Title

Idea Paper: improving forecasts of community composition with lightweight biodiversity monitoring across ecological and anthropogenic disturbance gradients

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Abstract

Accurate and up-to-date biodiversity forecasts enable robust planning for environmental management and conservation of landscapes under a wide range of uses. Future predictions of the species composition of ecological communities complement more frequently reported species richness estimates to better characterize the different dimensions of biodiversity. The models that make community composition forecasts are calibrated with data on species' geographic patterns for the present, which may not be good proxies for future patterns. The future establishment of novel communities represents data on species interactions unaccounted for by these models. However, detecting them in a systematic way presents challenges due to the lack of monitoring data for landscapes with high environmental turnover, where such communities are likely to establish. Here, we propose lightweight monitoring over both ecological and anthropogenic disturbance gradients using passive sensors (i.e., those that operate continuously without much human input) to detect novel communities with the aim of updating models that make community composition forecasts. Monitoring over these two gradients should maximize detection of novel communities and improve understanding of relationships between community composition and environmental change. Further, barriers regarding cost and effort are reduced by using relatively few sensors requiring minimal upkeep. Ongoing updates to community composition forecasts based on novel community data and better understanding of the associated uncertainty should improve future decision-making for both resource management and conservation efforts.

Keywords

community, global change, ideas for fundamental questions, species distribution modeling, observation, species interactions

Research question

How can we improve forecasts of community composition under ongoing global change without prohibitive cost or effort?

Value

Where species will be in the future, which will be found together, and how they will respond to ongoing global change are foundational questions for ecosystem management and conservation. Accurate forecasts of biodiversity enable better planning for allocation of resource use, maintenance of ecosystem services, response to invasive species, and establishment of protected areas (Newbold et al. 2015). Particularly, forecasts made across environmental gradients can lead to more informed management for areas that are natural (e.g., set aside for conservation), unnatural (e.g., under resource management), or semi-natural (e.g., socio-ecological production landscapes such as *satoyama*). However, models that make biodiversity forecasts can estimate inaccurate future environmental responses for species and communities if current data on species' geographic patterns are not reasonable proxies for future patterns (Blois et al. 2013a). Future colonizations of newly suitable areas by species, leading to the establishment of communities with new species combinations (i.e., novel communities), represent heretofore unknown information about community composition and species interactions. Novel communities, which emerge more frequently with rapid landscape change (Finsinger et al. 2017), can expand or alter existing species interactions (Williams & Jackson 2007) and lead to disruptions in ecosystem services (Hobbs et al. 2006). Ongoing detection and documentation of novel communities is thus of vital importance to update community composition predictions for biodiversity forecasts.

Unfortunately, locating novel communities in a systematic way is a challenging exercise due in large part to the lack of monitoring data across landscapes with high environmental turnover, where such communities are likely to establish. Many efforts to catalog biodiversity focus on flagship species or single estimates of species richness. On the other hand, biodiversity monitoring systems provide high-frequency data streams and could also be harnessed to update community forecasts (Bush et al. 2017). However, the high economic and labor costs can be prohibitive, and existing systems often have bias in their spatial coverage and representation of environmental heterogeneity (Metzger et al. 2013). Moreover, both conservation efforts (e.g., establishing protected areas; Kusumoto et al. 2017) and monitoring systems tend to prioritize specific ecosystems rather than the gradients between them (Fig. 1). The resulting lack of regularly updated data on novel communities can be seen as a bottleneck for prediction accuracy of community composition forecasts.

Relevant hypotheses

Community composition forecasts are typically made using space-for-time substitutions, which employ modeled relationships between the current geographic patterns of species and communities with environmental variables to predict future patterns (Blois et al. 2013b). These predictions are most often made using either stacked or joint species distribution models (SDMs). The stacked SDM approach involves combining the predictions of SDMs fit with abiotic variables for individual species to estimate the community composition per spatial grid cell, then applying a biotic filter by removing unlikely candidate species from predicted communities based on knowledge of species interactions (SESAM; Guisan & Rahbek 2011). The joint SDM approach models multiple species' distributions together in the same modeling framework and typically measures interaction strength based on co-occurrence correlations after accounting for shared environmental preferences (joint SDMs; Warton et al. 2015).

But as changes to known species interaction networks will alter community predictions for both approaches, information on novel communities is crucial to improve the accuracy of long-term community forecasts. Although some data exists on current novel community establishment, ongoing global change will result in further shifts to present-day community structure. As species turnover tends to increase with environmental heterogeneity (Buckley and Jetz 2008), monitoring over gradients between different environments should be ideal for detecting existing novel communities and their future emergence.

New research idea

We propose monitoring over environmental gradients to detect novel communities and use this information to update community composition forecasts. Long-term monitoring over environmental gradients at a fine temporal resolution has a high likelihood of detecting novel community establishment (Fig. 1). Such detections represent information that can be used to identify mismatches between observations and predictions, leading to changes in community composition forecasts that rely on known relationships between species. It is important to note that this approach cannot determine the causes of novel community emergence, as other casual factors that correlate with environmental gradients may exist.

Our proposal includes monitoring over two main gradients driving community change: ecological (e.g., forest to grassland, lowland to montane forest) and anthropogenic disturbance (e.g., forest to urban, primary to logged forest). Importantly, these two gradients have different temporal resolution: anthropogenic disturbance (e.g., land cover conversion) occurs on shorter timescales than natural ecosystem change. Monitoring over these gradients should both maximize detection of novel communities and improve understanding of community relationships with environmental change. Real-time predictions of change for heterogeneous landscapes using remote sensing data have exciting potential (e.g., Slingsby et al. 2020). There are also examples of in situ monitoring over natural gradients to increase coverage of conditions and detect species' niche shifts (Carvalho et al. 2016). However, to our knowledge this is the first proposal to use in situ monitoring data from both ecological and anthropogenic disturbance gradients to make real-time updates to community forecasts.

How to tackle the question through the proposed new idea

Here, we advocate for the implementation of lightweight, in situ monitoring systems composed of transects over ecological and anthropogenic disturbance gradients in representative ecoregions around the world to collect structured data on novel communities. To reduce cost and effort, these transects can be composed of strategically placed passive sensors (i.e., those that operate continuously without much human input) including camera traps or audio recorders (although we discuss monitoring of terrestrial, relatively motile animals, the concept could be applied to other systems). Large camera trap grids monitored over short time periods provide a good balance of cost and accuracy for modeling species occupancy and richness, though accounting for seasonality presents challenges (Kays et al. 2020). In contrast, the lightweight system we propose serves only to collect detection data rather than produce datasets for modeling, utilizes different sensors to improve detection and expand the taxa sampled, and addresses seasonality by monitoring over annual cycles (Ross et al. 2018). Hence, fewer sensors in smaller grids or transects can be sufficient. Information on novel communities can directly improve community composition forecasts by updating species interaction information used to correct stacks of individual-species SDMs (Fig. 2), or by updating co-occurrence patterns used by joint SDMs. Additionally, these structured data can be combined with unstructured datasets (i.e., opportunistic presence data) using data integration approaches to improve the accuracy of large-scale range models (Isaac et al. 2020).

As uncertainty remains an issue for community composition forecasts made over space and time, it must be recognized that model predictions need validation and should be interpreted with caution. Although the modeling approaches discussed above can serve as diagnostic tools to help generate hypotheses about community assembly processes, both have existing methodological limitations (Zurell et al. 2020). Further, presence of species in new areas could reflect itinerant dispersal or short-lived sink populations rather than self-sustaining populations, and models of global climate and anthropogenic change used to make community forecasts have inherently high uncertainty. Thus, field validation (i.e., community inventories to evaluate model performance) and consideration of ancillary data (i.e., population studies to confirm novel community establishment) are advisable before any management or policy decisions are made. It is important to note that uncertainty in community forecasts can also be harnessed to estimate different scenarios of community dynamics across a landscape.

The importance of updated forecasts of (novel) ecological communities and how best to apply them to improve future decision-making is crucial to demonstrate to managers and conservation practitioners. For example, we expect forecasts to show how ecological gradients themselves should be considered high priority areas for monitoring and conservation actions due to their ability to maintain processes that foster evolutionary potential and ecological resilience to change (Blair et al. 2013).

Motivation

The ideas we propose here originate from discussions between the authors about how to improve community composition forecasts using new biodiversity monitoring strategies, and we wanted to share these ideas with the field to spark new ways forward for predicting community change. We intend to use the ideas in this paper as a foundation for future grant proposals.

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Conflict of Interest

The authors have no conflicts of interest to report regarding this paper.

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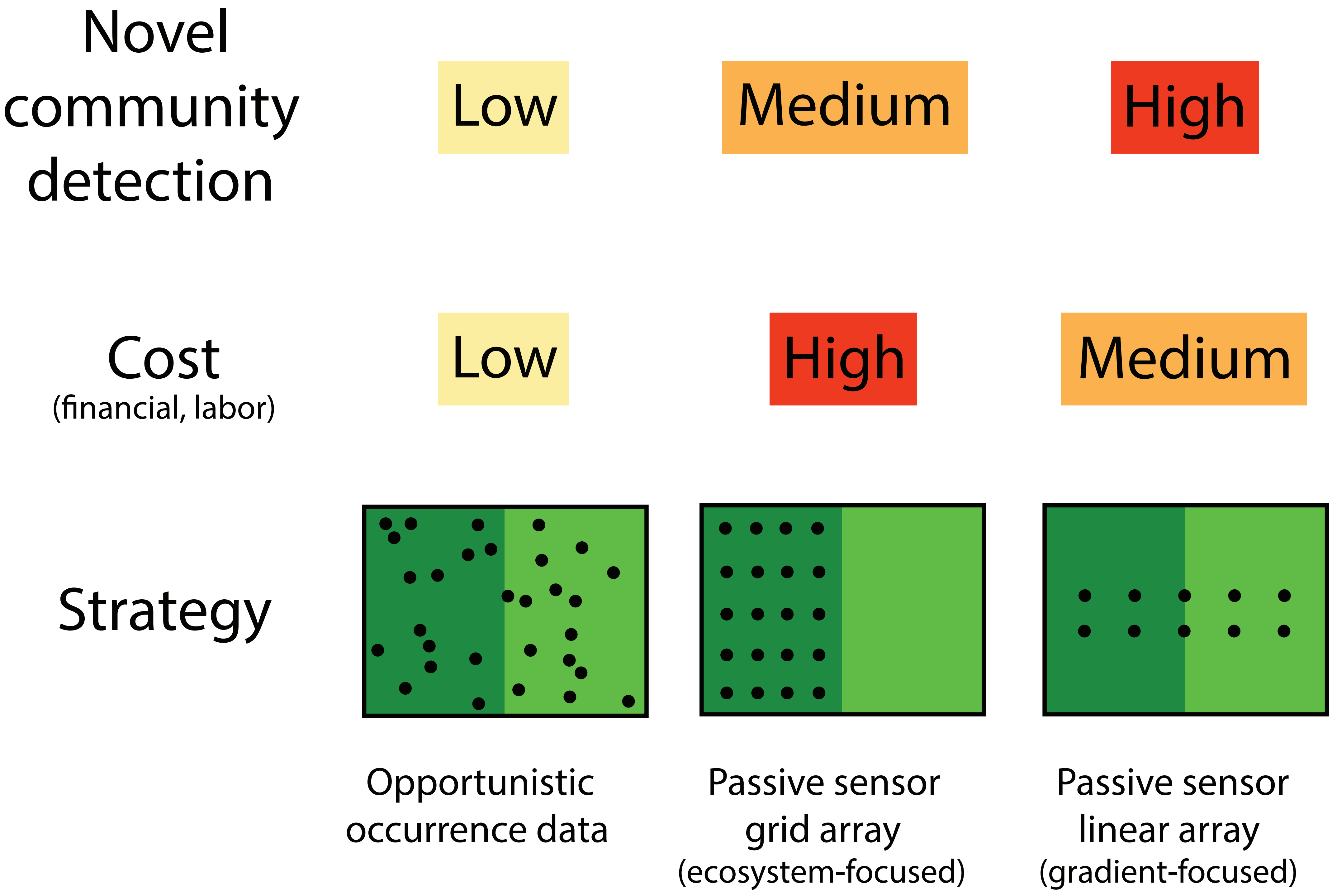
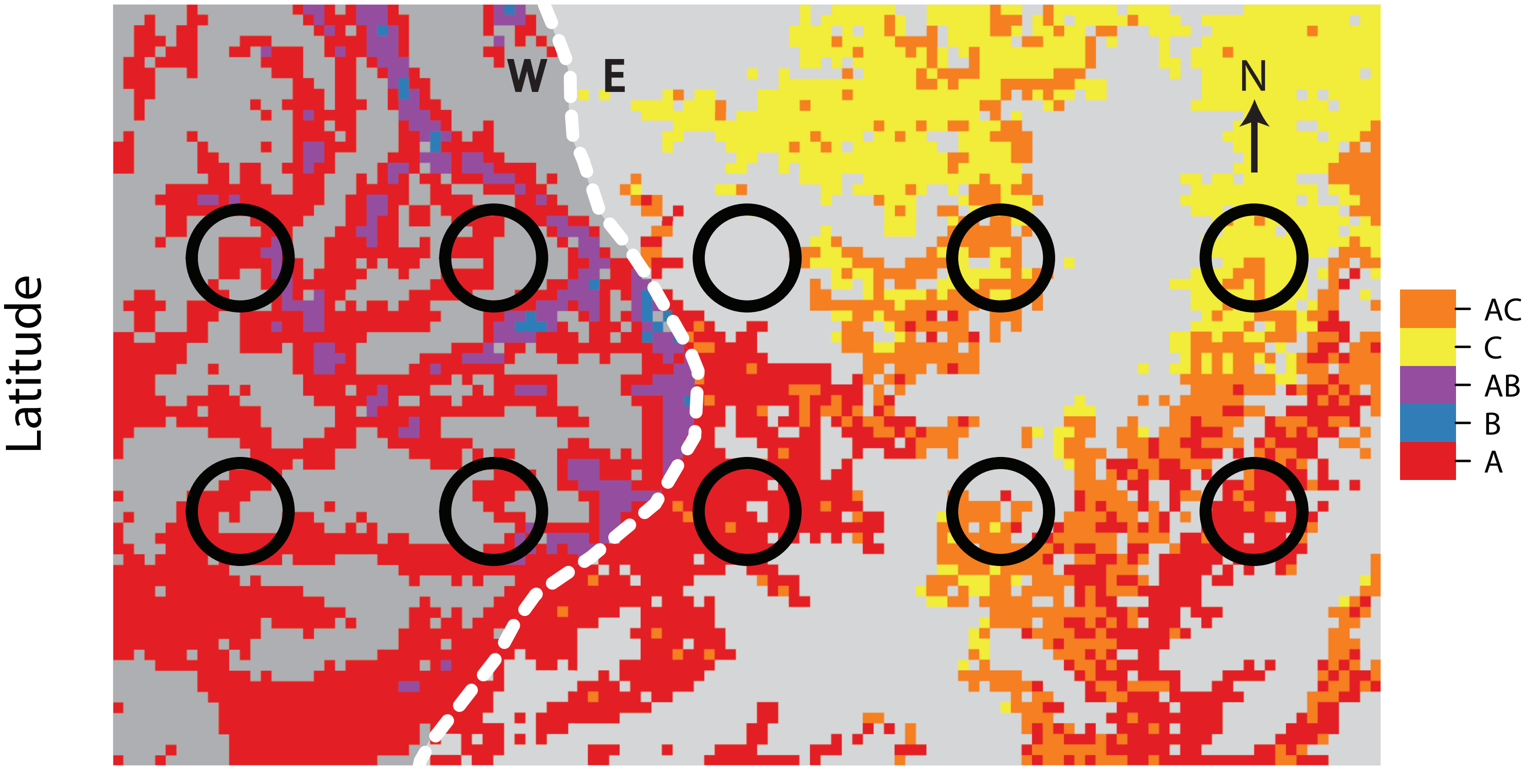
Figure 1. Comparison of different passive data collection approaches in terms of cost (financial and labor) and detecting novel communities, designated on a scale of "low" (yellow), "medium" (orange), and "high" (red). Opportunistic occurrence data is low-cost to acquire, but represents an amalgam of various sampling areas, times, and methodologies, making it difficult to detect the confirmed establishment of novel communities. Grid arrays ($n \times n$) of passive sensors for a single ecosystem collect structured data that can more reliably detect community occupancy yet are high-cost. Alternatively, a linear array ($n \times 1$) of passive sensors collects structured data along a gradient and samples areas with greater environmental heterogeneity, which should result in higher detectability of novel communities with a lower cost.

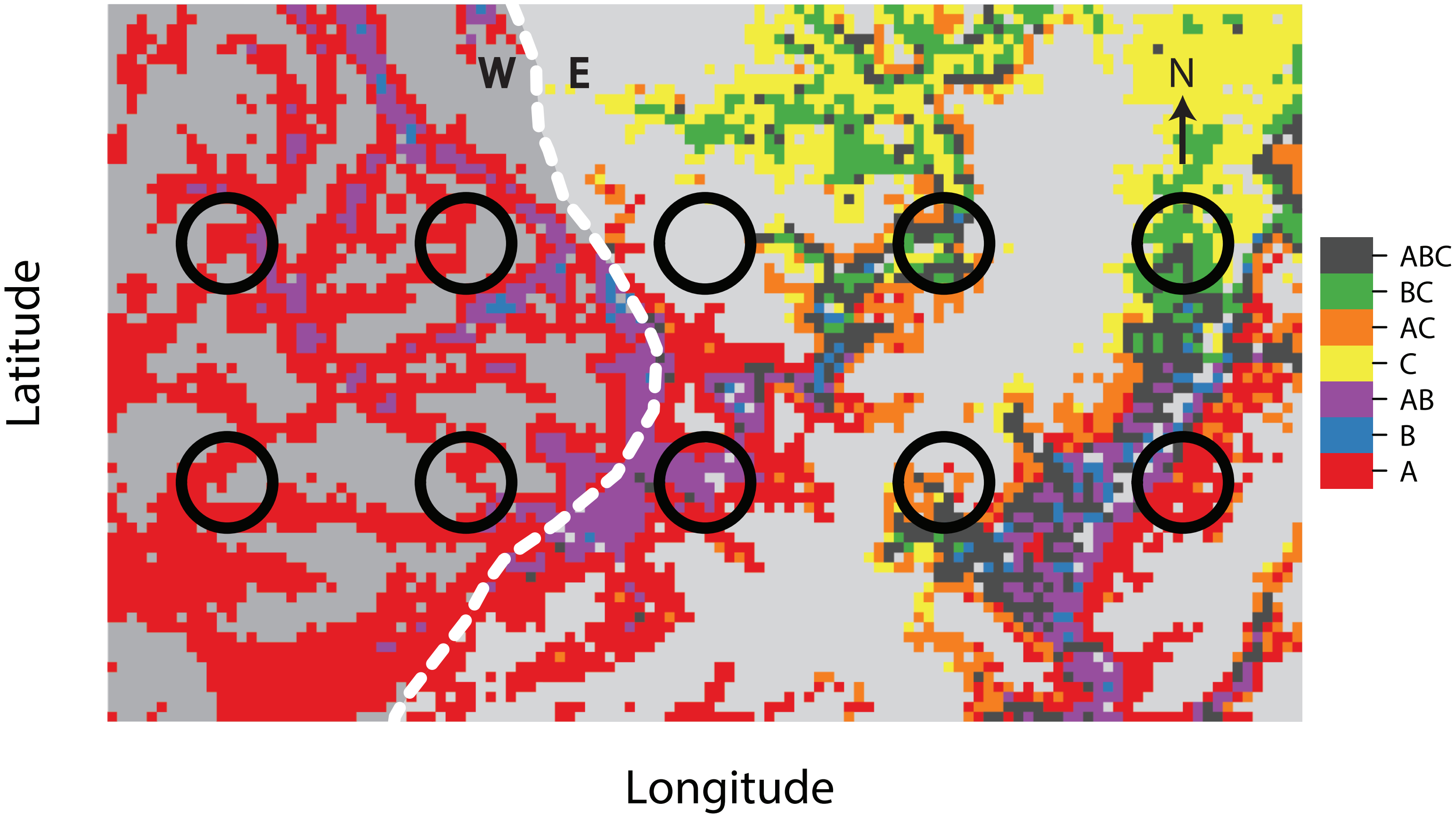
Figure 2. A conceptual example of how novel community detection can change landscape-level community composition forecasts on short timescales (no significant climate change, but possible ecological or anthropogenic change). This example was created using range estimates of virtual species in R and real data on climatic variables and Japanese ecoregions (Supplemental Information 1, 2). Two linear arrays of passive sensors monitor surrounding areas (black circles) across the gradient between two ecoregions (west: dark gray, east: light gray) delineated by a white dotted line. Species A occurs across both the east and west ecoregions, while species C occurs only in the east due to abiotic constraints. In time 1 (Panel (a)), species B occurs only in the west due to biotic constraints. Thus, although the fundamental niche of species B includes areas in the east ecoregion, it is not included in the eastern community predictions. In time 2 (Panel (b)), the biotic constraint is released and species B can colonize parts of the east ecoregion, resulting in the establishment of novel communities BC and ABC. This information is used to extend the range prediction of species B into the east ecoregion, resulting in an updated community composition forecast.


Novel community detection
Low
Medium
High
Cost (financial, labor)
Low
High
Medium
Strategy
Opportunistic occurrence data
Passive sensor grid array (ecosystem-focused)
Passive sensor linear array (gradient-focused)

(a) Time 1



(b) Time 2



Supplemental Information 1

We used virtual species with predefined climatic preferences to demonstrate how detection of a novel community can update landscape-level predictions of community composition (see Supplemental Information 2 for code). We focused on a transition area in central Honshu island, Japan (xmin = 137, xmax = 138, ymin = 35.3, ymax = 35.9) between the Taiheiyo evergreen forests (west) and Taiheiyo montane deciduous forests (east) WWF ecoregions (Olson et al. 2001) and defined virtual species' niches based on long-term average temperature and precipitation values (bio1 and bio12) from the CHELSA dataset (Karger et al. 2017, Karger et al. 2018). We simulated 3 species' niches (A, B, and C) with Gaussian responses to reflect different climatic preferences and used them to construct suitability rasters, which we then converted to presence-absence maps using a logistic function (Leroy et al. 2016). Species A has higher suitability in the west ecoregion, species C in the east ecoregion, and species B has high suitability throughout. In time step 1, to simulate species restricted to particular ecoregions, we masked the east ecoregion from the range of species B and the west ecoregion from that of species C. Thus, time step 1 does not have any grid-cell community predictions that include all species. In time step 2, we allowed the range of species B to extend to the east, demonstrating an update to a community forecast after discoveries of novel communities BC and ABC (see Fig. 2). All analyses were performed in R (R Core Team 2021); vector data operations were conducted with package *sf* (Pebesma 2018), gridded data operations with the package *raster* (Hijmans 2021), and plotting with the package *rasterVis* (Perpiñán Lamigueiro & Hijmans 2021).

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# Supplemental Information 2 for Kass et al. Ecological Research Idea
Paper 2021
# This code reproduces the analysis for Figure 2 described in
Supplemental Information 1

# load packages
# NOTE: make sure to update all packages
# rasterVis may need to be updated with
remotes::install_github('oscarperpinan/rasterVis')
# to plot the categorical raster legends correctly
library(virtualspecies)
library(sf)
library(dismo)
library(RColorBrewer)
library(rasterVis)
library(latticeExtra)
library(dplyr)

# define local directory where data lives and where files should be saved
# NOTE: data used in this analysis are publicly available from:
# CHELSA bioclimatic variables (bio1 and bio12; file names may differ):
# https://chelsa-climate.org/bioclim/
# WWF: https://www.worldwildlife.org/publications/terrestrial-ecoregions-
of-the-world
d <- ""

# load CHELSA bioclimatic data and rename variables
f.ras <- file.path(d, "CHELSA_bioclim")
envs <- stack(file.path(f.ras, "CHELSA_bio10_01.tif"),
                file.path(f.ras, "CHELSA_bio10_12.tif"))
names(envs) <- c("bio1", "bio12")
# define analysis extent
e <- extent(c(xmin=137,xmax=138,ymin=35.3,ymax=35.9))
# crop CHELSA data to extent
envs <- crop(envs, e)

# load WWF ecoregions polygon shapefile (free to download)
ecoreg <- read_sf(file.path(d, "wwf_ecoregions/wwf_terr_ecos.shp"))
# filter out the ecoregions of interest
ecoreg <- ecoreg %>% filter(grepl(c("Nihonkai|Taiheiyo|Honshu"),
ECO_NAME))

# make a mask of the climate rasters for each ecoregion
reg1 <- mask(envs, ecoreg %>%
               filter(ECO_NAME == "Taiheiyo evergreen forests"))
reg2 <- mask(envs, ecoreg %>%
               filter(ECO_NAME == "Taiheiyo montane deciduous forests"))

# define climatic responses for virtual species, chosen to make species A
# have higher suitability in the Taiheiyo evergreen forests, species C
# to have higher suitability in the Taiheiyo montane deciduous forests,
# and species B to have areas of high suitability throughout
spA.resp <- formatFunctions(bio1 = c(fun = 'dnorm', mean = 140, sd = 60),
                            bio12 = c(fun = 'dnorm', mean = 1500, sd =
400))
spB.resp <- formatFunctions(bio1 = c(fun = 'dnorm', mean = 120, sd = 40),
                            bio12 = c(fun = 'dnorm', mean = 1300, sd =
200))
```

```
spC.resp <- formatFunctions(bio1 = c(fun = 'dnorm', mean = 100, sd = 40),
                            bio12 = c(fun = 'dnorm', mean = 1200, sd =
600))

# generate suitability rasters for virtual species
spA <- generateSpFromFun(raster.stack = envs[[c("bio1", "bio12")]],
                         parameters = spA.resp, plot = TRUE)
plot(st_geometry(ecoreg), add=TRUE)
spB <- generateSpFromFun(raster.stack = envs[[c("bio1", "bio12")]],
                         parameters = spB.resp, plot = TRUE)
plot(st_geometry(ecoreg), add=TRUE)
spC <- generateSpFromFun(raster.stack = envs[[c("bio1", "bio12")]],
                         parameters = spC.resp, plot = TRUE)
plot(st_geometry(ecoreg), add=TRUE)

# use logistic function to convert suitability rasters to
# binary presence-absence rasters (i.e., range estimates)
# NOTE: seeds are set to ensure reproducibility of original analysis
set.seed(462)
spA.pa <- convertToPA(spA, beta = 0.75)
set.seed(462)
spB.pa <- convertToPA(spB, beta = 0.75)
set.seed(462)
spC.pa <- convertToPA(spC, beta = 0.75)

# make a mask of the PA map for species B for Taiheiyo evergreen forests
# and a mask for species C for Taiheiyo montane deciduous forests
# NOTE: this limits their distributions to these ecoregions
spB.pa.reg1 <- mask(spB.pa$pa.raster, reg1$bio1)
spB.pa.reg1[is.na(spB.pa.reg1)] <- 0
spC.pa.reg2 <- mask(spC.pa$pa.raster, reg2$bio1)
spC.pa.reg2[is.na(spC.pa.reg2)] <- 0

# overlay the PA maps for all species to get community composition for
two times,
# where time 1 has species B restricted to region 1 and species C to
region 2, and
# time 2 has species B allowed to extend to both regions
# NOTE: this is done by multiplying species B and C by different powers
of 10
# to create a community "code"
# NOTE: the levels set are different because time 2 has more different
communities
# than time 1
envs.cc.t1 <- overlay(spA.pa$pa.raster, spB.pa.reg1, spC.pa.reg2,
                      fun = function(x,y,z) x + 10*y + 100*z)
envs.cc.t1[envs.cc.t1==0] <- NA
envs.cc.t1 <- as.factor(envs.cc.t1)
levels(envs.cc.t1)[[1]]$community <- c("A","B","AB","C","AC")
envs.cc.t2 <- overlay(spA.pa$pa.raster, spB.pa$pa.raster, spC.pa.reg2,
                      fun = function(x,y,z) x + 10*y + 100*z)
envs.cc.t2[envs.cc.t2==0] <- NA
envs.cc.t2 <- as.factor(envs.cc.t2)
levels(envs.cc.t2)[[1]]$community <- c("A","B","AB","C","AC","BC","ABC")

# define colors for plotting different communities
cols <- c(brewer.pal(9, "Set1")[1:6], "#4d4d4d")
names(cols) <- c("A","B","BC","AB","AC","C","ABC")
```

```
theme1 <- rasterTheme(cols[levels(envs.cc.t1)[[1]][,2]])
theme2 <- rasterTheme(cols[levels(envs.cc.t2)[[1]][,2]])

# define points to depict passive sensors for biodiversity monitoring
pts <- matrix(c(rep(seq(137.1, 137.9, 0.2), 2),rep(35.7, 5),rep(35.5,
5)), ncol=2) %>% SpatialPoints()

# plot maps for time 1 and time 2
# NOTE: colors and lines in Figure 2 were further edited in Adobe
Illustrator
pdf(file.path(d, "fig2.pdf"), onefile = TRUE)
print(levelplot(envs.cc.t1, par.settings = theme1, main = "Time 1") +
        layer(sp.polygons(as(ecoreg, "Spatial"), lwd = 3, lty = 3)) +
        layer(sp.points(pts, col="black", lwd=5, pch=21, cex=5)))
print(levelplot(envs.cc.t2, par.settings = theme2, main = "Time 2") +
        layer(sp.polygons(as(ecoreg, "Spatial"), lwd = 3, lty = 3)) +
        layer(sp.points(pts, col="black", lwd=5, pch=21, cex=5)))
dev.off()
```