Received: 11 June 2018 | Accepted: 31 August 2018
DOI: 10.1111/1365-2664.13281

RESEARCH ARTICLE

Journal of Applied Ecology | BRITISH ECOLOGICAL SOCIETY

Practical considerations for operationalizing dynamic management tools

Heather Welch[1,2] | Elliott L. Hazen[1] | Steven J. Bograd[1] | Michael G. Jacox[1] | Stephanie Brodie[1,2] | Dale Robinson[1,2] | Kylie L. Scales[3] | Lynn Dewitt[2] | Rebecca Lewison[4]

[1]Institute of Marine Science, University of California, Santa Cruz, Santa Cruz, California

[2]NOAA Southwest Fisheries Science Center, Monterey, California

[3]School of Science and Engineering, University of the Sunshine Coast, Maroochydore, Qld, Australia

[4]Biology Department, San Diego State University, San Diego, California

Correspondence
Heather Welch
Email: heather.welch@noaa.gov

Funding information
NASA Ecoforecasting, Grant/Award Number: NNH12ZDA001N-ECOF; California SeaGrant; NOAA's BREP Program; NOAA's West Coast Regional Office; NOAA's Integrated Ecosystem Assessment Program

Handling Editor: Annabel Smith

Abstract

1. Dynamic management (DM) is a novel approach to spatial management that aligns scales of environmental variability, animal movement and human uses. While static approaches to spatial management rely on one-time assessments of biological, environmental, economic, and/or social conditions, dynamic approaches repeatedly assess conditions to produce regularly updated management recommendations. Owing to this complexity, particularly regarding operational challenges, examples of applied DM are rare. To implement DM, scientific methodologies are operationalized into tools, i.e., self-contained workflows that run automatically at a prescribed temporal frequency (e.g., daily, weekly, monthly).
2. Here we present a start-to-finish framework for operationalizing DM tools, consisting of four stages: Acquisition, Prediction, Dissemination, and Automation. We illustrate this operationalization framework using an applied DM tool as a case study.
3. Our DM tool operates in near real-time and was designed to maximize target catch and minimize bycatch of non-target and protected species in a US-based commercial fishery. It is important to quantify the sensitivity of DM tools to missing data, because dissemination streams for observed (i.e., remotely sensed or directly sampled) data can experience delays or gaps. To address this issue, we perform a detailed example sensitivity analysis using our case study tool.
4. *Synthesis and applications.* Dynamic management (DM) tools are emerging as viable management solutions to accommodate the biological, environmental, economic, and social variability in our fundamentally dynamic world. Our four-stage operationalization framework and case study can facilitate the implementation of DM tools for a wide array of resource and disturbance management objectives.

KEYWORDS
dynamic management, ecological modelling, fisheries bycatch, near real-time, nowcast, operationalization, sensitivity analysis, spatial management

1 | INTRODUCTION

Spatial management is frequently used by governing bodies to govern human interactions with natural resources (e.g., timber stands, wild fish stocks) and disturbances (e.g., shipping lanes, oil spills), thereby achieving objectives for nature conservation and human use (Margules & Pressey, 2000). Dynamic management (DM) is an emergent approach in which spatial boundaries and management recommendations (i.e., advisories that spatially and/or temporally affect human behaviour) are flexible in space and time, allowing scales of management to align with scales of environmental variability, resource and disturbance dynamism, and human uses (Maxwell et al., 2015). This contrasts with static management schemes, in which boundaries and management recommendations are fixed in space and time, for example, national parks and superfund sites. DM approaches are targeted at fine spatial (kilometres to hundreds of kilometres) and temporal (days to years) scales, allowing resultant management areas to entail lower opportunity costs than static approaches (Dunn, Maxwell, Boustany, & Halpin, 2016; Hazen et al., 2018). Although a number of operational examples of DM exist (e.g., Hobday & Hartmann, 2006; Kavanaugh, Fisher, & Derner, 2013; O'Keefe & DeCelles, 2013), traditional static management remains the most widely used approach (Chape, Harrison, Spalding, & Lysenko, 2005), due in part to challenges with DM operationalization. While static approaches rely on single assessments of biological, environmental, economic, and/or social (BEES) conditions and one resultant management recommendation, DM approaches regularly prescribe new management recommendations based on changing BEES conditions. To implement this complex task, DM schemes are often operationalized into tools, which are self-contained workflows that run automatically at an appropriate temporal frequency (e.g., daily, weekly, monthly).

Dynamic management tools can function as nowcast or forecast tools, producing near real-time or forecasted management recommendations respectively. Both types of DM tools rely on newly acquired BEES data relevant to describing the target features—often in combination with statistical models or algorithms—to calculate target feature attributes (e.g., location, intensity, or speed) for near real-time or forecasted BEES conditions. Target feature attributes are used to prescribe management recommendations, which are then disseminated to end-users. For example, WhaleWatch (Hazen et al., 2017) uses a species distribution model to describe relationships between blue whales (the target feature) and a suite of oceanographic variables (BEES data) in order to predict likelihood of whale occurrence (target feature attribute), which then affects the locations of marine operations such as fishing and shipping (management recommendation). The Active Fire Mapping Program (Quayle, Sohlberg, & Descloitres, 2004) uses an algorithm that describes the link between wildfires (the target feature) and satellite spectral bands (BEES data) to predict current fire activity, intensity, and extent (target feature attributes), which then guide homeowner evacuations (management recommendation). For example, mandatory evacuations in California, USA during summer 2018 were determined using Active Fire Mapping Program data (Sierra Sun Times, 2018). Coral Reef Watch (Liu, Strong, Skirving, & Arzayus, 2006) uses an algorithm that describes the relationship between coral bleaching events (the target feature) and sea surface temperature (BEES data) in order to predict bleaching hotspots (target feature attribute), which then directs restoration and monitoring efforts (management recommendation). For example, Bali Barat National Park in Indonesia has implemented a coral bleaching monitoring programme based on Coral Reef Watch data in which bleaching alerts trigger SCUBA field checks (Marshall & Schuttenberg, 2006).

Glossary

Near real-time:	Of current, or nearly current temporal status
Management recommendation:	An advisory that spatially and/or temporally affects human behaviour, e.g., areas to evacuate during floods
Algorithm:	A stepwise set of rules to solve a problem (e.g., which pixels have bleaching risk based on a temperature threshold?)
Statistical model:	A mathematical description of a problem including statistical assumptions underlying the data (e.g., which habitats do tuna prefer based on environmental correlates?)
BEES data or conditions:	Biological, environmental, economic, and/or social data or conditions
Observed data:	BEES data that are remotely sensed or directly sampled, e.g., satellite or gauge data
Modelled data:	BEES data that are predicted via statistical or dynamical models that may be initialized with observed data, e.g., climate forecasts
Dynamic management (DM) tool:	A family of spatial management tools in which management recommendations are regularly updated
Nowcast tool:	A DM tool that produces management recommendations for near real-time BEES conditions
Forecast tool:	A DM tool that produces management recommendations for future BEES conditions
Temporal frequency:	The rate at which a tool produces a management recommendation
Operationalization:	A stepwise process by which a DM tool is implemented and applied
Target feature:	A resource or threat managed by a DM tool
Target feature attribute:	A calculated characteristic of a target feature, e.g., size or severity
Product:	The end output of a DM tool that prescribes a management recommendation and optionally contains associated metadata
Latency:	The temporal delay in the dissemination of DM products or BEES data
Contingency plan:	A set of rules that govern DM tools' operational responses to missing or sparse BEES data

Four stages of operationalization
Acquisition: The regular collection of near real-time or forecasted data on BEES conditions
Prediction: The calculation of target feature attributes in near real-time or forecasted BEES conditions to produce final products that communicate management recommendations
Dissemination: The pathways by which products are distributed to end-users
Automation: The integration of Acquisition, Prediction, and Dissemination stages into streamlined workflows that run automatically at a prescribed temporal frequency

Dynamic management tools are increasingly recognized as core components of the spatial management toolbox, and rapidly advancing computer-processing power and Earth Observation technologies are likely to increase the rate of DM tool development. In the light of these developments, there is a need for a transparent step-wise framework to guide DM tool operationalization. The DM literature focuses heavily on the use of BEES data to describe target features, and frequently relegates the remainder of the operationalization process to technical reports and metadata. Here, we lay out a four-stage, start-to-finish framework for operationalizing DM tools: Acquisition, Prediction, Dissemination and Automation (Figure 1). The framework is designed to be trans-disciplinary and applicable to multiple environmental domains and to a diverse array of management aims. Below we introduce the framework and outline how existing DM tools fit within it, and discuss the trade-offs and practical considerations at each stage. We then use a case study to specify implementation of the framework in order to operationalize a DM tool. Finally, we discuss areas of future exploration for successful operationalization.

2 | MATERIALS AND METHODS

2.1 | Introduction to the four-stage framework for DM tool operationalization

In order to illustrate the framework, we collated 10 operationalized DM tools and identify tool components (e.g., BEES data sources, target feature attributes, management recommendations) within each of the four stages (Table 1). Tools were selected to cover diverse environments (marine, freshwater, terrestrial, atmospheric) and a wide array of management aims, such as natural disaster preparedness, natural resource management, and human health. Hyperlinks to the websites in which each tool is described and peer-reviewed references are provided in order to facilitate further tool exploration. The following sections are intended to be interpreted alongside Table 1 (e.g., to determine which tools acquire satellite data), Figure 1, and the Glossary.

2.2 | Stage 1: Acquisition

Acquisition is the regular collection of near real-time or forecast data on BEES conditions relevant to describing target features and their attributes. Acquired data can be either observed, i.e., collected via remote sensing (satellite data and radar) and direct sampling (gauges, airplane reconnaissance, participant reporting), or modelled, i.e., predicted via statistical or dynamical models that may be initialized with observed data (e.g., climate forecasts). When making decisions about acquiring data types, tool developers must balance trade-offs between accessibility, cost, spatiotemporal resolutions, data gaps, and latency. Satellite and radar data are publicly available, free, and served from a wide array of repositories that are easily integrated into automated workflows (e.g., SWFSC/Environmental Research Division's ERDDAP; Simons, 2017; The Copernicus Marine Environmental Monitoring Service). However, coarse spatiotemporal resolutions might render remotely sensed data unsuitable to describe highly dynamic and/or fine-scale features (Scales et al., 2017). Directly sampled BEES data can capture fine-scale spatiotemporal characteristics, but their acquisition must often be systematized specifically for the tool, making them costlier and less easily automated. For example, in WaterWatch's Acquisition stage, stream gauge readings are transmitted via satellite, radio, and telephone telemetry, depending on when gauges were installed. In SMAST's Bycatch Avoidance Program's Acquisition stage, bycatch events are transmitted by participating vessels via ship-to-shore email (O'Keefe & DeCelles, 2013). Dissemination streams for observed BEES data can experience

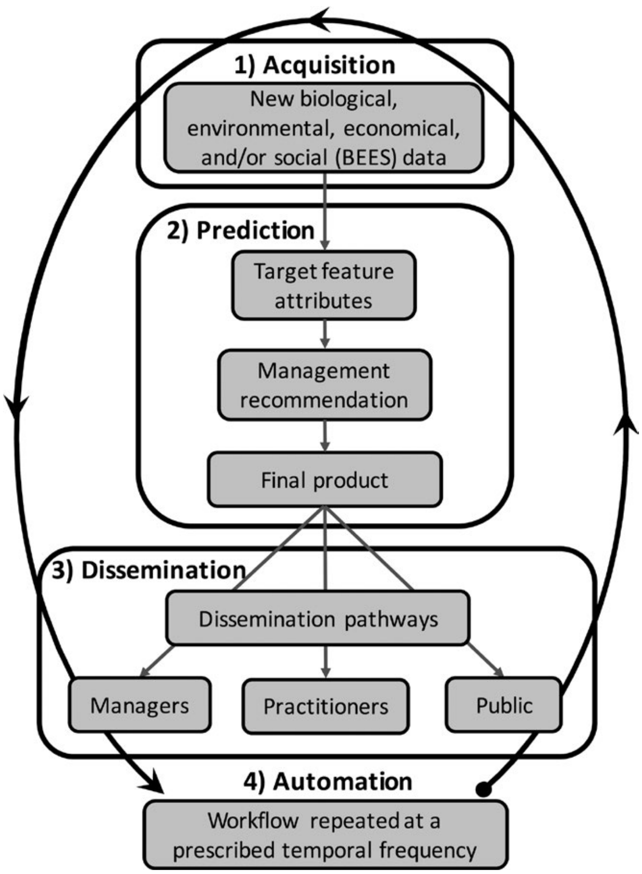

FIGURE 1 The four stages of operationalizing a dynamic management tool (hollow fill) and internal components (grey fill). The framework is relevant to operationalizing tools at one point in time and does not encompass tool updates as new data become available

TABLE 1 Ten examples of applied dynamic management tools and how they fit within the four-stage operationalization framework

Tool (+URL hyperlink)	National Hurricane Center	WaterWatch	Gulf of Mexico Harmful Algal Bloom Forecast	Coral Reef Watch	Tuna Seasonal Forecast System	MediSys	TurtleWatch	WhaleWatch	BirdCast	Active Fire Mapping Program
Reference	Sampson and Schrader 2000	USGS 2002	Kavanaugh et al. (2013)	Liu et al. (2006)	Eveson et al. (2015)	Linge et al. (2010)	Howell, Kobayashi, Parker, Balazs, and Polovina (2008)	Hazen et al. (2016)	Farnsworth et al. (2016)	Quayle et al. (2004)
Organization	NOAA	USGS	NOAA	NOAA	CSIRO	European Commission	NOAA	NOAA	Cornell University	USGS
System	Atmospheric	Freshwater	Freshwater	Marine	Marine	Terrestrial	Marine	Marine	Atmospheric	Terrestrial
Target feature	Hurricane	Flood	Harmful algal bloom	Temperature anomaly	Tuna	Public health threats	Turtle	Whale	Bird	Wildfire
Management aim	Natural disaster preparedness	Natural disaster preparedness	Human health	Natural disaster preparedness	Natural resource management	Human health	Natural resource management	Natural resource management	Natural resource management	Natural disaster preparedness
Tool type	Nowcast and forecast	Nowcast	Nowcast and forecast	Nowcast	Forecast	Nowcast	Nowcast	Nowcast	Nowcast	Nowcast
Four-stage framework										
(1) Acquisition										
BEES data source	Airplane reconnaissance, forecast models, satellite	USGS stream station readings	Satellite, Great Lakes Forecasting System	Satellite	Predictive Ocean Atmospheric Model for Australia	Media reports	Satellite	Satellite	Radar	Satellite
BEES data type	Observed and modelled	Observed	Observed and modelled	Observed	Modelled	Observed	Observed	Observed	Observed	Observed
(2) Prediction										
Target feature attribute	Hurricane location, intensity, movement	Flood and high flow conditions	Potential respiratory irritation	Coral heat stress	Tuna habitat suitability	Threat level	Turtle habitat suitability	Likelihood of whale occurrence	Bird migration traffic	Fire activity, intensity, extent
Target feature attributes calculated via:	Statistical model	Aggregation and summarization	Algorithm	Algorithm	Statistical model	Aggregation and summarization	Statistical model	Statistical model	Algorithm	Algorithm
Management recommenda-tion	Areas to evacuate	Areas to evacuate	Areas to avoid	Areas to target restoration and monitoring	Areas to fish	Areas to take preventative action	Areas to avoid fishing	Areas to avoid during ship transit	Areas to avoid industrial activities	Areas to evacuate
Final product	Mapped image, shapefile, KMZ file	Mapped image, CSV, XML	Mapped image	Mapped image, NetCDF, lati/lon coordinates	Mapped image	Mapped image, georeferenced descriptions	Mapped image	Mapped image	Mapped image	Mapped image, KMZ file
(3) Dissemination										
Pathway	Web, RSS, GIS data download	Web, interactive map, GIS data download	Web, email	Web, interactive map, email, text, GIS data download	Web	Web, RSS, interactive map, e-mail	Web	Web	Web, interactive map	Web, interactive map, GIS data download
(4) Automation										
Temporal frequency	Every 6 hr	Hourly	Weekly	Daily	Daily	Every 10 min	Daily	Monthly	Weekly	Every 6 hr

temporal delays and spatial gaps (e.g., gappiness in satellite data caused by clouds and aerosols, Roy et al., 2008), causing errors in the management recommendations produced by DM tools. By evaluating tool sensitivity to different scenarios of missing and spatially gappy data prior to operationalization, contingency plans can be developed to guide tools' operational responses during the Acquisition stage. Modelled BEES data are generated and housed on servers allowing them to be easily acquired and integrated into tools, and can alleviate issues with data gaps or latency. However, model output may introduce biases, and may be costly to create and maintain if models are being developed specifically for the tool (Christensen, Boberg, Christensen, & Lucas-Picher, 2008).

2.3 | Stage 2: Prediction

In the Prediction stage, newly acquired BEES data are post-processed into final products that communicate management recommendations that spatially and/or temporally affect human behaviour, advising for example, areas to fish, areas to evacuate, or areas to target environmental restoration. To produce management recommendations, tools often use statistical models or algorithms designed to describe target features based on newly acquired BEES data. For example in BirdWatch's predictions stage, an algorithm is applied to calculate bird migration velocity profiles from weather surveillance radars (Farnsworth et al., 2016). Eveson, Hobdaya, Hartoga, Spillman, and Rough (2015) coupled a statistical habitat preference model for tuna with an environmental forecasting model to forecast suitable habitat. Other tools produce management recommendations by aggregating and summarizing newly acquired BEES data (Bethoney, Schondelmeier, Stokesbury, & Hoffman, 2013; O'Keefe & DeCelles, 2013). For example, in WaterWatch's prediction stage, data from USGS stream station gauges are aggregated and summarized relative to baseline conditions. Because they spatially affect human behaviour, management recommendations are converted into final products that convey spatial information in some format, for example, in georeferenced files (e.g., shapefiles, rasters, NetCDFs, KMZ files), mapped images, latitude-longitude coordinate pairs, or text-based descriptions for known areas on the ground (O'Keefe & DeCelles, 2013). Product format should be tailored for—and developed in consultation with the end-users (Eveson et al., 2015; Petchey et al., 2015) to ensure that their technical capabilities, Internet and phone accessibility, and preferences are matched by product formats. Often, tools serve products in multiple formats to meet various scenarios of use, e.g., a simple format that works in low bandwidth areas and a detailed format for high bandwidth areas. The chosen product format will directly affect the dissemination (stage 3) pathway taken.

2.4 | Stage 3: Dissemination

Dissemination is the pathway by which final products reach the end-users. Simple web-based approaches can disseminate products via images hosted on websites or persistent URLs. A more advanced web-based approach is to host products as interactive maps with options to provide higher level detail. For technologically savvy end-users, georeferenced data can be downloaded and explored locally in GIS platforms. These options assume that the end-users will regularly check for new web content. Rich Site Summary, text and email (O'Keefe & DeCelles, 2013) based dissemination pathways require initial subscription, but afterwards do not necessitate end-user action. Smartphone-based apps, which are already widely used for near real-time data collection and display (e.g., WhaleAlert: http://www.whalealert.org/; eCatch: https://www.ecatch.org/), represent another promising dissemination pathway for DM products. The above pathways are not mutually exclusive, and in some circumstances the use of multiple dissemination pathways might be advantageous to meet the needs of different end-users.

2.5 | Stage 4: Automation

Automation is the integration of the Acquisition, Prediction, and Dissemination stages into streamlined workflows that self-initiate at prescribed temporal frequencies. Automation is the backbone of operationalization and a critical step to creating reliable products. However, automation happens behind the scenes and templates to follow are typically not readily available. To facilitate automation, code libraries can be made publicly available on open-access platforms (e.g., the open-access WhaleWatch code library: https://github.com/evanhowell/WhaleWatch). The details of automation depend on tool characteristics, but the following best practice principles are likely to be ubiquitous: (a) as far as possible, house all tool components in the same location (e.g., run tools on the same servers that store and process BEES data); (b) when building cross-platform workflows, ensure functional advantages are worth potential trade-offs with processing speed and complexity; and (c) log internal errors such as code breaks to aid debugging. Additionally, internal flags may be useful to trigger alternative tool behaviours (e.g., not producing a management recommendation) when acquired BEES data or predicted target feature attributes are outside normal ranges. Tools' temporal frequencies should align with desired temporal scales of management recommendation but will often be constrained by available BEES data.

3 | RESULTS

3.1 | Implementation of the four-stage framework: A fisheries sustainability case study

Here we demonstrate the four-stage operationalization framework outlined above using an established multispecies, multivariate dynamic ocean management tool (EcoCast) designed to balance fisheries' environmental and economic sustainability for a US-based commercial fishery (Hazen et al., 2018). EcoCast was developed for the California Drift Gillnet Fishery, which operates seasonally in the western United States' Exclusive Economic Zone from August to November. The Drift Gillnet Fishery targets swordfish (*Xiphius gladius*), but experiences unwanted catch (i.e., bycatch) of species including blue sharks (*Prionace glauca*), protected leatherback turtles (*Dermochelys coricea*), and California sea lions (*Zalophus californianus*), threatening the environmental sustainability of the Drift Gillnet Fishery. In response, an interdisciplinary team of governmental, academic, and NGO researchers developed EcoCast, a DM tool designed to reduce bycatch of protected and vulnerable species while minimizing reductions in target catch (Hazen et al., 2018).

EcoCast was developed by fitting statistical models (boosted regression trees, Elith, Leathwick, & Hastie, 2008) to describe the preferred habitats of the target species (swordfish; Scales et al., 2017), and three bycatch species (blue sharks, leatherback turtles, and California sea lions). In the operationalization framework, these species are the target features. Boosted regression trees for each species are predicted over environmental variable layers (BEES data; see Supporting Information Appendix S1: Table S1) to produce daily habitat suitability layers, i.e., georeferenced raster surfaces (target feature attributes). Species risk weightings—set to reflect management priorities and recent catch events—are then applied to increase or reduce the influence of each species in the final product (Hazen et al., 2018). The weighted habitat suitability layers are summed and standardized to values from −1 to 1, where negative values indicate relatively low target catch/high bycatch probabilities, and positive values indicate relatively high target catch/low bycatch probabilities (see Hazen et al., 2018 for details on environmental variables, model fit, and model validation). The EcoCast product (e.g., Figure 2) is a daily map that provides fishers with information on the spatial distribution of areas that are relatively better or poorer to fish (management recommendation) as a function of the relative distributions of target and bycatch species.

3.2 | Sensitivity to missing environmental data

The sensitivity of the EcoCast tool to scenarios of missing environmental data was evaluated to create a contingency plan that dictates the tool's operational response to missing data. Three possible responses to missing data were evaluated for each environmental variable: (a) substitute a lagged version of the variable, e.g., the variable from the previous day (lagged variable response); (b) leave the variable out entirely (leave-one-out response); and (c) substitute a lagged version of the EcoCast product, e.g., the product from the previous day (lagged product response). It is uncommon for variable latency to exceed 1 week; however, data lags up to 1 month were evaluated to account for the possibility of major outages. For the lagged variable response, each variable was lagged in turn by 1, 7, 14, 21, and 30 days. For the lagged product response, each variable (see Appendix S1: Table 1) was lagged in turn by 1–8, 14, and 30 days. Product accuracy, or the difference between a complete real-time product (i.e., the full product) and a product created under conditions of missing data (i.e., the contingency product), was evaluated across all responses. The three responses were evaluated for each day in the 2012 and 2015 fishing seasons (n = 306 days; an average year and an anomalously warm year respectively). Accuracy was quantified by subtracting the contingency product from the full product and then taking the absolute value to create a layer of difference. The mean per pixel difference between each layer was averaged across two example fishing seasons, 2012 and 2015. The sensitivity across responses was compared to develop a contingency plan for missing data, which was then built into the Acquisition stage (Section 3.3.1).

Results of this sensitivity analysis (Figure 3) indicated that the EcoCast tool performed poorly when leaving variables out entirely (leave-one-out response; bars in Figure 3). Contingency products with individual variables (excluding sea surface temperature) lagged up to 2 weeks (lagged variable response), and contingency products lagged up to 2 days (lagged product response) were more similar to the full product than contingency products created leaving out the least important variable (leave-one-out response). Contingency products with individual variables (excluding sea surface temperature) lagged up to a week (lagged variable response) were more similar to the full product than a contingency product with a 1-day lag (lagged product response). Because it is uncommon for variable latency to exceed 1 week, the following contingency plan was developed out to 1 week: For each missing variable except sea surface temperature, substitute lagged versions up to a 7-day lag, after which substitute a 1-day lagged product. For missing sea surface temperature, substitute lagged versions up to a 4-day lag, after which substitute a 1-day lagged product. If variable latency exceeds the aforementioned rules, the website will display a message that the current predictions are unavailable. Information on variable latency is included on the product image during the Prediction stage (Section 3.3.2) to ensure that metadata is not lost upon dissemination, and is communicated to end-users.

3.3 | Operationalizing a DM tool

Below we describe the implementation of the four-stage operationalization framework, using the EcoCast tool as an example. Unless stated, all operationalization stages for EcoCast (Figure 1) were implemented in RStudio (version 1.0.153). Original code is available at https://github.com/HeatherWelch/EcoCast_Operationalization. While the code library is unlikely to be generally applicable beyond EcoCast, specific functions may be relevant to other DM tools. The case study demonstrated here is implemented using the R coding language; however, the four-stage framework is applicable to other coding and software languages.

3.3.1 | Stage 1: Acquisition

Near real-time environmental variables (see Appendix S1: Table S1) are downloaded daily as netCDF (Network Common Data Form) files from two online repositories, SWFSC/Environmental Research Division ERDDAP and the Copernicus Marine Environmental Monitoring Service, via Representational State Transfer (RESTful) web services. Custom functions construct RESTful URLs that contain the desired time-stamp and spatial extent specifications. The URLs are then used to query the web services and resultant gridded netCDF files are downloaded using the functions curlPerform (R package RCurl and writeBin [R package base]) and used in post-processing (see Appendix S1: Table S1). For days in which environmental variables are missing, the contingency plan developed in the sensitivity analysis (Section 3.2) is applied to guide the tool's handling of missing data.

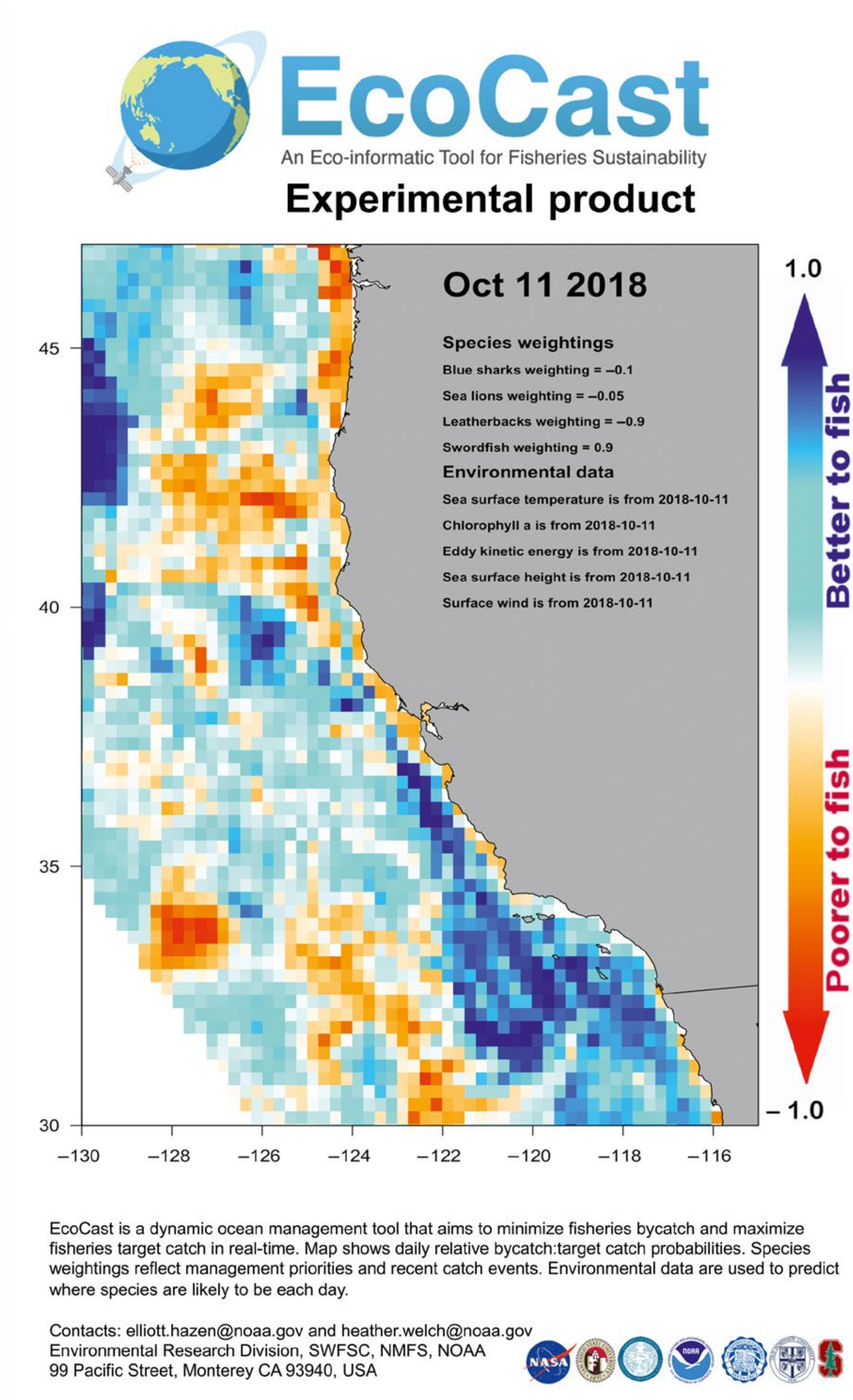

FIGURE 2 An example of a daily EcoCast product disseminated to end-users

3.3.2 | Stage 2: Prediction

The species-specific boosted regression tree models described by Scales et al. (2017) and Hazen et al. (2018) were saved as.rds files for convenient reuse (function saveRDS—R package Base). Each day, the boosted regression tree model.rds files are read into R (function readRDS—R package Base) and predicted over the post-processed environmental variables (function fit.gbm—R Package GBM) to produce daily habitat suitability layers for each species. Each species habitat suitability layer is multiplied by its risk weighting, and then all layers are summed and standardized to values from −1 to 1 to create the final daily product (e.g., Figure 2). The daily product is a mapped image that displays predicted fishing quality, providing fishers and managers with information on the spatial distribution of areas that are relatively better or worse to fish (i.e., the management recommendation). Relevant metadata embedded on the image include the latency of each variable, the species risk weightings, contact information, and a logo (R package Magick).

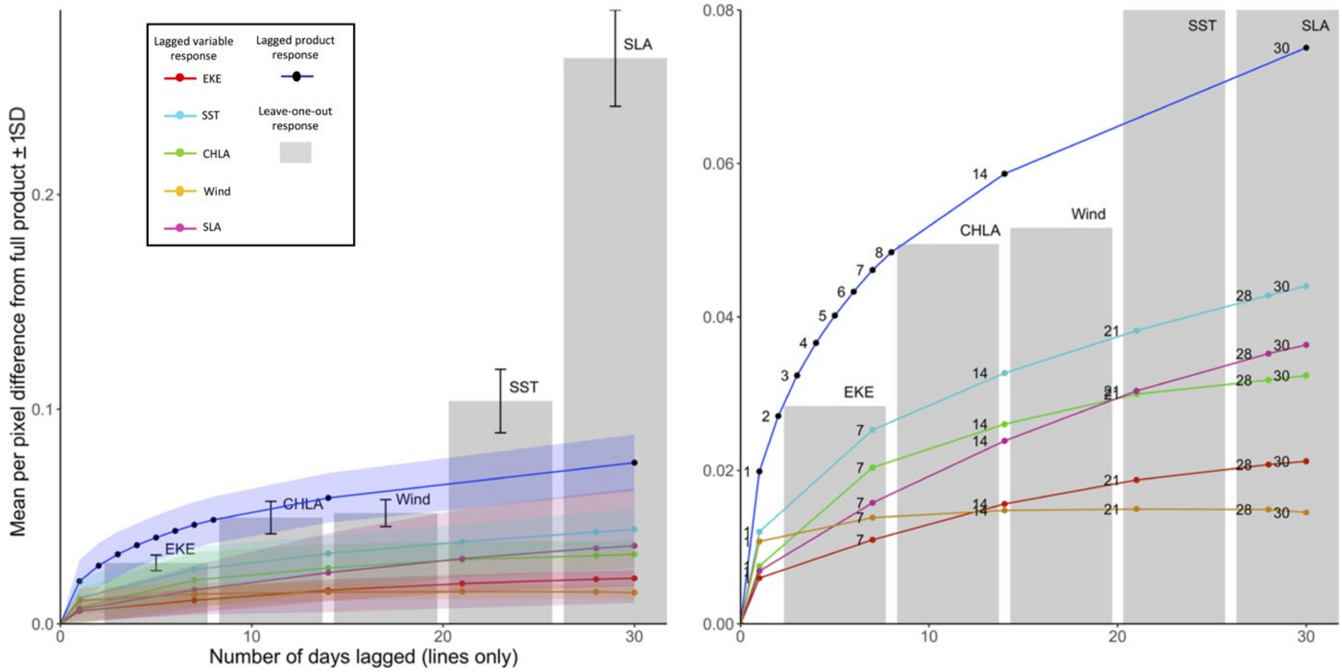

FIGURE 3 EcoCast tool sensitivity to scenarios of missing data. Plots show the mean per pixel difference between contingency and official products. The plot on the right shows the same data but on a different *y*-axis scale. Grey bars representing the leave-one-out response are independent of the *x*-axis. Error bars indicate ± 1*SD*. EKE: eddy kinetic energy; CHLA: chlorophyll *a*; SST: sea surface temperature, SLA: sea level anomaly

3.3.3 | Stage 3: Dissemination

The EcoCast dissemination pathways were developed in consultation with industry stakeholders and product end-users. Through an iterative feedback process, drift gillnet fishers and the governing management body (Pacific Fishery Management Council) refined product delivery to meet end-user needs. Three dissemination pathways were developed: a persistent URL, a web-based application built using the R package Shiny, and the SWFSC/Environmental Research Division ERDDAP server. The persistent URL (http://oceanview.pfeg.noaa.gov/ecocast/) is a web address where content is updated daily to provide the most current EcoCast product while the URL remains consistent (e.g., Figure 2). Because the URL only hosts a small amount of data (a single image), it allows fishers to access EcoCast while they are out at sea in low bandwidth areas.

The second dissemination pathway, the Shiny application, is an interactive web application that allows stakeholders and the public to explore historical patterns in EcoCast management recommendations from the previous fishing season. Within the Shiny application, end-users can select management recommendations from dates of interest, and use sliders to adjust the species risk weightings and filter the displayed values. Additional tick boxes provide options to display management boundaries and NOAA's navigational charts. The Shiny application can be accessed at: https://coastwatch.pfeg.noaa.gov/ecocast/explorer.html. Lastly, the SWFSC/Environmental Research Division ERDDAP server hosts EcoCast products in multiple georeferenced formats for public download and analysis (https://coastwatch.pfeg.noaa.gov/erddap/griddap/ecocast.html). More information on dissemination pathway access and metadata can be found on the EcoCast website: https://coastwatch.pfeg.noaa.gov/ecocast/.

3.3.4 | Stage 4: Automation

To automate the operationalization workflow, each R script in the Acquisition, Prediction and Dissemination stages was written as a function that initialized itself at the end of the script. Scheduling of the execution of each function was carried out within a shell script using the cron utility. The functions were scheduled to run each day at the top of every hour between 8 am and 3 pm to accommodate environmental data latency (see progression of scripts in Appendix S2: Figure S1). Each script writes errors and status reports to a daily log file. The EcoCast tool currently resides on the same network node as the environmental data, which has reduced the latency of environmental data during the Acquisition stage.

4 | DISCUSSION

This study has presented a trans-disciplinary four-stage, start-to-finish framework for operationalizing DM tools, and provided examples from multiple environmental domains to explore trade-offs and practical considerations at each stage. Although specifics will vary between tools, the generalized framework can serve as a guide to help developers foresee and assemble tool components. Using a fisheries sustainability tool—EcoCast—as a case study, we demonstrated an applied example of the methodological approach for each operationalization stage, and a sensitivity analysis to guide the tool's handling of missing data. The sensitivity of DM tools to missing or sparse BEES data is infrequently evaluated, and we argue that these sensitivity analyses are critical for tools that use observed data in order to minimize errors in management recommendations.

When evaluating tool sensitivity, development teams should consider several caveats. First, for tools that use statistical models or algorithms, acceptable operational responses in the contingency plan will be dictated by model or algorithm type. For example, some model types are able to predict over missing data (e.g., boosted regression trees, MaxEnt, Phillips, Anderson, & Schapire, 2006) making dropping out data a viable response; however, other types such as generalized linear models and generalized additive models cannot. Second, results are likely to be influenced by the spatial resolution of the BEES data used, with finer scale data likely to be more sensitive to latency due to an enhanced ability to resolve ephemeral features. And lastly, errors introduced in the contingency plan need to be consistent with acceptable errors in the management recommendation. For example, while it might be acceptable for fishers to respond to day old data when deciding where to fish, it would be inadvisable for homeowners to respond to day old data in terms of deciding where to evacuate from fires.

To ensure DM tools are able to meet the accuracy, precision, and delivery needs of their end-users, they should be operationalized in direct consultation with industry stakeholders and managers (Eveson et al., 2015; Spillman & Hobday, 2014). Workshops and focus groups with end-users can help tool developers determine the most suitable format, temporal frequency, and dissemination pathway for final products. Regular meetings also help build and maintain working relationships between parties, creating communication lines for discussing future tool developments, troubleshooting issues, or ground-truthing management recommendations (see an example of a ground-truthing programme in Turner et al. 2017). Additionally, bottom-up stakeholder-driven approaches (such as the DM tools described in O'Keefe & DeCelles 2013 and Eveson et al. 2015) are widely recognized as critical to achieving management goals such as stakeholder compliance and participation (Dalton, Forrester, & Pollnac, 2012; Halvorsen, 2003; Oyanedel, Marín, Castilla, & Gelcich, 2016).

For DM tools that use statistical models or algorithms to predict target feature attributes (e.g., Coral Reef Watch, Table 1), predictive skill should be evaluated. These types of tools calculate management recommendations by extrapolating beyond observed BEES data, and therefore ground-truthing predictions is critical to ensuring management recommendations are appropriate. This is in contrast with DM tools that aggregate and summarize BEES data (e.g., WaterWatch, MediSys Table 1), which do not introduce extrapolative errors. Tool predictive ability can be evaluated using hindcast (i.e., historical) analyses that test tool ability to predict appropriate management recommendations to known historical events. For example, the National Hurricane Center evaluates its annual forecast error against observed hurricane tracks (Cangialosi & Franklin, 2011), and the MODIS fire products used by the Active Fire Mapping Program are evaluated against known fire events (Morisette, Privette, & Justice, 2002). Discrepancies between the predicted management response and known historical events can be used to refine the underlying models and algorithms, or presented alongside products to improve decision-making, e.g., "the cone of uncertainty" displayed around hurricane forecast tracks (Cangialosi & Franklin, 2011).

To simplify our framework, we include only operationalization components that occur during the initial implementation; howeve, DM tools require ongoing upkeep, and it is important that tools have the necessary resources for maintenance. Both observed and modelled BEES data dissemination streams will require funding to be produced into the future. Code will break as upgrades and package depreciations cause changes to syntax. Additionally, statistical models and algorithms are subject to concerns of non-stationarity and can introduce extrapolation errors if the BEES conditions over which they are predicted fall outside the range of BEES data on which they were trained. Ongoing testing of predictive skill using newly collected data will be critical to ensure relationships between BEES data and target features have not changed, and that predictions are still within acceptable accuracy limits. Operationalized DM tools require personnel and funding to address these maintenance items, and their long-term continuance will require institutional investment. To help secure resources, it will be important for national governments and international treaties (e.g., The Convention on Biological Diversity, Balmford et al., 2005; The World Parks Congress Promise of Sydney, Andersen & Enkerlin-Hoeflich, 2015) to recognize DM tools as a core part of the management toolbox. It is also important that resource management and Earth Observation remain line items in federal budgets. DM tools help individuals and governing bodies save money (e.g., by increasing fisheries sustainability or reducing property loss), and feedback mechanisms could be put in place to quantify and recycle avoided monetary losses back into tool maintenance.

5 | CONCLUSIONS

Dynamic management is emerging as a solution to some of the drawbacks of static management, such as inflexibility to climate variability and change, and larger area requirements to meet management objectives (Dunn et al., 2016; Spillman & Hobday, 2014). DM tools are applicable to a wide range of management purposes, including natural disaster preparedness, resource management, and human health, and to a wide range of natural systems. Because DM tool operationalization is relatively complex compared to that of static tools, it will be important for future studies to make their workflows transparent to serve as guides for subsequent tools. As a starting point, we have presented a reproducible and transparent operationalization framework, standardized across marine, freshwater, terrestrial, and atmospheric DM applications. While DM operational challenges might seem prohibitive, they should be viewed as stepping stones—rather than barriers—to widespread DM implementation. The practice of static management has been progressively redefined and refined over the past 150 years (Margules & Pressey, 2000; Pressey, Visconti, & Ferraro, 2015; Runte, 1997), and it would be myopic to not expect a similar maturation process for DM. In a fundamentally dynamic world, it is important that we continue to allocate technological, scientific, and monetary resources to develop management solutions that accommodate biological, environmental, economic, and social variability.

ACKNOWLEDGEMENTS

This study has been conducted using E.U. Copernicus Marine Service Information. This manuscript is part of a NASA Ecoforecasting funded project (NNH12ZDA001N-ECOF) with additional support from California SeaGrant, NOAA's BREP Program, NOAA's West Coast Regional Office, and NOAA's Integrated Ecosystem Assessment Program.

AUTHORS' CONTRIBUTIONS

H.W., E.L.H., S.J.B., and R.L. conceived the ideas and designed methodology; E.L.H. and K.L.S. built and validated the species distribution models; HW lead the operationalization and sensitivity analysis with significant contribution from E.L.H., M.G.J., S.B., K.L.S., D.R., and L.D.; H.W. drafted the manuscript and all co-authors contributed critically to the drafts and gave final approval for publication.

DATA ACCESSIBILITY

Original GitHub code is archived via Zenodo https://doi.org/10.5281/zenodo.1410674 (Welch, 2018). Original data underlying EcoCast were published in Hazen et al. (2018).

ORCID

Heather Welch http://orcid.org/0000-0002-5464-1140

REFERENCES

Andersen, I., & Enkerlin-Hoeflich, E. (2015). The World Parks Congress 2014: Inspiring solutions for parks, people and planet. *PARKS*, *21*, 7–12. https://doi.org/10.2305/IUCN.CH.2014.PARKS

Balmford, A., Bennun, L., Brink, B. T., Cooper, D., Côte, I. M., Crane, P., … Walther, B. A. (2005). The convention on biological diversity's 2010 target. *Science*, *307*, 212–213. https://doi.org/10.1126/science.1106281

Bethoney, N. D., Schondelmeier, B. P., Stokesbury, K. D., & Hoffman, W. S., (2013). Developing a fine scale system to address river herring (Alosa pseudoharengus, A. aestivalis) and American shad (A. sapidissima) bycatch in the US Northwest Atlantic mid-water trawl fishery. *Fisheries Research*, *141*, 79–87. https://doi.org/10.1016/j.fishres.2012.09.003

Cangialosi, J. P., & Franklin, J. L. (2011). 2010 National Hurricane Center Forecast Verification Report. National Hurricane Center. Retrieved from http://www.nhc.noaa.gov/verification/pdfs/Verification_2010.pdf

Chape, S., Harrison, J., Spalding, M., & Lysenko, I. (2005). Measuring the extent and effectiveness of protected areas as an indicator for meeting global biodiversity targets. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *360*, 443–455. https://doi.org/10.1098/rstb.2004.1592

Christensen, J. H., Boberg, F., Christensen, O. B., & Lucas-Picher, P. (2008). On the need for bias correction of regional climate change projections of temperature and precipitation. *Geophysical Research Letters*, *35*, L20709. https://doi.org/10.1029/2008GL035694

Dalton, T., Forrester, G., & Pollnac, R. (2012). Participation, process quality, and performance of marine protected areas in the wider Caribbean. *Environmental Management*, *49*, 1224–1237. https://doi.org/10.1007/s00267-012-9855-0

Dunn, D. C., Maxwell, S. M., Boustany, A. M., & Halpin, P. N. (2016). Dynamic ocean management increases the efficiency and efficacy of fisheries management. *Proceedings of the National Academy of Sciences of the United States of America*, *113*, 668–673. https://doi.org/10.1073/pnas.1513626113

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, *77*, 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Eveson, J. P., Hobdaya, A. J., Hartoga, J. R., Spillman, C. M., & Rough, K. M. (2015). Seasonal forecasting of tuna habitat in the Great Australian Bight. *Fisheries Research*, *170*, 39–49. https://doi.org/10.1016/j.fishres.2015.05.008

Farnsworth, A., van Doren, B. M., Hochachka, W. M., Sheldon, D., Winner, K., Irvine, J., … Kelling, S. (2016). A characterization of autumn nocturnal migration detected by weather surveillance radars in the northeastern USA. *Ecological Applications*, *26*, 752–770. https://doi.org/10.1890/15-0023

Halvorsen, K. E. (2003). Assessing the effects of public participation. *Public Administration Review*, *63*, 535–543. https://doi.org/10.1111/1540-6210.00317

Hazen, E. L., Palacios, D. M., Forney, K. A., Howell, E. A., Becker, E., Hoover, A. L., … Bailey, H. (2017). WhaleWatch: A dynamic management tool for predicting blue whale density in the California Current. *Journal of Applied Ecology*, *54*, 1415–1428. https://doi.org/10.1111/1365-2664.12820

Hazen, E. L., Scales, K. L., Maxwell, S. M., Briscoe, D. K., Welch, H., Bograd, S. J., … Lewison, R. L. (2018). A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. *Science Advances*, *7*, 1–7. https://doi.org/10.1126/sciadv.aar3001

Hobday, A., & Hartmann, K. (2006). Near real-time spatial management based on habitat predictions for a longline bycatch species. *Fisheries Management and Ecology*, *13*, 365–380. https://doi.org/10.1111/j.1365-2400.2006.00515.x

Howell, E. A., Kobayashi, D., Parker, D., Balazs, G., & Polovina, aJ.J. (2008). TurtleWatch: A tool to aid in the bycatch reduction of loggerhead turtles Caretta caretta in the Hawaii-based pelagic longline fishery. *Endangered Species Research*, *5*, 267–278. https://doi.org/10.3354/esr00096

Kavanaugh, K., Fisher, K., & Derner, K. (2013). Assessment of the Eastern Gulf of Mexico harmful algal bloom operational forecast system: A comparative analysis of forecast skill and utilization from 2004 to 2008 (NOAA Technical Report NOS CO-OPS, 66).

Lewison, R., Hobday, A. J., Maxwell, S., Hazen, E., Hartog, J. R., Dunn, D. C., … Crowder, L. B. (2015). Dynamic ocean management: Identifying the critical ingredients of dynamic approaches to ocean resource management. *BioScience*, *65*, 486–498. https://doi.org/10.1093/biosci/biv018

Linge, J. P., Steinberger, R., Fuart, F., Bucci, S., Belyaeva, J., Gemo, M., … van der Goot, E. (2010). MediSys: Medical Information System. In E. Asimakopoulou, & N. Bessis (Eds.), *Advanced ICTs for* *disaster management and threat detection: Collaborative and distributed frameworks* (pp. 131–142). Hershey, PA: IGI Global. https://doi.org/10.4018/978-1-61520-987-3

Liu, G., Strong, A. E., Skirving, W. J., & Arzayus, F. (2006). Overview of NOAA coral reef watch program's near-real time satellite global coral bleaching monitoring activities. Proceedings of the 10th International Coral Reef Symposium, pp. 1783–1793.

Margules, C. R., & Pressey, R. L. (2000). Systematic conservation planning. *Nature*, *405*, 243–253. https://doi.org/10.1038/35012251

Marshall, P. A., & Schuttenberg, H. Z. (2006). *A reef manager's guide to coral bleaching*. Townsville, Qld, Australia: Great Barrier Reef Marine Park Authority. ISBN 1-876945-40-0.

Maxwell, S. M., Hazen, E. L., Lewison, R. L., Dunn, D. C., Bailey, H., Bograd, S. J., … Crowder, L. B. (2015). Dynamic ocean management: Defining and conceptualizing real-time management of the ocean. *Marine Policy*, *58*, 42–50. https://doi.org/10.1016/j.marpol.2015.03.014

Morisette, J. T., Privette, J. L., & Justice, C. O. (2002). A framework for the validation of MODIS land products. *Remote Sensing of Environment*, *83*, 77–96. https://doi.org/10.1016/S0034-4257(02)00088-3

O'Keefe, C. E., & DeCelles, G. R. (2013). Forming a partnership to avoid bycatch. *Fisheries*, *38*, 434–444. https://doi.org/10.1080/03632415.2013.838122

Oyanedel, R., Marín, A., Castilla, J. C., & Gelcich, S. (2016). Establishing marine protected areas through bottom-up processes: Insights from two contrasting initiatives in Chile. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *26*, 184–195. https://doi.org/10.1002/aqc.2546

Petchey, O. L., Pontarp, M., Massie, T. M., Kéfi, S., Ozgul, A., Weilenmann, M., … Pearse, I. S. (2015). The ecological forecast horizon, and examples of its uses and determinants. *Ecology Letters*, *18*, 597–611. https://doi.org/10.1111/ele.12443

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, *190*, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Pressey, R. L., Visconti, P., & Ferraro, P. J. (2015). Making parks make a difference: Poor alignment of policy, planning and management with protected-area impact, and ways forward. *Philosophical Transactions of the Royal Society*, *B*, *370*, 20140280. https://doi.org/10.1098/rstb.2014.0280

Quayle, B., Sohlberg, R., & Descloitres, J. (2004). Operational remote sensing technologies for wildfire assessment. Geoscience and Remote Sensing Symposium, 2004. IGARSS'04. Proceedings. 2004 IEEE International, IEEE.

Roy, D. P., Ju, J., Lewis, P., Schaaf, C., Gao, F., Hansen, M., & Lindquist, E. (2008). Multi-temporal MODIS–Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data. *Remote Sensing of Environment*, *112*, 3112–3130. https://doi.org/10.1016/j.rse.2008.03.009

Runte, A. (1997). *National parks: The American experience*. Lincoln, NB: University of Nebraska Press.

Scales, K. L., Hazen, E. L., Jacox, M. G., Edwards, C. A., Boustany, A. M., Oliver, M. J., & Bograd, S. J. (2017). Scale of inference: On the sensitivity of habitat models for wide-ranging marine predators to the resolution of environmental data. *Ecography*, *40*, 210–220. https://doi.org/10.1111/ecog.02272

Sierra Sun Times (2018, July 25). Ferguson fire near Yosemite National Park in Mariposa County Monday updates. Retrieved from http://goldrushcam.com/sierrasuntimes/index.php/news/local-news/14628-ferguson-fire-near-yosemite-national-park-in-mariposa-county-Monday-updates

Simons, R. A. (2017). *ERDDAP*. Monterey, CA: NOAA/NMFS/SWFSC/ERD. https://coastwatch.pfeg.noaa.gov/erddap

Spillman, C. M., & Hobday, A. J. (2014). Dynamical seasonal ocean forecasts to aid salmon farm management in a climate hotspot. *Climate Risk Management*, *1*, 25–38. https://doi.org/10.1016/j.crm.2013.12.001

Turner, S. M., Hare, J. A., Manderson, J. P., Hoey, J. J., Richardson, D. E., Sarro, C. L., & Silva, R. (2017). Cooperative research to evaluate an incidental catch distribution forecast. *Frontiers in Marine Science*, *4*, 116. https://doi.org/10.3389/fmars.2017.00116

USGS. (2002). WaterWatch – Maps and graphs of current water resources conditions. Retrieved from https://pubs.usgs.gov/fs/fs-052-02/pdf/Hold_On/fs05202web.pdf

Welch, H. (2018). EcoCast_Operationalization: Release of EcoCast operationalization code for publication. *Zenodo*, https://doi.org/10.5281/zenodo.1410674

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Welch H, Hazen EL, Bograd SJ, et al. Practical considerations for operationalizing dynamic management tools. *J Appl Ecol*. 2018;00:1–11. https://doi.org/10.1111/1365-2664.13281