to the network traveled a greater cumulative distance than those who contributed fewer edges (Figure 5.2E, $r = 0.7$). Edge weights range from one to 112 with a mean of one (Figure 5.2D), and edge weights were not strongly correlated with distance (Figure 5.2F, $r = -0.07$).

There are many cross-basin edges within the network (Figure 5.3). Though the majority of cross-basin edges are between adjacent basins on either side of the Continental Divide (e.g., California to Great Basin, Missouri to Arkansas-Red-White), 18% of edges crossed the Divide in the westward direction and another 18% go eastward (Figure 5.4). Additionally, 23% of the edges are interstate (Figure 5.5).

Compared to random null network simulations with the same number of nodes and edges, the empirical network has significantly more components and a higher shortest mean path length (both 100th percentile, Figure 5.6). Distributions of degree centrality ($D = 9.4 * 10^{-12}$, $p = 1$), out-degree centrality ($D = 1.5 * 10^{-11}$, $p = 1$), and in-degree centrality ($D = 1.5 * 10^{-11}$, $p = 1$) of nodes were similar between the null network and the empirical network derived from Flickr (n_1 = 6337650, n_2 = 6325). Empirical network medians of node betweenness centrality ($D = 0.12$, $p < 0.001$) and Katz centrality ($D = 0.97$, $p < 0.001$) were significantly higher than those of the null networks (Figure 5.7).

The lake attributes we tested in our models of node measures explained little of the variance in network metrics (n = 7168 for all models, Figure 5.8). Waterbody surface area and catchment population density both had significant positive coefficient estimates and elevation had a negative or neutral estimate for node degree centrality (*conditional* R^2 = 0.07, Figure 5.8A), out-degree centrality (*conditional* R^2 = 0.08, Figure 5.8B), in-degree centrality (*conditional* R^2 = 0.07, Figure 5.8C), and betweenness centrality (*conditional* R^2 = 0.07, Figure 5.8D). For Katz centrality, only waterbody surface density had a significant positive coefficient estimate while population density and elevation coefficient estimates were neutral (*conditional* R^2 = 0.1, Figure 5.8E).

5.5 Discussion

In this study, we leveraged timeseries of Flickr user activity to visualize overland connectivity of waterbodies across the western two-thirds of the continental US via human movement. We show that human movement between waterbodies in this region creates a highly connected network with a single large component. Here, we compare our results to other studies of waterbody user movement with survey-based data, provide context for our models of node influence measures as a function of waterbody environmental attributes, and discuss limitations and considerations for VGI as well as future directions.

Our movement network demonstrates that waterbodies are connected at varying spatial and temporal scales across the landscape, through human activity. This finding echoes prior studies conducted using survey-based methods to estimate human movement (Muirhead and MacIsaac 2005, Escobar et al. 2019). Similar to previous findings inferred from angler-specific VGI sources, our results affirm that most inter-waterbody movements occur over short distances and timeframes (Fricke et al. 2020). The geographic distribution of waterbodies connected by Flickr activity appears to be less urban-biased that of waterbody networks derived from angler-specific VGI (Weir et al., 2022), offering evidence that Flickr reflects a more diverse range of lake visitors than VGI sources dedicated to a particular activity. In addition, we found a significant proportion of movements span major river basins, state boundaries, and the Continental Divide. This reinforces the need for continued investment in collaborative, interstate prevention initiatives to stem the tide of AIS across the US (Kinsley et al. 2024).

Compared to similarly-sized random network simulations, the empirical network derived from VGI is less connected with more components and a longer shortest mean path length. However, the empirical network also has a significantly greater median betweenness and Katz centrality than random networks, suggesting that individual nodes in the empirical network have a greater influence on other nodes through direct and indirect connections. Collectively, these findings suggest that the empirical network is more influenced by individual highly centralized and weighted nodes than we would expect from a randomly distributed network with the same number of nodes and edges. In terms of AIS, this indicates that individual waterbodies play an inordinate role in connecting other waterbodies to one another through human movement patterns. Network and node metrics are particularly useful from a management perspective because they indicate to practitioners which waterbodies may be management priorities for preventative measures based on their roles in the network (Weir et al. 2022, Schwoerer et al. 2024). For example, lakes with high degree centrality, especially those that we know contain invasive species, are ideal locations for required boat and gear cleanings to prevent the distribution of aquatic hitchhikers among lakes within this cluster. Waterbodies with high betweenness serve as bridges between many different regions of lakes in the network, making them prime locations for additional watercraft and gear inspection stations to intercept the flow of invasive species.

As expected, waterbody degree centrality, betweenness centrality, and out-degree centrality were positively correlated with lake surface area and surrounding population density in our network. Previous work has shown that larger, more accessible lakes attract more visitors (Keeler et al. 2015, Nelson et al. 2023) – and therefore are likely to be more connected to other waterbodies and have higher centrality measures. We considered including waterbody type – natural lake versus reservoir – as an independent variable in our models, given that previous studies have demonstrated the outsize role of reservoirs in attracting significant visitors and acting as invasion hubs (Stewart-Koster et al. 2015). However, a very low proportion (0.37%, n = 29) of empirical waterbodies in the network are reservoirs – suggesting that reservoirs may be underrepresented among waterbodies visited by Flickr users. Since Flickr posts are photos, the relative lack of Flickr data on reservoirs could also be attributed to their typically lower aesthetic value when compared to natural lakes.

Previous studies have employed shorter time thresholds between trips to filter VGI occurring on waterbodies, aiming to estimate potential propagule pressure for specific AIS based on individual species' temporal tolerance of exposure to desiccation (Fricke et al. 2020, Weir et al. 2022). We chose to include movements spanning a longer time scale between trips because Flickr posts do not reflect all visitation at waterbodies, nor do they likely represent all visits by the subpopulation of Flickr users. Furthermore, photographs posted to Flickr do not necessarily equate to the actual introduction of a viable AIS propagule. By examining a wider timeframe we are establishing broad human movement patterns connecting lakes, rather than focusing on specific VGI user movements that happen to occur within the timeframes of invasive species' dessication tolerances. To leverage Flickr data more robustly, future work could leverage image activity classification through image content analysis (e.g., Winder et al. 2022) to identify specific photographs indicating high-risk activities (e.g., fishing, boating) for AIS transmission.

Geolocated Flickr images, and VGI more broadly, have several known biases that researchers and practitioners should consider when interpreting our results. These data do not represent all individuals visiting lakes (Wood et al. 2013). Individuals represented by VGI are typically younger and sometimes biased toward one gender (Longley et al. 2015, Hausmann et al. 2018). In addition, VGI data collected on waterbodies may be more sparse and biased toward particular activities compared to data from terrestrial settings, which could bias the network toward waterbodies that support more terrestrial than water-based activities. Previous work has surmised that people fishing, boating or swimming are likely to use their phone less while on or in water (Wood et al. 2013, Keeler et al. 2015). However, individuals recreating with watercraft (particularly motorized) may be the most likely to share photographs on Flickr because their images would geolocate to the lake surface rather than varying distances from lake shorelines.

Our conservative shoreline buffer (50 m) should limit an overreliance on data contributed by Flickr users on land.

Future studies should aim to supplement and ground-truth Flickr-based estimates of movement between waterbodies with empirical data from creel-surveys or mail-in questionnaires. Although numbers of geolocated Flickr images generally reflect visitation to lakes (Keeler et al. 2015), whether this performance extends to movements between points of interest remains untested. Furthermore, researchers could also relate pathways of human-mediated transport inferred from VGI to invasion risk assessments for recipient waterbodies (Johnson et al. 2001, Kolar and Lodge 2002, Tamayo and Olden 2014). In addition, future work could consider estimating lake visitors' home locations (Wood et al. 2013, Sessions et al. 2016), in order to better understand their radii of dispersal. While this exercise maybe quite time-consuming and computationally demanding, assessing the variance in waterbody users' typical radii of dispersal across the country would help further refine the local and regional scales at which managers consider deploying AIS prevention measures.

In conclusion, VGI derived from geolocated Flickr phogoraphs offers an opportunity to broaden the spatial and temporal scales at which we evaluate human movement as a pathway for AIS. We proposed and implemented an approach to conceptualize human movement – based on Flickr photographs – as a network, and measured network properties that may be related to waterbody invasibility. Our results suggest movement networks are more prone to AIS spread than random networks of similar size, given the relatively high connectedness of individual nodes in the movement network. Identification of influential waterbodies based on human movement and potential propagule pressure will support proactive location of preventive measures aimed at halting the tide of AIS spread.

5.6 ACKNOWLEDGMENT

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5.7 Figures

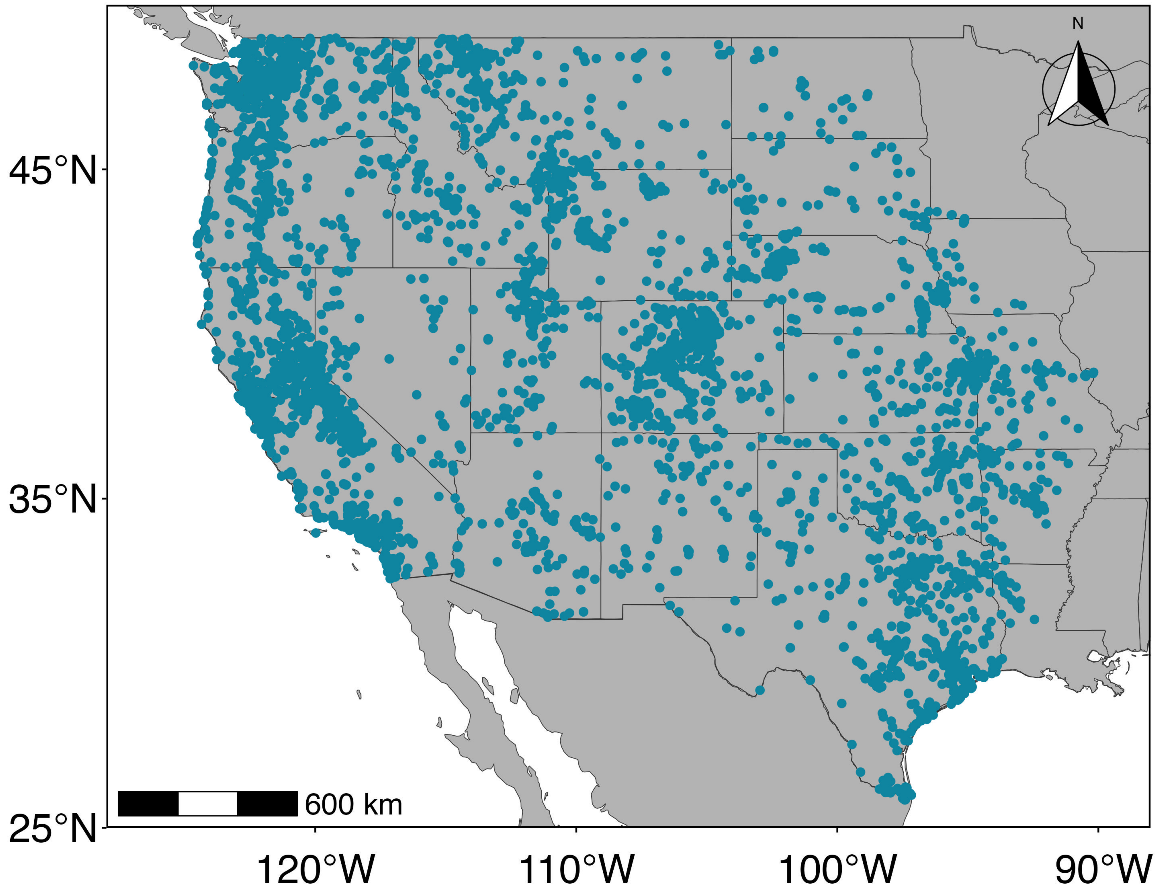

Figure 5.1 Waterbodies where images were posted to Flickr (blue) and connected by user movement to at least two other waterbodies (n = 6,325) in the western continental United States from 2006 through 2024.

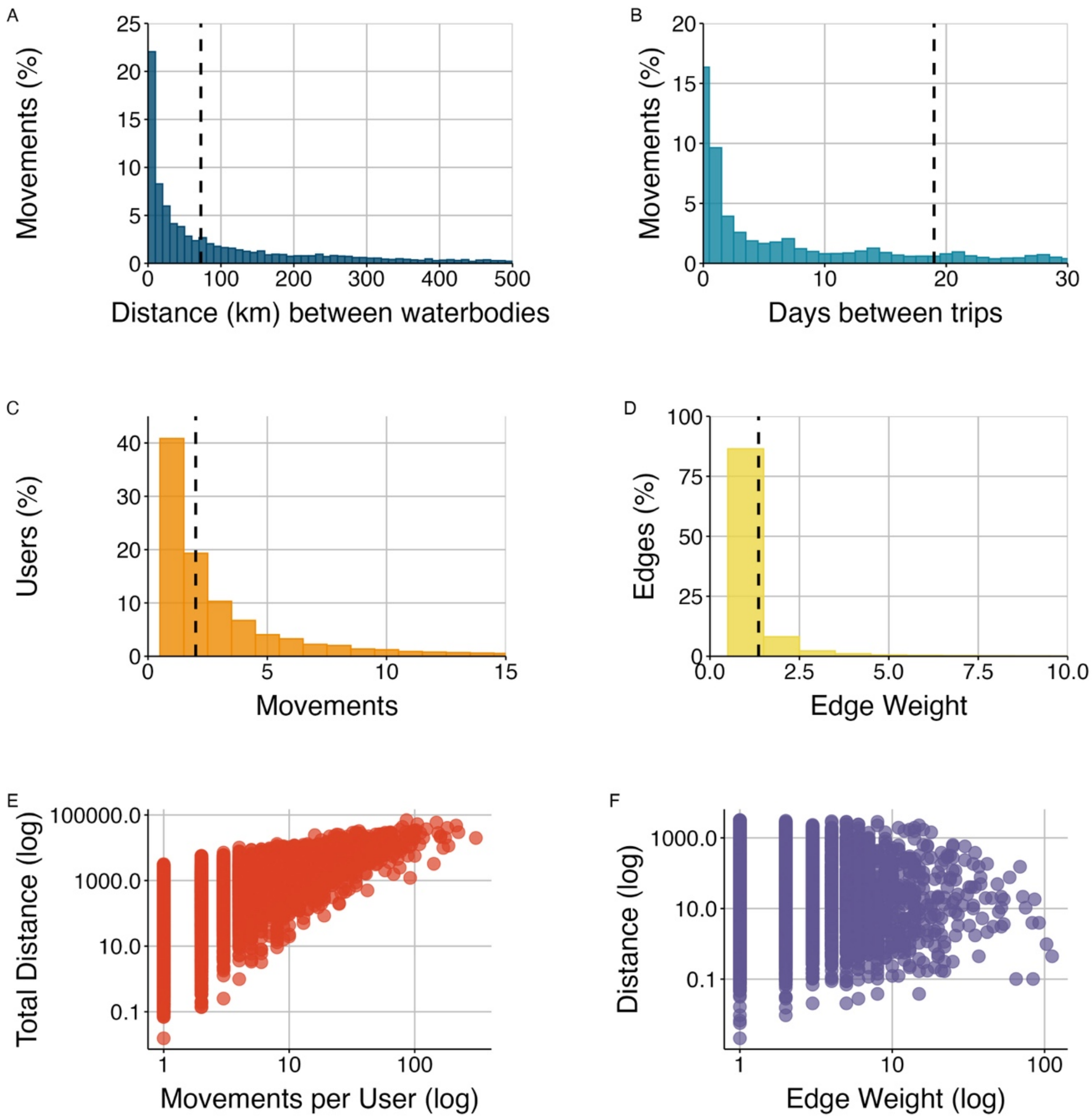

Figure 5.2 (A) Movements (%) binned by distance (km) between each pair of visited waterbodies creating an edge (bin size = 10). Values exceeding 500 km were omitted to enhance clarity, and vertical line is the mean in all histograms. **(B)** Proportion (%) of movements binned by the number of days between trips to different waterbodies. Values exceeding 30 days were omitted to enhance clarity (hereafter, bin size = 1). **(C)** Flickr users (%) binned by number of movements contributed to the network. Values exceeding 15 movements were omitted to enhance clarity, and and vertical line is the mean. **(D)** Edges (%) binned by edge weight. Values exceeding an edge weight of 10 were omitted to enhance clarity. **(E)** Total distance (log) between all lakes visited by each Flickr user in the movement network from 2006 to 2024, relative to the number of movements (log) each user contributed to the network (r = 0.7). **(F)** Distance (log) between waterbodies, relative to the edge weight (log) of edges connecting waterbodies (r = –0.07).

Figure 5.3 Entire network with edges (grey lines) and waterbodies (circles) colored by component membership and sized by relative degree centrality. Waterbodies are arranged by geographic location.

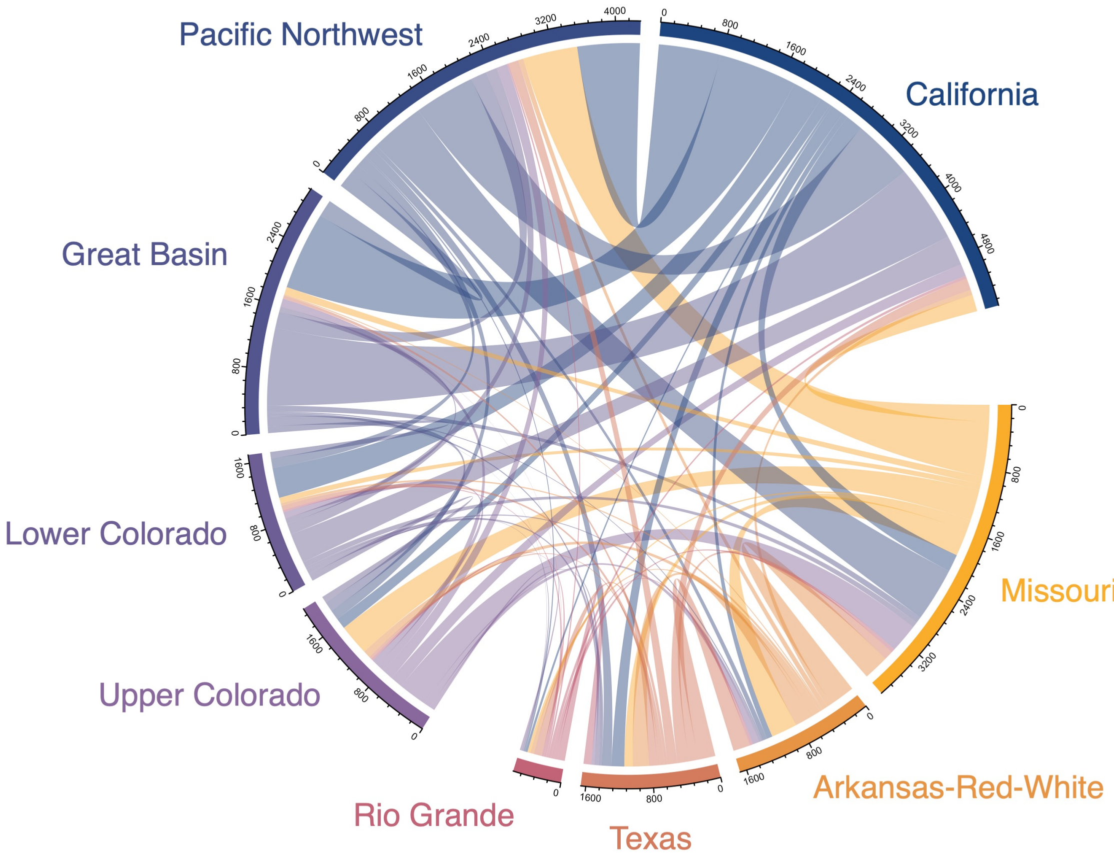

Figure 5.4 Chord diagram of Flickr user movement between major river basins East (Missouri, Arkansas-Red-White, Texas, and Rio Grande) and West (Upper Colorado, Lower Colorado, Great Basin, Pacific Northwest, California) of the Continental Divide. Inter-basin pathways are colored by the basin of origin, and edge widths indicate the number (n) of edges between each cross-basin pair identified between 2006 and 2024.

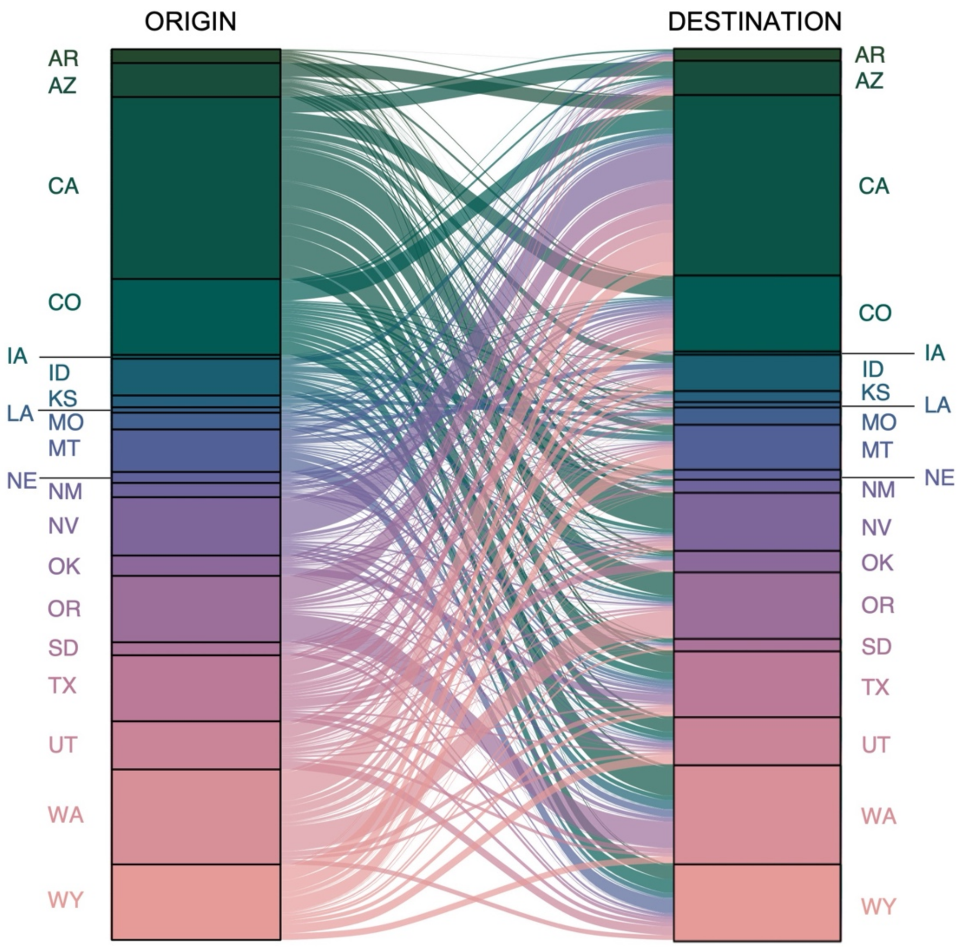

Figure 5.5 Sankey plot of inter-state movement (lines) colored by state of origin (n = 10,722). States (squares) are sized by the cumulative weight of outgoing (left) or incoming (right) movements.

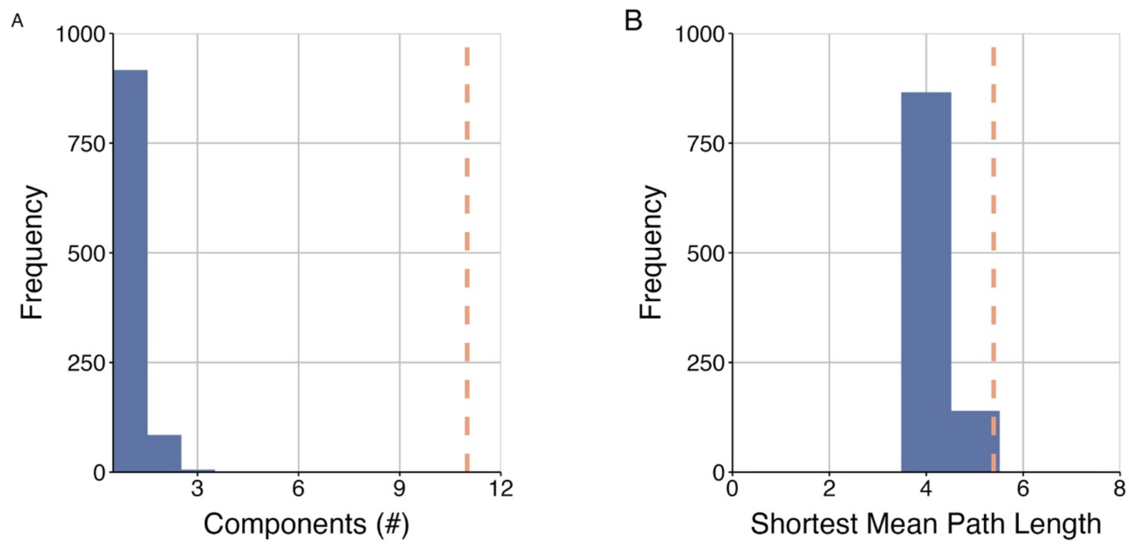

Figure 5.6 Frequency distributions of **(A)** the number of components and **(B)** mean shortest path length from null network simulations (blue), and the values of these same network measures from the Flickr movement network (orange).

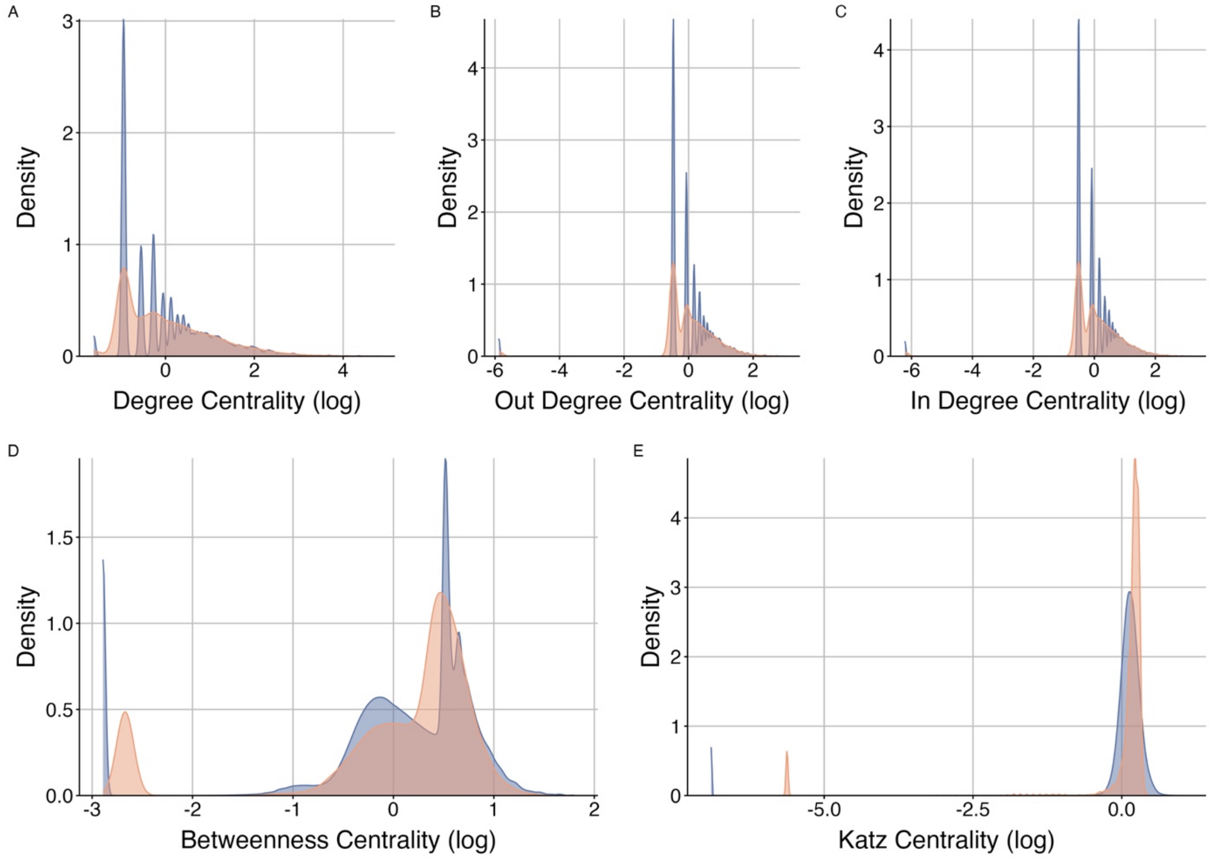

Figure 5.7 Probability distribution functions of node **(A)** degree centrality ($D = 9.4 * 10^{-12}$, $p = 1$), **(B)** out-degree centrality ($D = 1.5 * 10^{-11}$, $p = 1$), **(C)** in-degree centrality ($D = 1.5 * 10^{-11}$, $p = 1$), **(D)** betweenness centrality ($D = 0.12$, $p < 0.001$), and **(E)** Katz centrality ($D = 0.97$, $p < 0.001$) for null network simulations (blue) and the Flickr movement network (orange) ($n_1 = 6337650$, $n_2 = 6325$).

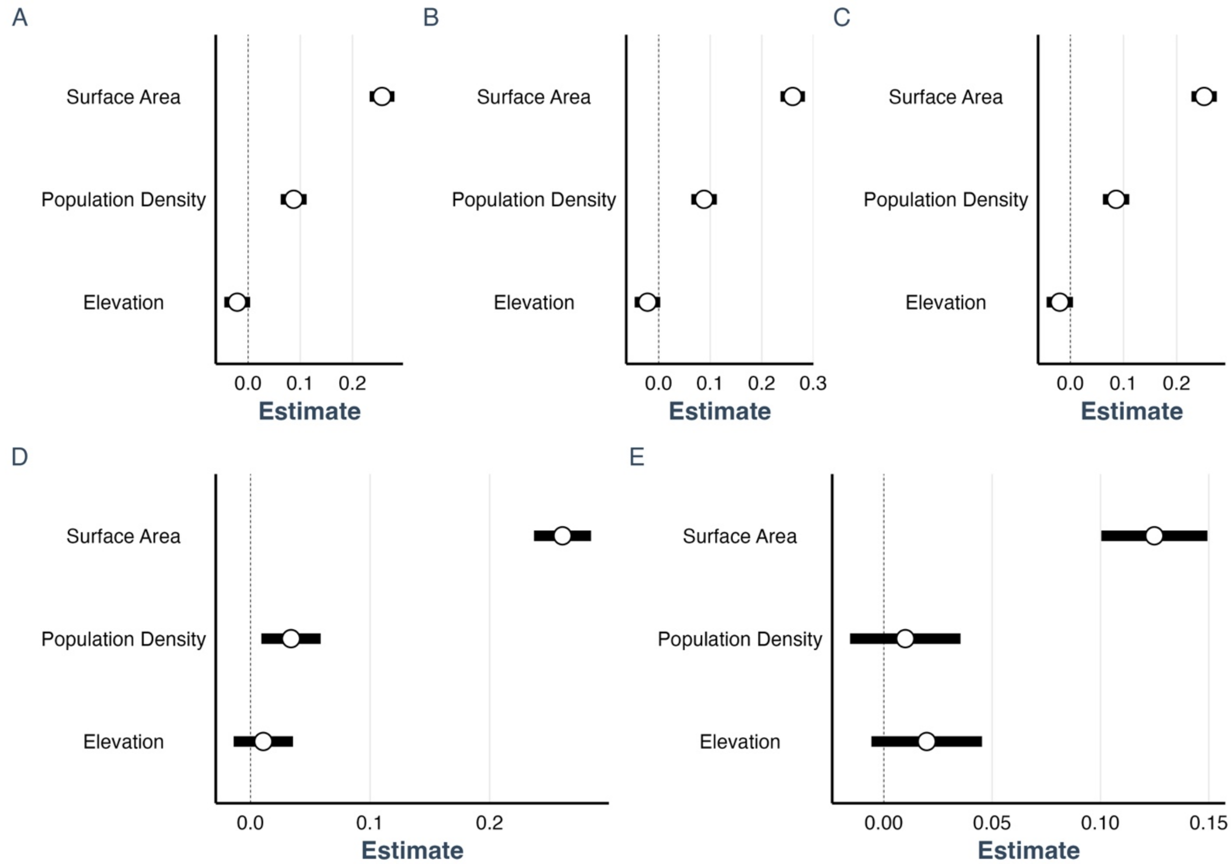

Figure 5.8 Coefficient estimates from the linear mixed effects models of waterbody **(A)** degree centrality, **(B)** out-degree centrality, **(C)** in-degree centrality, **(D)** betweenness centrality, and **(E)** Katz centrality. White circles represent means and bars are 95% confidence intervals of the estimates.

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