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Snapshot Wisconsin: networking community scientists and remote sensing to improve ecological monitoring and management

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Abstract. Biological data collection is entering a new era. Community science, satellite remote sensing (SRS), and local forms of remote sensing (e.g., camera traps and acoustic recordings) have enabled biological data to be collected at unprecedented spatial and temporal scales and resolution. There is growing interest in developing observation networks to collect and synthesize data to improve broad-scale ecological monitoring, but no examples of such networks have emerged to inform decision-making by agencies. Here, we present the implementation of one such jurisdictional observation network (JON), Snapshot Wisconsin, which links synoptic environmental data derived from SRS to biodiversity observations collected continuously from a trail camera network to support management decision-making. We use several examples to illustrate that Snapshot Wisconsin improves the spatial, temporal, and biological resolution and extent of information available to support management, filling gaps associated with traditional monitoring and enabling consideration of new management strategies. JONs like Snapshot Wisconsin further strengthen monitoring inference by contributing novel lines of evidence useful for corroboration or integration. SRS provides environmental context that facilitates inference, prediction, and forecasting, and ultimately helps managers formulate, test, and refine conceptual models for the monitored systems. Although these approaches pose challenges, Snapshot Wisconsin demonstrates that expansive observation networks can be tractably managed by agencies to support decision making, providing a powerful new tool for agencies to better achieve their missions and reshape the nature of environmental decision-making.

Key words: black bear; bobcat; camera trap; citizen science; Landsat; management agency; MODIS; observation network; remote sensing; trail cameras; white-tailed deer; wildlife.

Introduction

The emergence of community (citizen) science and localized remote sensors (e.g., trail cameras or acoustic recorders) have enabled biological data to be collected more quickly and continuously over larger scales than ever before (Bonney et al. 2009, Shonfield and Bayne 2017, Steenweg et al. 2017). Concurrently, new satellite remote sensing (SRS) missions and openings of SRS archives have unearthed a similar wealth of data related to land cover, plant phenology, and other characteristics of Earth's surface (Wulder et al. 2012). This combination of remotely sensed biodiversity and environmental data at multiple observation scales provides new opportunities to understand anthropogenic impacts to biodiversity and guide decision-making.

Observation networks are programs to collect and synthesize broad-extent environmental and biological data (Keller et al. 2008, Scholes et al. 2012, Lindenmayer et al. 2018). These enterprises vary in scope, sampling structure and data collection methodologies, but commonly involve locally sensed data collected by humans or automated sensors. Examples include eBird, which aggregates bird observations submitted by community scientists globally (Sullivan et al. 2009), the Urban Wildlife Information Network, which compiles trail camera images of wildlife in U.S. cities (Magle et al. 2019), the National Phenology Network (Schwartz et al. 2012), and the U.S. National Ecological Observatory Network (NEON). The objectives of observation

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networks are to improve ecological inference, prediction, and forecasting; geospatial data derived from SRS operate within observation networks as a source of input variables that enable these objectives (Turner 2014). Fusing locally sensed biodiversity observations with geospatial data provided by SRS observations is a topic of substantial research interest critical to the implementation of many large-scale (even global) conservation efforts such as the development of essential biodiversity variables (Kissling et al. 2018, Jetz et al. 2019).

Although conservation goals and objectives are often continentally or globally defined via convention or agreement (e.g., the Aichi Biodiversity Targets), most natural resource management and conservation decisions are made at sub-national scales (e.g., regions, provinces, counties). Decision-making across these smaller extents still must contend with biodiversity monitoring that is imperfect and incomplete along biological, temporal, and spatial axes (Kissling et al. 2018, Jetz et al. 2019). Most species are not monitored, biological sampling is often non-representative spatially or temporally, and data may be aggregated at coarse grains that hinder effective management solutions (Aceves-Bueno et al. 2015, Marra et al. 2015, Artelle et al. 2018). For example, game species are often monitored using harvest data collected during a brief timeframe and with unknown spatial biases; to account for spatial uncertainty, these data are often aggregated to coarse resolutions (areas ~1,000 km^2 or greater) for analysis. This combination of narrow temporal extent and coarse spatial resolution makes it challenging to understand how populations respond to fine grained (e.g., home range scale) processes that occur at varied times of year (Marra et al. 2015). Concurrently, there is growing appreciation that local biodiversity changes can be driven by broad-scale environmental processes such as climate, land cover, or land use change (Parmesan et al. 2000). Although it is difficult for agencies to manipulate these drivers, they can often be monitored using SRS (e.g., Clare et al. 2019*a*), and quantifying their effects on biodiversity can improve understanding of the system needed to anticipate emerging problems and formulate effective solutions (Sultaire et al. 2016, Wilson et al. 2019).

Natural resource agencies are increasingly interested in developing observation networks to inform decision-making. We call these jurisdictional observation networks (JONs): monitoring efforts operated by or in collaboration with management agencies that seek to fill spatial, temporal or taxonomic information gaps to support decision-making across regions where the participating agencies have jurisdiction. The size of jurisdictional regions may vary considerably and often show hierarchical structure; for example, wildlife management decision-making by agencies can occur at multiple levels, ranging from entire states down to more granular management units. JON sampling design, methodology, and frequency may vary considerably, ranging from infrequently occurring but spatially comprehensive biological atlases (e.g., the Wisconsin Breeding Bird Atlas conducted every 20 yr) to more intensive, regular, or continuous sampling protocols facilitated by local remote sensors. The defining feature of JONs is an explicit intent to support decision-making and decision-makers play a role in defining network goals and design. We posit that effective implementation of JONs will require the integration of satellite and ground sensor networks to support biological inference and prediction across space and time.

Here, we describe the implementation of a JON that combines SRS and a volunteer-powered trail camera network to generate new insights into wildlife distributions and wildlife management across space and time. We present Snapshot Wisconsin (SW) as proof of concept that agencies can manage efforts that link structured biodiversity observations to earth observations, providing data with unparalleled resolution and volume that can free agency managers and scientists from certain constraints found within traditional monitoring frameworks, but raise other considerations. We provide examples that demonstrate the potential of fusing JONs with remote sensing to guide decision-making across a range of taxa and spatiotemporal scales.

Snapshot Wisconsin

The Wisconsin Department of Natural Resources (WDNR) initiated Snapshot Wisconsin (SW) in 2014 in partnership with the University of Wisconsin and NASA. SW has the joint goals of improving information for wildlife decision-making and broadening stakeholder engagement with natural resources management. Motivation for SW reflects common monitoring limitations. Existing monitoring uses sampling strategies tailored to a narrow range of species, and primarily focuses upon species of conservation concern or sportsman interest. Sampling constraints often compel agencies to employ incomplete spatial or temporal sampling based on convenience, with data typically aggregated to spatiotemporal scales that may be poorly defined, inconsistently sized, or misaligned with the focal biological processes. Reconciling differences between the extent and resolution of sampling, biological processes, and jurisdictional units is challenging, and often forces decision-makers to use information that is not perfectly fit for this purpose (Millspaugh et al. 2009, MacFarland and Van Deelen 2011).

Community Scientists and Sensor-based Sampling

SW relies on community scientists to deploy trail cameras across the state and to classify images. Interested volunteers can use a web-based platform to apply to host a camera trap on their own property or on public land within open “blocks” on a first come, first served basis. Blocks are delineated as U.S. Public Land Survey System quarter-township (comprising a 4.8 × 4.8 km cell). Typically, blocks house a single camera, although denser camera deployments have been enacted in certain regions to support specific objectives (Fig. 1A). Successful applicants are required to place cameras >100 m from buildings or heavily trafficked roads to avoid regularly detecting humans, and the use of baits or lures is prohibited. WDNR trains volunteers to set cameras to sample locations expected to see use from a variety of species and where wildlife are likely to be detected if passing through (typically ~0.75 m above ground and ~3–4 m away from an unobstructed target region). Volunteers are expected to maintain camera stations (i.e., clear blocking vegetation, swap batteries) and upload images to a central web-based repository multiple times per year to maintain continuous monitoring. The SW trail camera network is in many ways analogous to SRS, as the cameras operate continuously—indeed with finer temporal granularity than most SRS missions at comparable spatial scales. This ongoing sampling is designed to inform decision-making processes that occur at different times of year, and facilitates understanding of how wildlife respond to finer-scaled (e.g., seasonal) variation in the environment (Fig. 1).

SW cameras are motion-activated Bushnell Trophy Cam models (Bushnell, Overland Park, Kansas, USA) and record a three-image burst when triggered, with a 15-s gap between triggers. Much like SRS missions, SW exerts standardization to ensure data quality and compatibility across image collections. The WDNR provides volunteers cameras with fixed settings that produce encrypted photos to prevent manipulation. Image classification options (Appendix S1) are standardized to include species identification, number of individuals, presence of juveniles or radio-collared animals, and behaviors exhibited in the image burst such as foraging, vigilance, or resting. Volunteers have latitude to place cameras within a variety of habitat types and along a variety of features. Thus, SW collects additional metadata regarding camera placement (aboveground height, distance to the target area, the type of feature targeted, and local descriptors) to help account for observation variation within downstream analysis (Kelling et al. 2019). Image classification (Appendix S1) is a three-part process involving classifications by camera hosts, consensus-based classification by additional volunteers on a Zooniverse-hosted crowdsourcing platform (*available online*),[6] and expert evaluation that feeds into design and model-based strategies to account for detection and classification errors (Clare et al. 2019*b*, 2021), with the intent to integrate artificial intelligence approaches to expedite classification (e.g., Willi et al. 2019).

Integration with Satellite Remote Sensing

Acquiring and processing SRS data is a critical component of SW. The continuous sampling design of SW captures intra- and inter-annual variability in species distributions at the camera level. However, even complex analysis of patterns in the trail camera data alone provides limited insights into how distributions or populations function, how they are impacted by the broader environment, and how they might be managed (Nichols and Williams 2006). Linking species occurrence data to spatially contiguous data regularly collected from airborne or satellite-mounted sensors can improve predictions and forecasts of patterns beyond pure geostatistical or time-series approaches. It is also useful for identifying factors that can be manipulated to achieve management objectives or that may hamper management actions. For example, land cover or nighttime light intensity can be locally or ephemerally manipulated to meet objectives (Horton et al. 2019, Wilson et al. 2019). Other factors such as vegetation phenology and vigor, snow cover and frozen ground, and land surface and air temperature are challenging or impossible to manipulate, but are readily observable using SRS and have strong effects on biodiversity (Pettorelli et al. 2005, Albright et al. 2010, Zhu et al. 2019). Quantifying their effects aids assessment of population vulnerability and management prioritizations (Sultaire et al. 2016), and accounting for uncontrollable effects allows managers to better assess tractable manipulations (e.g., whether more conservative harvest limits buffer populations against the negative impacts of climate change).

In short, leveraging spatially explicit environmental data within monitoring efforts is a critical determinant of agency capacity to manage wildlife effectively. Here, we present applications where predictors are derived exclusively from SRS. Although we recognize that geospatial predictors from other sources are also useful (e.g., road networks), an approach rooted in remote sensing prepares a foundation for what we believe SW will become (see *Discussion*).

SW has been a massive success with respect to data collection and volunteer participation. As of October 2020, >49 million images have been recorded across a sampling effort of >4,000 combined trap-years (some cameras have operated continuously since 2015) at more than 4,000 distinct camera locations, with more than 10 million images currently known to contain wildlife (Fig. 1). Nearly 1,900 volunteers host >2,200 active cameras, with >11,000 other volunteers assisting with image classification on the project's crowdsourcing platform. In terms of overall sampling effort, SW is, to the best of our knowledge, the largest single continuous and centrally managed camera trapping effort to date.

Below, we use examples to describe six ways in which JONs and SRS can enhance biological monitoring. Our purpose in presenting these examples is to provoke further thought about how improved information extent and resolution leads to effective management. We do not intend to highlight specific methodologies, and refer readers interested in technical details to the Supporting Information. Moreover, in keeping with the philosophy of monitoring and management as iterative processes (Nichols and Williams 2006, Dietze et al. 2018), we

[6] snapshotwisconsin.org

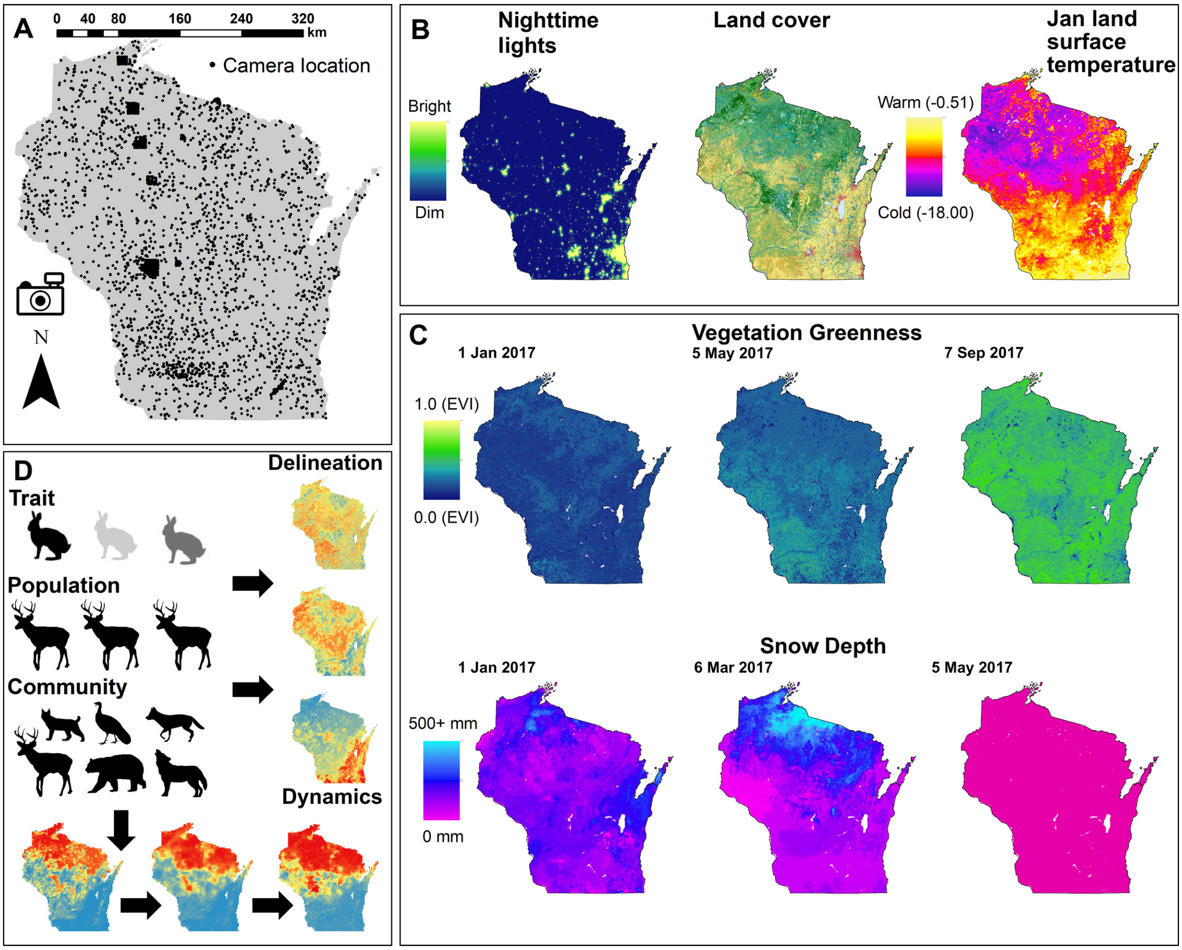


Fig. 1. (A) The location of cameras contributing data to Snapshot Wisconsin (SW) at any point in the project's duration through May 2020 (n = 3,364). Locations with greater camera density resemble dark boxes. (B) Static satellite remote sensing data layers used for prediction/inference include nighttime light intensity as an indicator of human presence, Landsat-derived land cover, and longer-term averages in winter land surface temperature. (C) Dynamic spatial predictors at finer temporal resolution include vegetation greenness indices and snow depth. (D) Combining information about species traits (phenotypes, behaviors), populations, and assemblages derived from cameras with the spatial data from satellite remote sensing enables biodiversity variables to be delineated, monitored, and forecast.

emphasize that these are not completed applications or modeling excercises. Rather, each example represents an incremental improvement in information over what was previously available: as is the case for all monitoring efforts, focus and rigor depend upon existing knowledge of the system.

Example 1. Increasing Spatial Resolution

Species of significant managerial interest are subject to more regular and rigorous monitoring by agencies, but existing monitoring programs may lack spatial or temporal resolution to address targeted questions. For example, black bear (*Ursus americanus*) distribution is believed to be expanding into the more populated and agricultural regions of southern Wisconsin, which brings increased potential for conflict and property damage. Thus, the WDNR is interested in predicting the expansion of this population to anticipate conflict or regulatory changes. Existing models based upon population reconstruction from harvest data can track changes in statewide population size (Allen et al. 2018*a*), but cannot predict population spread. Modeling linkages between forest and forested wetland land cover data provided by SRS with bear occurrence dynamics from SW provides the resolution to address these needs. Predictions from a dynamic occupancy model at 5 × 5 km resolution (reflecting the home range size of female bears) suggest a stable or potentially declining distribution from 2015 to 2018 (Appendix S2: Fig. S2), consistent with estimated population decline during the same time period based on population reconstruction of harvested animals (Allen et al. 2018*a*). Coefficient estimates suggest that forest, forested wetland, and the number of occupied neighboring cells all increase the likelihood of bear persistence, and that colonization is influenced by the number of nearby occupied cells (Appendix S2: Table S1). Forecasts suggest that bears are unlikely to become established in southern Wisconsin in the near future (i.e., by 2024) assuming current conditions (i.e., land cover distribution) hold (Fig. 2), as a large swath of intensive agriculture separates the current distribution of bears from potentially suitable habitat. Thus, managers may have time to develop management goals and objectives for bears in this part of the state.

Example 2. Increasing Temporal Resolution

For many species, linking JON and SRS data can support decision-making at finer (and potentially more useful) temporal resolutions than static or annual products. Species distributions and their environmental associations change throughout the annual cycle (Conn et al. 2015), and understanding these dynamics can inform more effective management and conservation actions. For example, deterrence actions to reduce livestock depredation or crop damage are more effective when implemented in places and seasons with high probability of conflict (Olson et al. 2019), and these finer-grained actions are preferable to blunter approaches such as changing harvest regulations. Human–bear conflict is ephemeral, and understanding changes in bear distributions and habitat associations across the year provides baseline insights into predicting likely conflicts. The combination of SW images and regularly collected SRS data can support models that describe seasonal patterns in black bear occurrence (Fig. 3 and Appendix S3). While asymptotic bear occupancy (i.e., the probability of ever occurring over the course of the year) was positively associated with the proportion of forest cover across a broad (5 km) spatial grain (e.g., Example 1), bear occurrence at a finer temporal scale (i.e., availability for detection, or the estimated probability of being within a 500-m region on a specific day) was positively associated with concurrent daily estimates of the enhanced vegetation index (Appendix S3: Table S1, Fig. S1). Associations between daily bear occurrence and finer-grained (500 m) forest and cropland cover further vary seasonally. For example, bears avoid cropland during summer months but appear more likely to use it during spring and autumn, with activity peaking in late spring (Fig. 3 and Appendix S3: Fig. S1). Model predictions appear consistent with existing understanding of patterns in bear conflict. For example, daily likelihood of bear occurrence integrated across the year is predicted to be greatest within northwestern Wisconsin, which coincides with areas where the WDNR has made recent changes to harvest delineations to address increased conflict. However, further model development and testing is necessary to operationalize a tool that might forecast distributions at fine-temporal scales to support formal decision-making. This could include using more discriminatory SRS covariates and better leveraging data from areas with denser sampling to accommodate a more explicit spatiotemporal structure for bear occurrence. The regularity of SW's data collection lends itself to such iterative development and improvement (Dietze et al. 2018).

Example 3. Expanding Biological Extent

A key contribution of SW has been the capacity to provide information about species that are not otherwise monitored. Species believed to be extirpated or incidental across the state (e.g., moose [*Alces alces*], cougar [*Felis concolor*], lynx [*Lynx canadensis*]) are difficult to monitor by virtue of their scarcity. Previous monitoring for rare species relied on voluntarily contributed sightings with coarse spatial resolution (Olson et al. 2020) that contain little information about sampling effort, species prevalence, or the area of occurrence. Because SW's sampling effort is extensive, continuous, and quantifiable, it provides stronger evidence for scarcity than opportunistically collected large-scale sampling designs (Bayraktarov et al. 2019, Kays et al. 2020). As of early 2020, SW has generated <10 detections of moose and only 2 of cougar, suggesting (but not confirming) that these are extremely rare in Wisconsin. Similarly, SW enables the monitoring of common species that may have managerial importance but are not otherwise monitored or managed due to resource constraints. For example, the distributions and environmental associations of coyote (*Canis latrans*), opossum (*Didelphis virginiana*), and striped skunk (*Mephitis mephitis*) in Wisconsin are poorly understood because the species are not actively monitored, and yet these species play a range of important ecological roles, including roles related to the spread or control of different diseases (Levi et al. 2016). These species are readily detected by SW, allowing their distributions across the state to be delineated at high resolution with useful accuracy (Fig. 4 and Appendix S4). Species distribution models suggest that all three species appear to be more common in southern Wisconsin, and patterns in their occurrence derived from SW are associated with differences in satellite-derived land cover composition and climatic conditions between the northern and southern parts of the state. While this information is primarily useful for establishing the baseline status of these species, SW's ongoing sampling and integration with SRS enable the implementation of dynamic process-based models capable of providing more reliable inference (Yackulic et al 2015; *Example 1*). In turn, such information could expand the scope of management decision-making to incorporate disease risk for humans or other wildlife species (Rohr et al. 2020). Deeper knowledge of the distributions, habitat associations, and dynamics of a larger pool of species carries many other potential benefits, such as improved delineation of biodiversity hot spots (Falconer and Ford 2020) and better understanding of how different natural or anthropogenic forces structure biodiversity patterns.

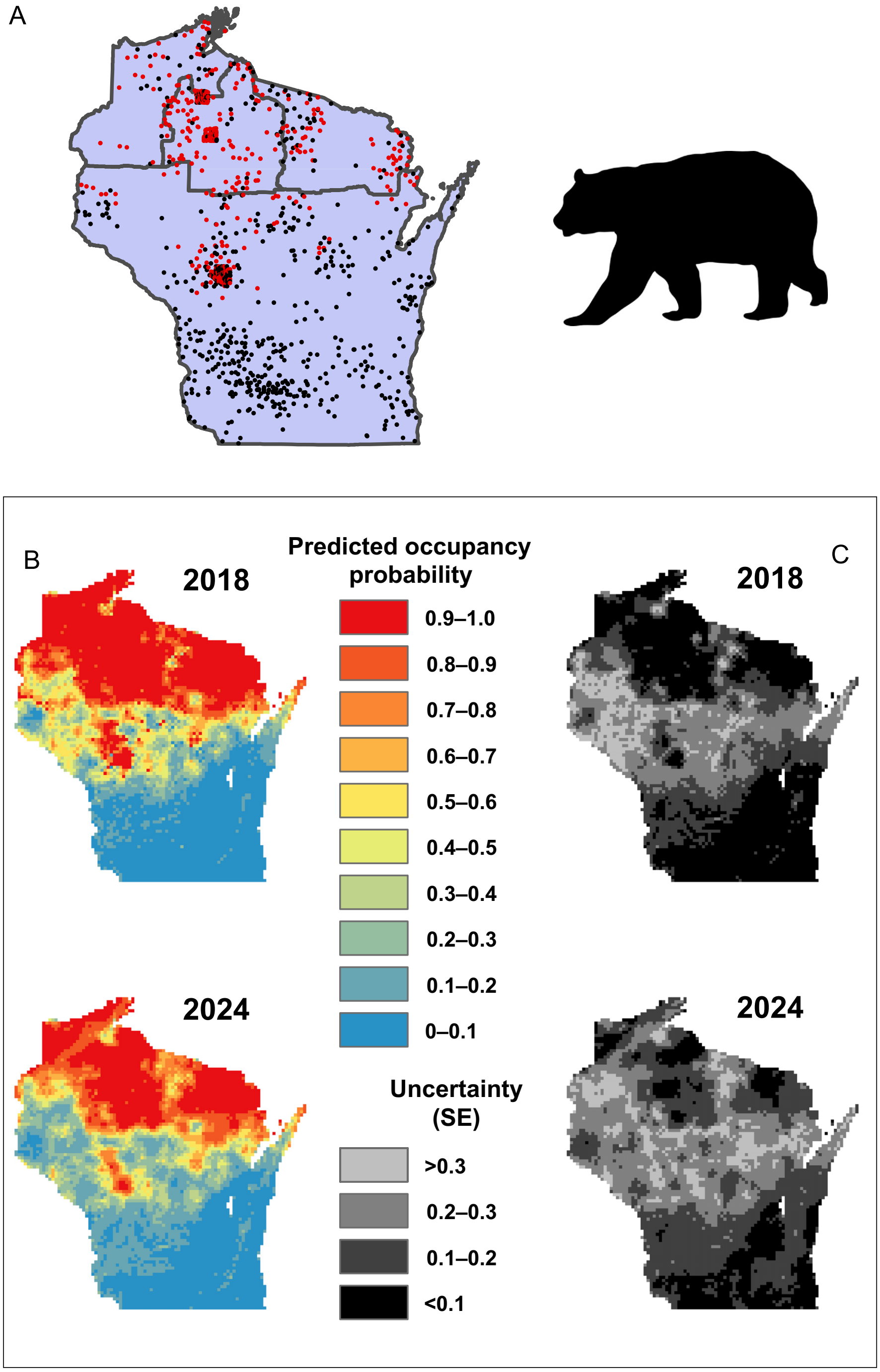


Fig. 2. (A) Detection (red)/non-detection (black) of bears in Snapshot Wisconsin cameras from 2018 and coarse spatial scale bear harvest monitoring units. (B) Predicted bear occupancy and (C) associated uncertainty for 2018 and forecast out to 2024.

Example 4. Increasing Biological Resolution

SW provides information at biological resolution that exceeds species detection/non-detection. Trail camera images contain information about species traits, phenotypes, or behaviors that can provide insights into the mechanisms underlying population changes (Zimova et al. 2020). White-tailed deer population dynamics in Wisconsin pose a challenge for effective management, with both bottom-up (food) and top-down (natural and anthropogenic predation) forces believed to have important effects (Warbington et al. 2017). Top-down effects may manifest in varying ways: predators may influence prey populations directly via consumption or indirectly

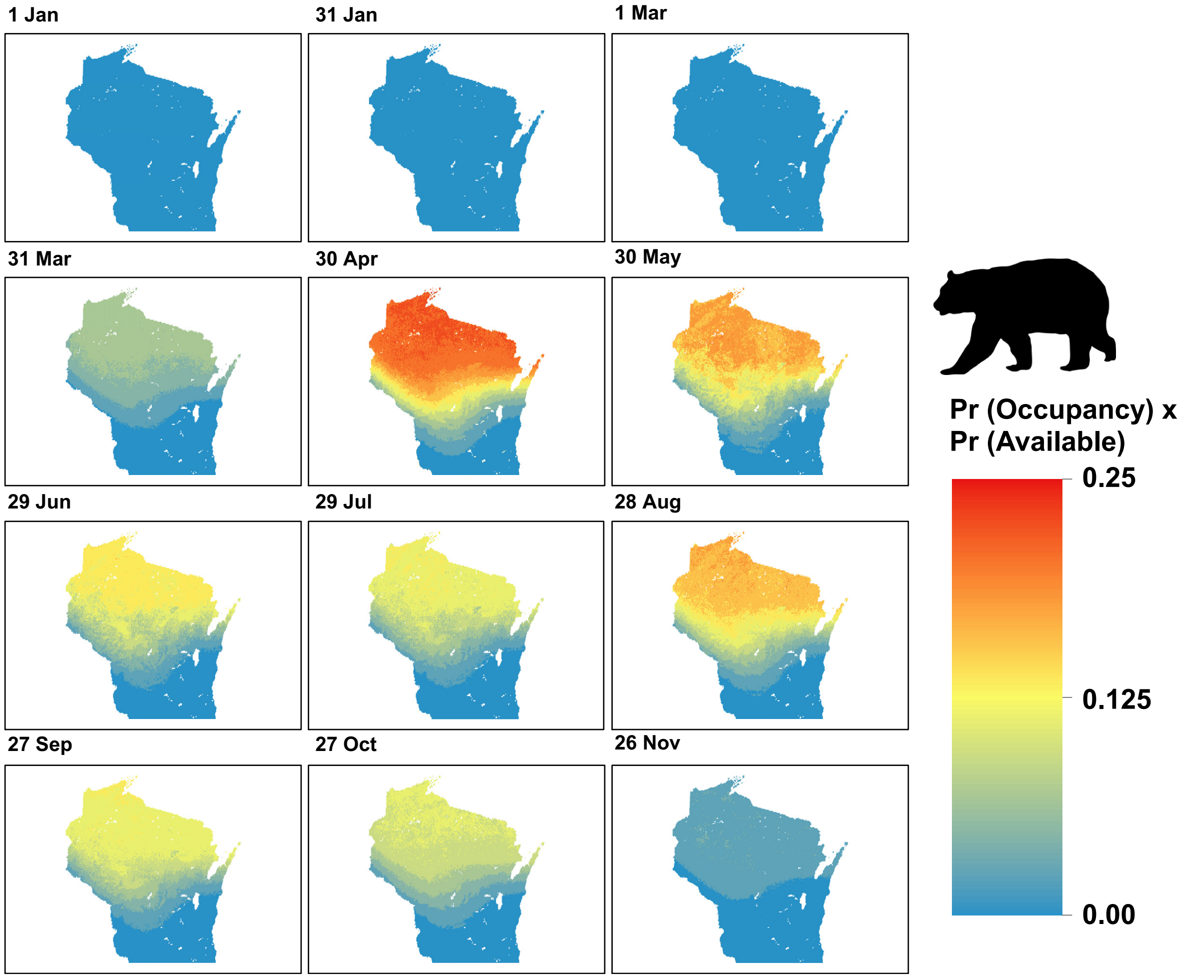


Fig. 3. Use of continuous satellite remote sensing (SRS) and SW data to predict daily bear occurrence over the course of 2017. Predictions are derived from a multi-scale occupancy model, as the product of asymptotic occupancy probability (the probability of ever using a cell) and the daily probability of a bear being "available" for detection (i.e., active within the cell on a given day).

by intimidating prey and reducing their foraging efficiency (Brown and Kotler 2004). As a consequence, understanding the behavioral landscape can provide insights into underlying population variation related to predation risk and foraging opportunities, which may subsequently inform management of the system through approaches such as predator control or regulating human disturbance (Dwinnell et al. 2019). SRS plays a critical role in delineating spatial and temporal variation in forage resources, and SW images can be mined to generate behavioral data that are not otherwise available over relevant spatiotemporal scales, with the caveat that the interpretation of still images that are increasingly being used for behavioral analysis (e.g., Palmer et al. 2017) may be imperfect (Appendix S5). Analysis of deer foraging and vigilance behavior derived using crowdsourced classification of SW images (ignoring any proxies for predation risk), and results suggest that deer spend relatively less time foraging in areas with greater land cover diversity and greater remotely sensed plant productivity using annually integrated MODIS enhanced vegetation index as a proxy for annual productivity (Appendix S5). Deer appear to allocate relatively less time to vigilance and more time to foraging in areas such as northern Wisconsin (Fig. 5), which SRS data suggests is less productive and commonly features deeper snow pack, and where both camera analysis (J. Clare, *unpublished data*) and other data indicate that predator richness and density is greater. Together, these patterns suggest that deer in northern Wisconsin may operate under greater nutritional stress and may perceive resource limitation as a greater risk than predation. Moreover, the predicted incidence of foraging peaks during early spring when nutritional demands are also peaking (due to fawn birthing and metabolic changes) and in late summer (prior to rutting season, Fig. 5). Any potential non-consumptive predator effects may be more important during these specific times of year: landscapes of fear are recognized to be dynamic entities (Palmer et al.

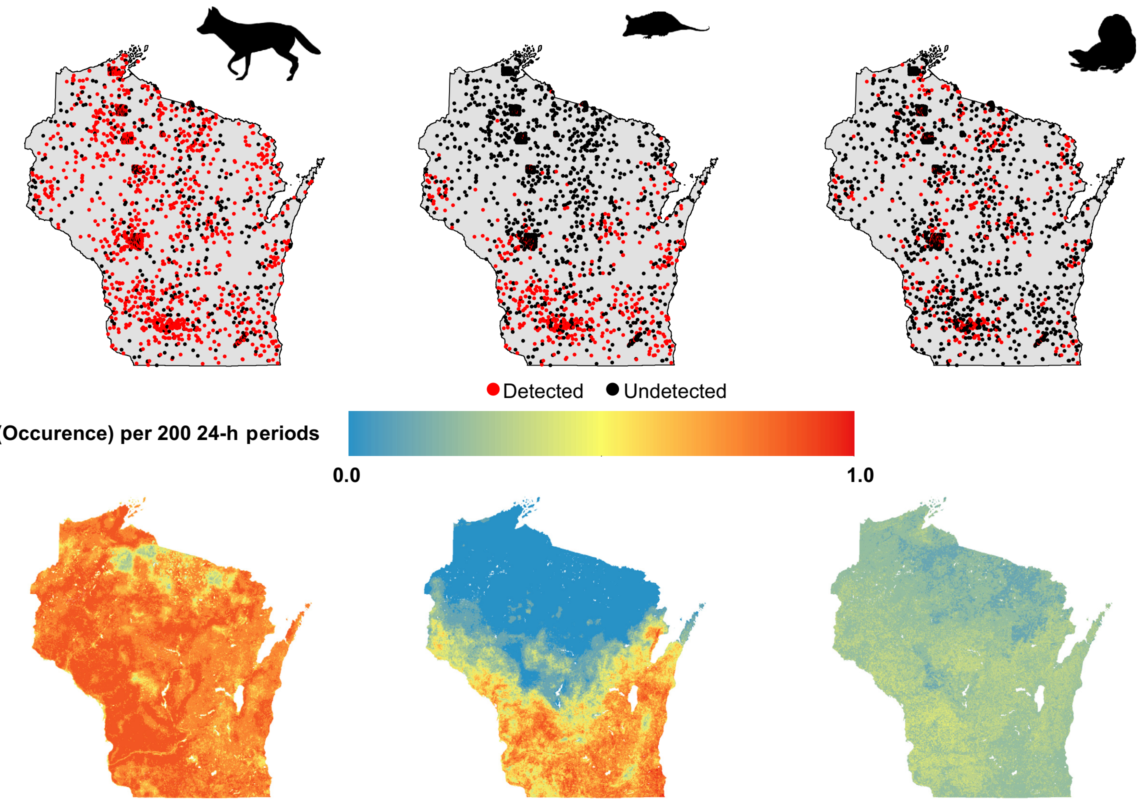


FIG. 4. Trail-camera- and SRS-based predictions of occurrence probabilities for species that are not otherwise monitored: coyote, opossum, and striped skunk. Top row shows SW observations (detection/non-detection) across 2015–2018; bottom row shows predicted observed occurrence probability standardized for an effort of 200 trap-nights.

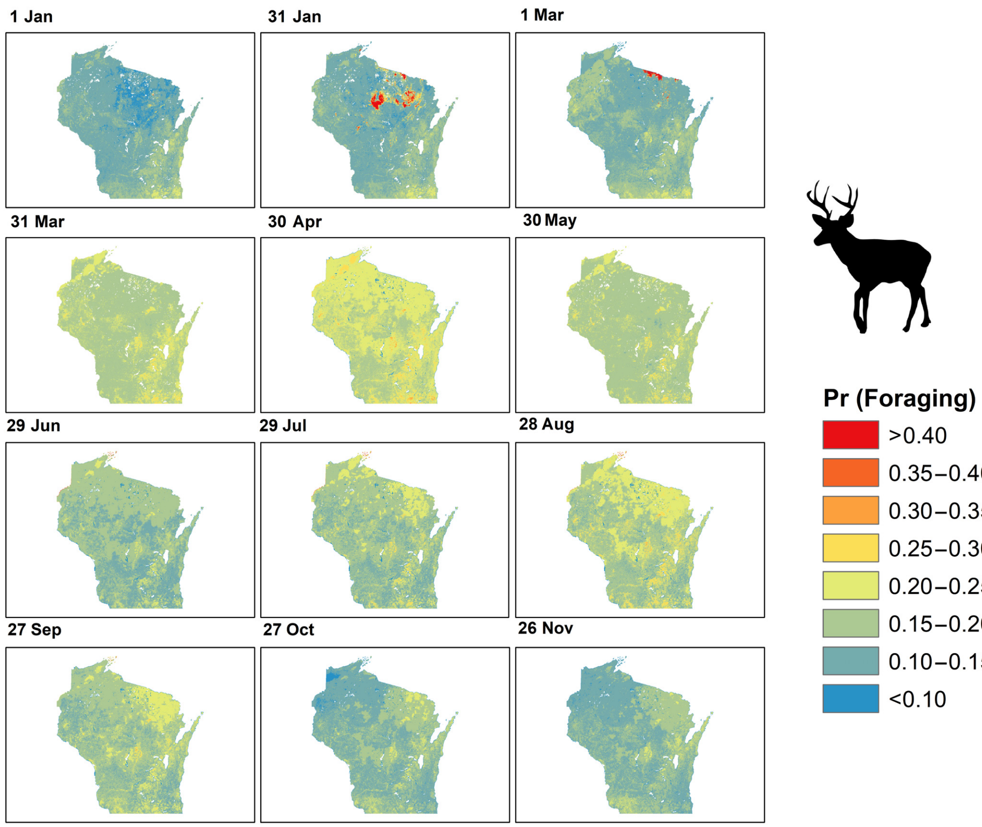
2017), and SW's continuous sampling is well-equipped to capture these dynamics.

EXAMPLE 5. STRENGTHENING INFERENCE VIA CORROBORATION AND CONTRAST

To date, most research that has drawn upon the growing body of biodiversity observations produced by observation networks has focused on exploring patterns and changes in species distributions or populations at broader extents or finer resolutions than have traditionally been studied (Fink et al. 2010). At jurisdictional scales, data collected using JONs often coexists with information from targeted surveys and existing monitoring streams. There is a growing appreciation for synergies between data sources, and the development of broader monitoring networks may not only be useful for addressing new questions or issues, but for strengthening the integration of data types across multiple scales (Stenglein et al. 2015).

A simple but meaningful synergy afforded by SW is its ability to generate independent information that can be compared with existing lines of evidence, which may either clarify decisions via corroboration, or weaken support for specific decisions if there is lack of concordance (Cook et al. 2012). Deer are monitored by WDNR using a population reconstruction model (Roseberry and Woolf 1991) that depends upon assumptions regarding stable age distributions and buck harvest rates (Millspaugh et al. 2009) and is implemented at a resolution too coarse to draw linkages between population changes and potential drivers other than harvest regulations. Consequently, the WDNR is interested in developing independent monitoring metrics. Camera-based detection indices are appealing due to their ease of implementation, but their accuracy is contingent upon the assumption that detection rates are proportional to density (Broadley et al. 2019). We compared harvest-based population estimates of deer in 2018 used by the WDNR with encounter rates derived from concurrent

FIG. 5. The predicted relative likelihood of deer foraging and vigilance behaviors (conditional upon occurrence and being detected) varies substantially across space and over the course of 2017, with highly outsized behavioral responses (e.g., top, 31 Jan and 1 Mar) associated with ephemeral but dramatic weather events. During the year, deer in Wisconsin's low productivity but predator-rich northern and central forests appear to spend relatively more time foraging and less time vigilant.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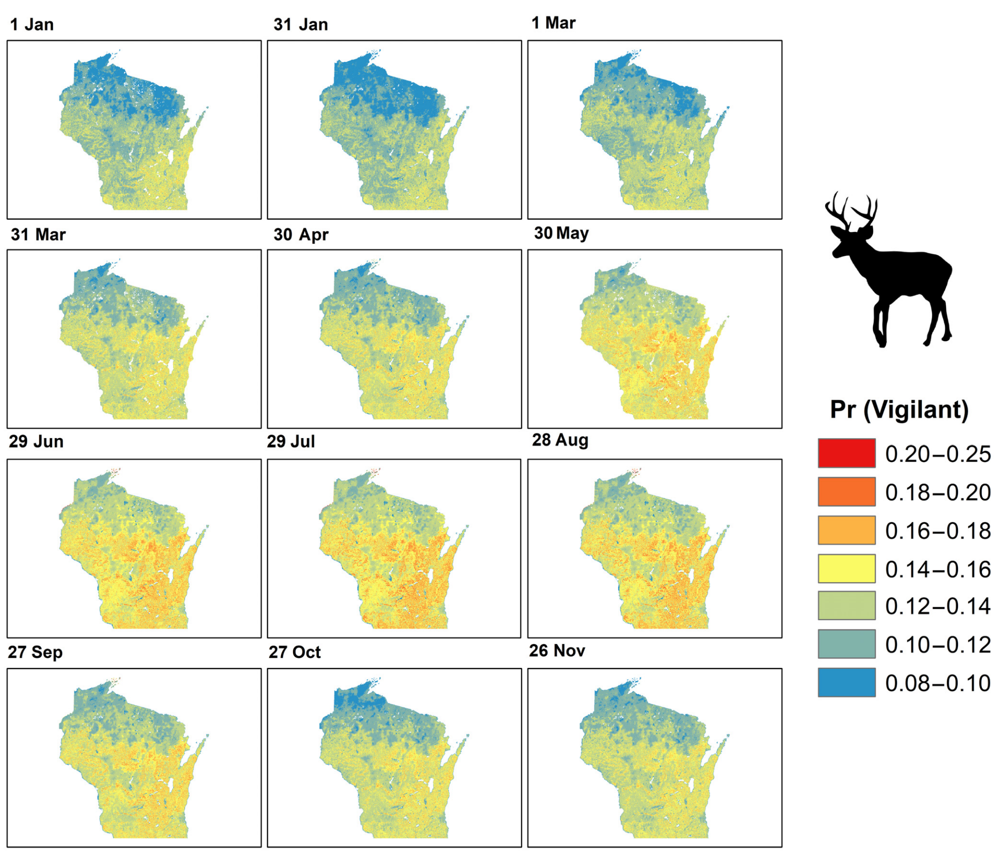
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SW data based on remotely sensed land cover, phenology, and other abiotic factors aggregated to a common county-level spatial unit (Appendix S6). Results (r = 0.55, Fig. 6) suggest that both approaches yield similar, but not congruent, patterns in deer abundance and thus may be complementary monitoring sources. Although SW permits prediction at finer resolution (Fig. 6C), these predictions are not necessarily more accurate: regions of discrepancy could represent areas where closer investigation of the underlying assumptions is warranted. Predictions from SW (but not harvest-based models) suggest northwestern Wisconsin is a region of relatively high deer density (Fig. 6). This may reflect confounding variation in detection rates driven by movement differences or detection variation (Broadley et al. 2019), sex or age-related hunter selection biases (Millspaugh et al. 2009), or other factors. Both growing season phenology and land cover metrics showed associations with indices of deer abundance from SW, suggesting that growing season phenology, like existing winter severity indices, could play a useful role in forecasting population changes to guide harvest regulations (Hurley et al. 2017).

The role of SW as complement to or replacement for existing monitoring efforts is a major research focus. WDNR is particularly interested in replacing practices that are expensive, sensitive to survey conditions, or for which varied detection errors are difficult to ascertain (e.g., aerial or snow-track surveys). Although comparing independent data streams is a useful starting point, integrated models may allow researchers to identify and reconcile specific methodological limitations (Stenglein et al. 2015, Clare et al. 2017).

Example 6: Expanding Extent Through Integrated Modeling

Integrated models provide further opportunity to “scale up” information from local studies and estimate otherwise inscrutable parameters, and can be useful when some data types are difficult to collect over large scales (Sun et al. 2019). For example, bobcats are managed in two zones in Wisconsin. The northern zone is monitored using a harvest-based accounting model that appears unreliable due to hunter selection for older males (Allen et al. 2018*b*). The WDNR recently opened the southern zone to harvest using results from a targeted capture–recapture effort (Clare et al. 2015), but the conservative quotas enacted to avoid overexploitation do not provide sufficient data for monitoring. Extrapolation risks are commonly encountered with small-scale, targeted studies often used to support management decision-making and can be particularly pronounced for harvest-based monitoring programs if harvest is geographically constrained. Integrating detection/non-detection data from SW with previous bobcat capture-recapture data (Appendix S7) provides the first initial estimates of statewide population size and reveals substantial spatial structure in bobcat density that was inestimable with only the capture-recapture study or harvest data alone (Fig. 7). Results suggest that the northern and southern zones have similar population sizes, but also that the environmental drivers of bobcat density are poorly understood or geographically variable across the state. Ongoing model development and monitoring is needed to clarify the germane drivers and refine population estimates.

Discussion: Opportunities, Considerations, and Caveats

Emerging technologies provide great power to characterize biodiversity across larger extents and with finer levels of detail than traditional monitoring techniques. The utility of SRS for global monitoring in an era of rapid anthropogenic change has been well established (Pettorelli et al. 2014, Jetz et al. 2016, Schimel et al. 2019). JONs complement SRS by sampling aspects of biodiversity such as species composition and understory vegetation characteristics that are not readily detected via traditional remote sensing platforms (Turner 2014). Combining SRS with data from localized sensors facilitates the discovery of new patterns and enables previously untenable lines of research (e.g., Kelling et al. 2009, La Sorte et al. 2018). SW demonstrates that linking SRS with observation networks that follow a structured design is a tractable monitoring option for management agencies, even if the network involves even year-round, state-wide sampling. Such programs can provide agencies information across previously untenable combinations of extent and resolution: SW has collected more wildlife observations than all other monitoring programs focused on similar species in the state, with transparent and quantifiable sampling parameters that allow users to assess and account for issues such as imperfect detection.

More importantly, our examples suggest several ways in which such data could lead to improved management. The fusion of biodiversity and earth observation data through JONs has the potential to enhance performance across each primary role of science within the decision-making process: framing issues, delineating potential management actions, predicting the effects of these actions, and evaluating their efficacy (Keller 2009). JONs can provide information about combinations of species, environmental conditions, and spatiotemporal scales that is often otherwise non-existent, which allows agencies to consider a broader set of emerging issues and management actions. JONs also provide information that can supplement existing monitoring efforts by providing alternative lines of evidence, more rigorous estimation, and via integration with SRS, greater capacity to understand variability in the state variables and functional relationships of interest. This enables agencies to more effectively predict the effects of potential actions and monitor the efficacy of management

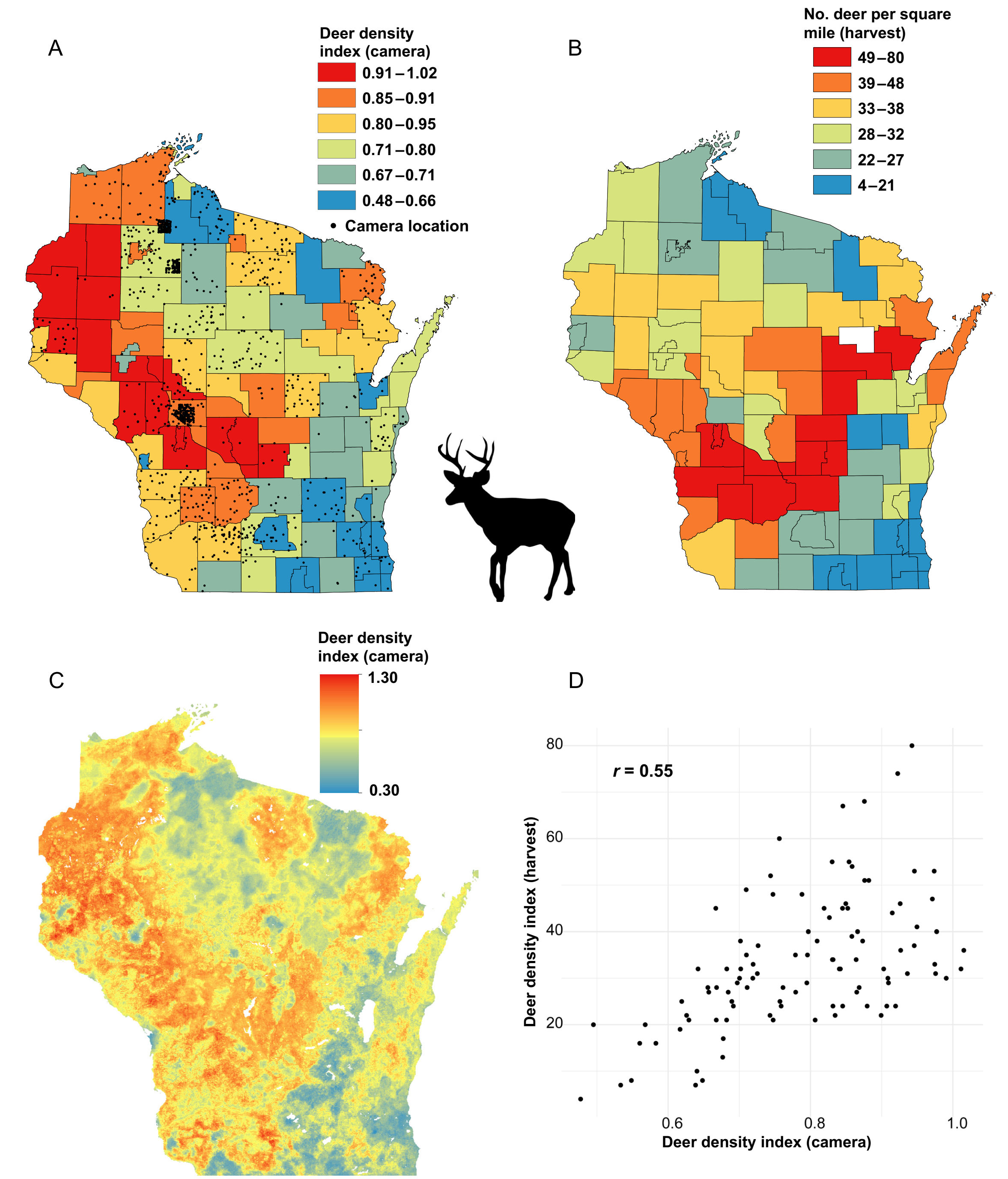

FIG. 6. Patterns in 2018 deer density indices aggregated to the management unit derived from (A) prediction using Snapshot Wisconsin trail cameras and remote sensing and (B) 2018 density estimates using a harvest-based population reconstruction model (1 square mile = 2.59 km^2). (C) Spatially explicit (50- m cell) predictions used in panel A. (D) Results from panels A and B are well correlated, although the potential resolution of inference or prediction is much greater using SW's density index (C) or more formal estimates of density that might be produced from alternative modeling exercises.

implementations with respect to issues of existing interest. Widely available SRS data includes many important but underutilized proximal predictors (e.g., nighttime light intensity, vegetation indices, frozen ground or snow cover), and new missions promise pronounced improvements in its spatial, temporal, and biological resolution (e.g., measurements of vegetation structure and foliar traits; Schimel et al. 2019). Enhancing the dimensions of

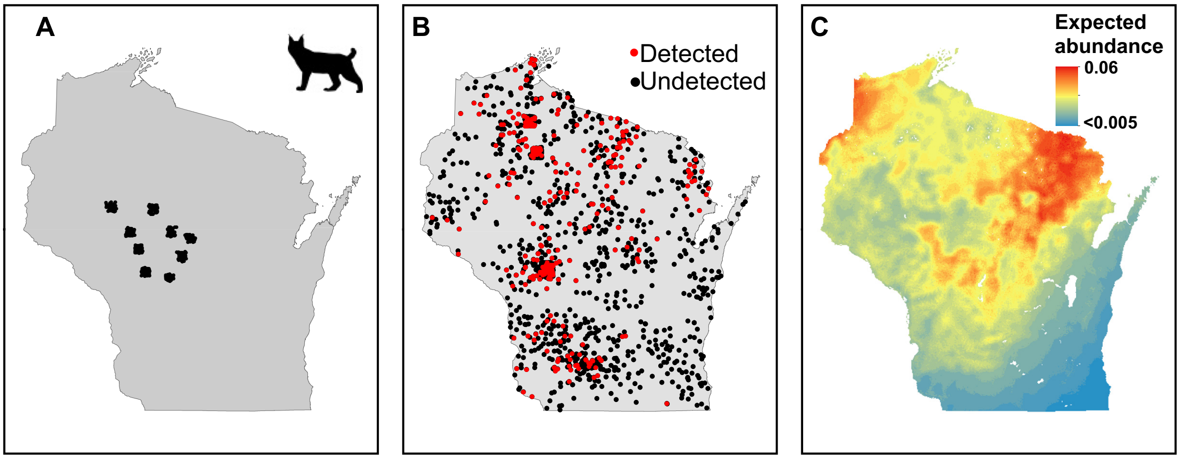

FIG. 7. Smaller-scale bobcat studies (capture–recapture sampling, locations in A) were combined with the broader-scale SW sampling (locations in B) to scale up to state-wide bobcat density estimation (C).

biodiversity monitoring may also provide agencies information needed to redefine objectives to align with spatial and temporal heterogeneity in stakeholder interests. Indeed, two of the most pointed challenges for wildlife management involve generating a strong evidential basis for decisions, and engaging a broader range of stakeholders to help define management objectives (Artelle et al. 2018).

Thus, the extent to which JONs can improve biodiversity monitoring and management is partially dependent on the degree to which networks enhance the spatial, temporal, and biological extent or resolution relative to existing monitoring. The optimal sampling properties of a JON and the appropriate analytical extent and resolution emerge from the spatiotemporal structure and dynamics of the organisms targeted and their environment. Some processes of interest may be reasonably well described with discrete annual dynamics, but applications involving migratory, transient, or irruptive species responding to environmental dynamics (Van Moorter et al. 2013) or focusing on the effects of extreme and ephemeral events may require greater sampling density, extent, and resolution. However, no observation network, regardless of extent, resolution, or intensity, samples optimally or even effectively for all possible research foci, and comparison or integration with alternative data sources, where appropriate, is critical for making the most of the available information.

Opportunities

The examples presented here largely follow standard wildlife science approaches implemented at unusual (although not unique) extent and resolution. In the near-term and especially during program initiation phases, most applications employing JONs will likewise focus on filling information gaps of existing managerial interest. We believe these applications are sufficiently beneficial to resource managers to justify developing such networks. However, JONs may enable more synthetic and transformative approaches to research and monitoring.

First, by capturing information about the environment and different levels of biological aggregation such as traits or behaviors, populations or distributions, and communities (Fig. 1), SW and other JONs provide opportunity to better characterize the processes contributing to biodiversity patterns and generate improved predictions of their dynamics. It is generally accepted that species distributions are driven by interactions between organism traits, community composition, and environmental context. For example, snowshoe hare are undergoing a range contraction within Wisconsin believed to be driven by increased predation resulting from increased phenotypic mismatch due to a declining snowpack (Sultaire et al. 2016, Wilson et al. 2019). Combining data and models for hare distribution, the dynamics of hare phenophase (Zimova et al. 2020), the distribution and dynamics of remotely sensed snow cover, and variation in landscape and community composition (i.e., the distributions of predators and alternative prey) could generate more rigorous predictions of hare range shifts, and richer synthetic understanding of their cause, their broader community consequences, the intrinsic adaptive capacity of hares, and managerial capacity to buffer hares from extrinsic threats.

Secondly, we believe the concurrent collection and combination of locally and remotely sensed data creates further synergies between the two data-streams. Most applications linking the two use environmental data derived from SRS to test associations with locally sensed biodiversity phenomena and make predictions. The converse is also possible. Local wildlife observations may also be used to interpolate or extrapolate missing SRS observations by exploiting their covariance (Clark et al. 2017), or, recognizing that wildlife also influence their environment (e.g., via herbivory), variables derived from locally sensed biodiversity observations could be used to predict changes in SRS surface measures for forest or rangeland applications. Moreover, space-borne and local sensors may provide measurements of surface phenomena like snow or plant phenology from different perspectives, e.g., below and above canopy (Siren et al. 2018, Liu et al. 2021). SW cameras record time-lapse images synched to the approximate overpass time of several satellites, and these have been used to aid interpretation of and assess measurement error in SRS-derived land surface phenology (Liu et al. 2021). Such locally sensed data could be leveraged to downscale SRS observations to for wildlife or other applications. Finally, products from both local and space-borne sensors are subject to measurement, classification, and estimation error. We believe practitioners could reduce error in modeled products as well as generate much stronger insights by fusing classification and process models for the surface environment and its biodiversity (sensu Joseph 2020, Kery and Royle 2021: section 7.6).

Ultimately, we expect that large, integrated data streams will provide better capacity to characterize multiple parameters of interest. For SW, there are many opportunities to further grow the network by co-deploying other sensors to detect taxa poorly sampled by trail cameras, or to provide supplementary local measurements of the understory environment. A further appeal of relying on remote sensing inputs is that their frequent and regular data collection facilitates the development of iterative, near-term forecasting platforms (Dietze et al. 2018). Indeed, we envision that the evolution of JONs will trend towards systems that absorb multiple data streams and regularly generate predictions that are subsequently assessed and used to refine data processing and model parameters. However, several barriers remain.

Challenges

Increased extent, resolution, and integration creates increased data volume, and classification, curation, and computation can be limiting steps (La Sorte et al. 2018, Lindenmayer et al. 2018, Bayraktarov et al. 2019). Technological developments, such as fast automated classification of images or audio recordings (Willi et al. 2019) and data portals that provide curation, processing, and classification services (Sullivan et al. 2009, Ahumada et al. 2020) have emerged to deal with these challenges. It will generally be substantially more efficient for JONs to interface with existing cyberinfrastructure rather than develop their own. However, further efficiency gains are needed to limit latency between data collection and analysis. Advances such as platforms to help automate the synthesis of multiple data streams or cost-effective recording units with capacity to transmit locally sensed data in near real-time would help achieve these gains.

A further challenge is that the novelty, volume, scale, and resolution of the data produced by JONs can create inefficiencies with respect to generating actionable information (Lindemayer and Likens 2018, Lindenmayer et al. 2018). A consequence of sampling and modeling more species distributions with enhanced extent and resolution is that the observations are driven by an increasing number of processes (local movement, demographics, dispersal, etc.) that operate at different scales (Yackulic and Ginsberg 2016). Articulating such complexity presents a formidable intellectual challenge. Fast and flexible descriptive analyses can be invaluable for tasks such as generating baseline information, but models rooted in processes, hypotheses, and theory are likely more useful for decision-making: fully leveraging the data may require simultaneously advancing theory and integrating it into tractable analytical tools (Coveney et al. 2016, La Sorte et al. 2018, Joseph 2020). This requires considerable and continuous intellectual investment along many fronts.

As such, implementing JONs requires agencies to effectively prioritize staff and resource allocation towards different project components or infrastructure (Locke et al. 2019), while making sure the data are accessible to and used by researchers (either agency and external) who can advance methodology, theory, and system understanding (Lindenmayer et al. 2018). Both tasks require clearly defined monitoring objectives (Yoccoz et al. 2001). Without such objectives, it is easy to generate purposeless products, and fundamental design and informatic decisions (e.g., the data classification task) can become daunting. For example, characterizing communities using bio-acoustic indices, measures of observed species composition, and estimates of species composition after accounting for varied observation errors each present different data processing and classification considerations. Rather than seek to do many things immediately (Lindenmayer and Likens 2018), it may be useful to view the set of monitoring objectives as something that iteratively evolves in concert with advances in methodology, system understanding, and managerial need.

While JONs can generate data to support management at broad scales and a range of resolutions, ecological information is only one component within the decision-making process. Several factors may restrict the degree to which improved information leads to better management decisions. It takes time for decision-makers to process new information, information availability may be misaligned with the decision-making timeline, and considerations other than ecological information may take precedence (e.g., McNie 2007, Sarewitz and Pielke 2007, Fuller et al. 2020). Given the volume of data production and rate of acquisition, integrating JONs into decision-making will benefit from (1) making products easily and quickly digestible (for example, on-demand “real-time” data access, processing, analysis, and visualization; Ahumada et al. 2020); (2) increasing decision-making's capacity to absorb and adapt to new information (i.e., investment in decision-science tools); and (3) clearly articulating management problems and information needs to ensure that the effort expended results in actionable products (Beier et al. 2017). It may be equally important for researchers to clarify what could be done with the data, and for other stakeholders, perhaps informed by emergent patterns in the data, to provide input into how management objectives are defined (McNie 2007, Beier et al. 2017).

Indeed, engaging a broader pool of stakeholders in management or decision-making is often one objective for JONs like SW that are reliant upon community scientists for data collection (Bonney et al. 2014). SW's engagement and outreach efforts for camera hosts and volunteers classifying images include regular interactions on the associated platforms and associated newsletters, blogs, and volunteer appreciation events. To permit broader outreach, the project has partnered with environmental educators across the state to provide equipment, developed classroom curricula, and created open web-apps for data visualization and summarization. These efforts are supported by research to assess how interventions influence volunteer engagement with the project, and how involvement with SW shapes engagement with and opinions of natural resources management. There is some tension between the desire to involve the public in data classification, which provides greater transparency and engagement, and the desire to generate data quickly, which may better be achieved via computational means. Hybrid approaches where a (reliable) subset of volunteer classifications provide labeled data to train algorithms (Willi et al. 2019) or where deep clustering makes the volunteer task more efficient (Wright et al. 2019) may balance these needs. If not, further prioritization of objectives will be necessary.

Effective biological monitoring jointly quantifies changes in the system variables of interest, helps identify drivers of any changes in the system variables, and ultimately improves management (Nichols and Williams 2006, Lindenmayer and Likens 2010). Data limitation hampers conservation and management efforts, and engaging community scientists to deploy sensors over large scales provides great value by generating information at increased spatial, temporal, and ecological resolution and extent. The proliferation of SRS provides opportunities to improve these efforts, especially in regions where in-situ sampling is limited, and remote sensing imagery and other geospatial data are necessary for JONs to effectively test hypotheses and make predictions. We ultimately believe JONs may enable management agencies to break free from narrowly focused, agenda driven, or tautological monitoring (Clare et al. 2019*a*) and better achieve their missions.

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Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.2436/full

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Data and code (Clare and Townsend 2021) used in this study are archived at https://doi.org/10.5281/zenodo.4716378