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Software note

CEAMEC 1.0: a 'Shiny' application for cost-effective animal management via environmental capacity

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Managing over-abundant nuisance species in anthropogenic environments typically depends on the removal of individuals, even though theoretical and empirical studies suggest that limiting environmental resources can be more effective. However, quantifying resources to be manipulated in order to achieve a desired reduction in target species can be difficult, which complicates cost estimation for a given management target. We present CEAMEC 1.0 (cost-effective animal management via environmental capacity), a 'Shiny' application in the HTML user interface (available at https://qt37t247.shinyapps.io/ceamec) programmed in the R language, as a tool to provide managers with optimal management strategies based on cost estimates of manipulating different environmental resources. Based on user-defined targets and periods of management, CEAMEC calculates an optimal combination and quantity of different resources to be manipulated at the lowest cost to achieve a desired reduction level of a target population. CEAMEC provides stakeholders with a user-friendly decision support tool for integrated management plans targeting nuisance species in man-made environments.

Keywords: biological invasions, decision support system, environmental engineering, human–wildlife conflict, pest control, urban ecosystem

Background

The worldwide expansion of anthropogenic environments has increased niche space for the establishment of invasive and human commensal species (Simberloff et al. 2013, Hulme-Beaman et al. 2016, Albuquerque et al. 2018). Well-established invasive species (such as termites, cockroaches and rats) and feralized domesticated species (such as pigeons, dogs and cats), which are highly adapted to anthropogenic environments and dependent on anthropogenic resources, compete with humans for resources and space, thereby generating human–wildlife conflict and incurring considerable economic loss (Woodroffe et al. 2005, Barua et al. 2013). Management of such species requires constant effort and substantial annual investment (Simberloff 2008). Removal

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of individuals (eradication or culling) is the most frequent management approach (Clout and Veitch 2002, Tobin et al. 2014). Yet, in theory, limiting obligate resources to reduce the environmental carrying capacity (environmental capacity hereafter) of pests and invasives can be a more effective solution compared to the removal of individuals, especially when the species being managed are well-established and reproduce rapidly (Lurgi et al. 2016). Empirical studies confirm that limiting certain resources may be effective in reducing the abundance of target species (Avery et al. 2002, Soh et al. 2002, 2021, Tang et al. 2018). However, there is little comparative insight into the effectiveness of different management strategies, including those that manipulate certain environmental resources (Bino et al. 2010, Doherty et al. 2015). Managers are more prone to practising removal of individuals instead of manipulating environmental resources, because it is difficult to quantify the resources to be managed in terms of population reduction, especially when in-depth ecological understanding is missing (Coll and Wajnberg 2017).

The recent integration of hierarchical modelling in measuring species' environment-specific abundance (Royle 2004a, b, Royle et al. 2004) has considerably expanded options in animal management in the absence of in-depth ecological understanding. One of the most popular packages performing such modelling, 'unmarked' (Fiske and Chandler 2011), estimates species abundance using survey data from a variety of commonly used field sampling techniques, such as removal sampling, distance sampling and repeated counts. By detecting correlations between the population density of a target species and specific resources, hierarchical modelling approaches hold the promise of calculating the cost-effectiveness of various resource-based management regimes to select an optimal strategy.

To help managers evaluate the cost-effectiveness of manipulating different resources and choose optimal strategies, we designed CEAMEC 1.0 (cost-effective animal management via environmental capacity), a 'Shiny' application in *R* language (available at https://qt37t247.shinyapps.io/ceamec). CEAMEC is user-friendly for managers to design and budget management approaches based on the manipulation of environmental resources as an alternative to the removal of individuals. Instead of running 'unmarked' and 'CEAMEC' through R scripts, we developed an HTML user interface (UI) using the R packages 'Shiny' (Chang et al. 2017) and 'leaflet' (Cheng et al. 2018). Users can select input survey data, perform model selection, assign areas for a management plan and download the results in the UI. To demonstrate, we apply CEAMEC to a dataset of feralized populations of the domestic pigeon, *Columba livia* (henceforth 'pigeon'), in Singapore.

Methods and features

Workflow

The underlying principle of CEAMEC is to calculate the change in environmental capacity from the observed pre-management density of a target species (which may be subject to existing management efforts) to the desired post-management density. The change in environmental capacity is then used to optimize combinations of resources to be manipulated at the lowest economic cost. CEAMEC's mechanisms are summarized in the following paragraphs, with a brief workflow given in Fig. 1.

Before using CEAMEC, users need to prepare raw survey data in comma-separated values (csv) format, following the

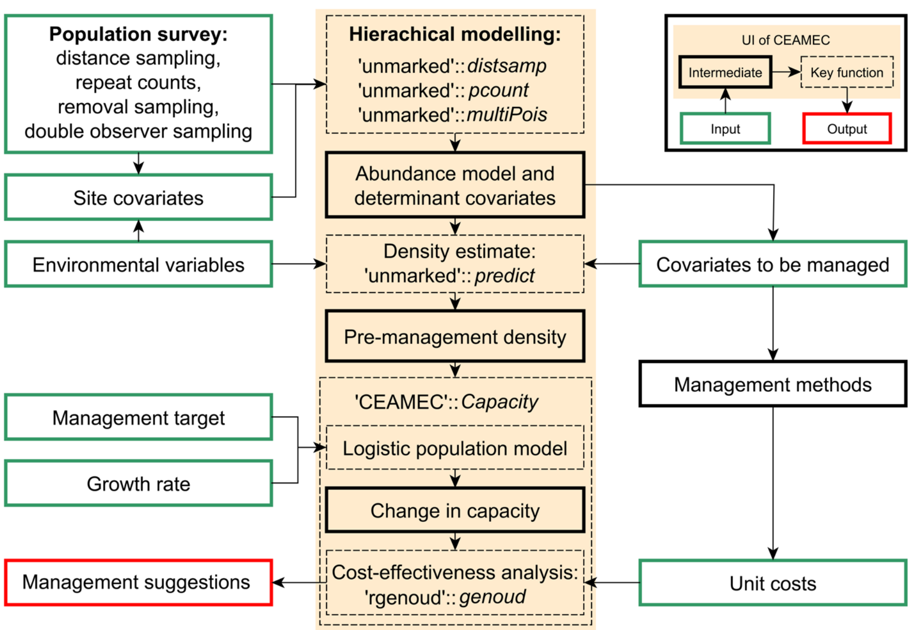

Figure 1. Workflow of CEAMEC.

data structure of 'unmarked', which specifies the count data, observation covariates (i.e. variables encountered at the same site across multiple visits, typically time, weather, season) and site covariates (i.e. environmental variables at the survey sites). Users also need to input the combinations of covariates for the hierarchical modelling. As 'unmarked' has been integrated within CEAMEC, all input data can be inserted via the UI of CEAMEC. Each hierarchical model comprises a detection model and an abundance model, which are computed simultaneously. A table is presented after the model computation, listing the relative quality of all models, presented as Akaike information criterion (AIC) values, which can be compared for the selection of the best model to describe the correlation between the environmental variables and the observed population density. The abundance model of the best model is used for the density estimation and cost-effectiveness analysis. The site covariates in the best abundance model are the determinant covariates, which are the most relevant environmental variables for the population density.

The pre-management density of the target species across the study area is estimated based on the best model. Users need to upload a csv-formatted data frame (named 'newdata file') of rasterized environmental variables, including all determinant covariates, across the entire area of study. Users also need to provide the extent and dimension of the raster of environmental variables in the text to create an interactive map of pre-management density. The resolution of the raster of environmental variables used for pre-management density estimation defines the basic spatial unit (management unit hereafter) in the CEAMEC analyses. CEAMEC considers each management unit as a closed system, which assumes negligible exchange of individuals with other management units, in line with the assumption of the hierarchical modelling functions of 'unmarked': *pcount* for repeated counts, *distsamp* for distance sampling and *multinomPois* for removal sampling and double observer sampling (Royle 2004a, b, Royle et al. 2004). CEAMEC's calculations are carried out independently for each management unit, where the dynamics of the population density is subjected to a logistic population growth model (Pearl and Reed 1920). Therefore, as users provide a desired post-management density (N_t), period of management (t) and population growth rate (r), CEAMEC calculates the post-management environmental capacity (K') (Eq. 1), as:

$$K' = \frac{N_0 N_t \left(e^{rt} - 1\right)}{N_0 e^{rt} - N_t} \tag{1}$$

where N_0 is the pre-management density.

To design appropriate management methods, users may need to select a subset of resource-based covariates to be managed, preferably those which most affect population density (e.g. food sources), from among all determinant covariates. Moreover, the covariates to be managed should be numeric (either continuous or integers). For categorical determinant covariates that may contribute essentially to the species' density, users may consider converting them into numeric variables. For example, instead of using vegetation categories as a site covariate, users may consider using the area or proportion of a specific vegetation category. The determinant covariates not to be managed are still included in the density estimation and subsequent analyses as contributors of background density. The case study of pigeons in Singapore in the following section provides examples on how to design management methods corresponding with specific determinant covariates and calculate unit costs for each management method.

For each selected management unit, different combinations of management methods can lead to different total costs (V_t), which are calculated (Eq. 2) as:

$$V_t = \sum_{i=1}^{n} V_i \tag{2}$$

where i is the ith covariate from n selected covariates to be managed, and V_i is the cost of managing the ith covariate, which is linear with respect to period of management (t) and changes of covariates (Δx_i) (Eq. 3):

$$V_i = a_i \Delta x_i t + b_i \Delta x_i + c_i t + d_i \tag{3}$$

where a_i is cost per unit of the ith covariate per unit time, b_i is cost per unit of the ith covariate, c_i is cost per unit time and d_i is fixed cost.

CEAMEC directly uses the pre-management density (N_0) as the pre-management capacity by assuming that the population had reached capacity before the planned management, given that, in most cases, species to be managed breed fast and have been established as a nuisance for a relatively long time. Therefore, the total of the changes in each covariate to be managed can be translated in terms of change of environmental capacity as (Eq. 4):

$$\ln(N_0) - \ln\left(K'\right) \le \sum_{i=1}^{n} k_i \Delta x_i \tag{4}$$

where k_i is the coefficient of the ith covariate in the abundance model and Δx_i is the change in covariates to be managed. Whereas for the changes in each covariate to be managed, which correspond to the cost of different management methods, we applied a genetic algorithm as implemented in the R package 'rgenoud' (Mebane and Sekhon 2011) to perform evolutionary searching, with derivative-based approaches across combinations to find the one with the lowest total cost V_t. Finally, the combination of changes among different covariates is considered as the optimal combination of management methods of least cost. In general, the cheaper methods corresponding to covariates with higher coefficients

(k_i) in the abundance model are preferred, but also subject to the quantity of the covariates.

In the end, users may download two output files: a keyhole markup language (kml) file suggesting the most cost-effective management method for each management unit selected; and/or a multi-tab Excel sheet comparing costs of different combinations of management methods for each management unit.

The UI

The UI of CEAMEC consists of three tabs: the ‘field data input’ tab (Fig. 2a and b) for survey data input and hierarchical modelling; the ‘CEAMEC’ tab (Fig. 2c) for density visualization, cost-effectiveness analysis and results output; and the ‘Help’ tab for the access to useful links. Under the ‘field data input’ tab, there are three sub-tabs corresponding with different types of population survey methods and different hierarchical modelling methods in ‘unmarked’. In each of these sub-tabs, there are three sections: a ‘Survey information’ section allows user to upload and examine the survey data; a ‘Modelling with covariates’ section allows users to generate models by inputting combinations of covariates; and a ‘Models with covariates’ section summarizes model information for the selection of the best abundance model and the covariates to be managed.

Example

We tested CEAMEC on an example dataset, which is modified from a pigeon population modelling study in Singapore based on a distance sampling survey carried out in 2016 (Tang et al. 2018) with additional covariates.

We first prepared two csv files for the hierarchical modelling in the ‘field data input’ tab: a distance sampling survey data file and a site covariate file. In the ‘Survey information’ section, we uploaded the survey data file and the site covariate file. We used ‘10’ m as bin size for creating discrete distance classes to model correlation between detection and distance. After checking that the survey data summary and histogram displaying data distribution looked correct, we clicked the ‘Check detection functions’ button to generate a table, from which we confirmed that the ‘hazard’ model (exhibiting the lowest AIC across all four detection models) best described detections (Fig. 2b).

In the ‘Modelling with covariates’ section, we listed combinations of covariates to generate models that appeared worthwhile to explore. Again, ‘hazard’ was selected as the

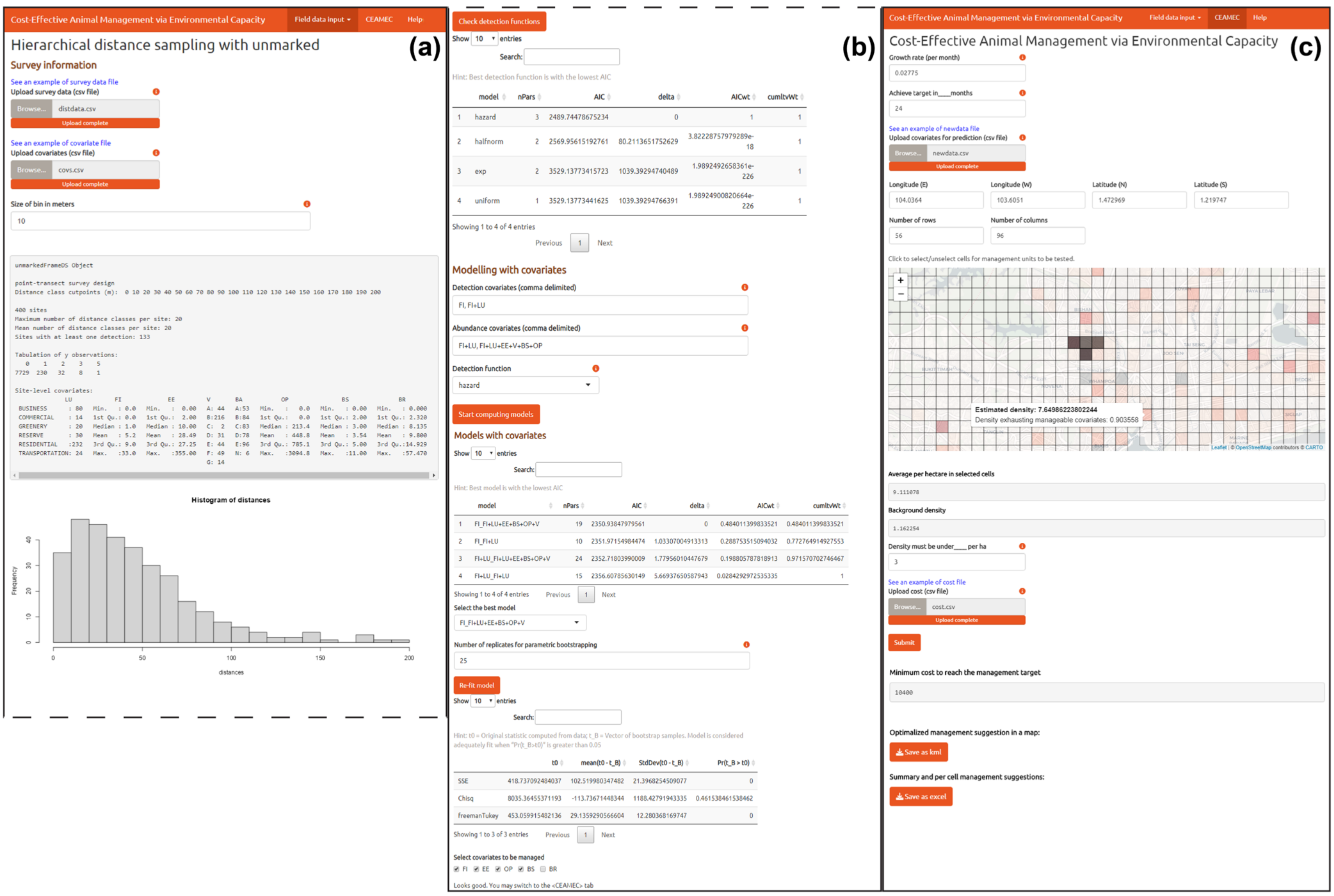

Figure 2. Screenshot of fully executed CEAMEC UI with the demonstration dataset of pigeons in Singapore. (a) and (b) interface under the ‘field data input’ tab (distance sampling sub-tab); (c) interface under the ‘CEAMEC’ tab.

‘Detection function’. After model computation, models were presented in the table at the beginning of the ‘Models with covariates’ section, sorted by their AIC values. We checked the adequacy of model fit for the best model of choice. In the example, we simulated data 25 times with the best model and checked the statistics to find whether distribution of simulated data is significantly different from observed data. We selected ‘FI_FI+LU+V+EE+BS+OP’ as the best model as it exhibited the lowest AIC value (Fig. 2b). The model consists of a detection model and an abundance model, whose covariates are delimited by ‘_’. As CEAMEC utilizes the abundance model in the subsequent analyses, the covariates in the abundance model are identified as determinant covariates, which are ‘FI’ (number of feeding incidents), ‘LU’ (land use types), ‘V’ (vegetation types), ‘EE’ (number of eating establishments), ‘BS’ (number of bus stops) and ‘OP’ (length of overpasses). By checking the corresponding checkboxes, we chose four of the determinant covariates to be managed, as they are directly associated with resources that support the population density of pigeons in Singapore: ‘FI’, ‘EE’ and ‘BS’ are associated with food sources whereas ‘OP’ is associated with sheltered roosts. We chose these four covariates to be managed also because they make it straightforward to demonstrate the relationship between the quantity of covariates and the quantity of resources during management method design. The following outlines the costs associated with each of these four management methods:

1) To reduce feeding incidents, we proposed a policy whereby persons engaging in illegal pigeon feeding (‘feeders’) are identified, approached and educated by management personnel. For each management unit, the resultant cost comprises a fixed cost (*d*) of SGD500 for the investigation over the entire management unit and a cost per feeding incident (*b*) of SGD200 for visiting and educating a feeder to avert one feeding incident.
2) To reduce food sources generated by eating establishments, we proposed a management plan to combine regular inspections with the disposal of exposed food waste. For each management unit, the resultant cost comprises a cost per eating establishment per month (*a*) of SGD30 covering administrative fees and disposal costs.
3) To reduce the food sources (through feeding or littering) generated at or near bus stops, we proposed to install ‘no feeding/littering’ signs and warnings that such behaviour will incur fines when caught by surveillance cameras at bus stops. The resultant cost comprises a cost per bus stop (*b*) of SGD25 for sign installations.
4) To reduce roosts beneath overpasses, we proposed to install nets to deter pigeon entry into crevices and expansion gaps. For each management unit, the resultant cost comprises a cost per metre of overpass (*b*) of SGD24 for net installation and a cost per metre of overpass per month (*a*) of SGD0.12 for net maintenance.

We generated a cost file, in the csv format, with rows of selected covariates to be managed and columns of unit costs. We set a growth rate of 0.02775 per month for pigeons as suggested by previous studies (Johnston and Janiga 1995). This growth rate assumes that approximately one-third of pigeons in the entire population breeds every year; that each pair produces an average of five fledged offspring per year; and that approximately one-half of the population dies every year. We also set a 24-month period of management.

Switching to the ‘CEAMEC’ tab, we set the study area to encompass the entire Republic of Singapore with geographic limits at 104.0364°E to 103.6051°E (east–west) and 1.472969°N to 1.219747°N (north–south). By specifying ‘number of rows’ and ‘number of columns’, we rasterized the study area into 96 × 56 raster cells (500 × 500 m for each raster cell). We uploaded the newdata file, which includes all determinant covariates across the entire area of study, into CEAMEC to start the density estimation. A map displays estimated densities across all management units (Fig. 2c). Redder colour hues imply a higher pigeon density in each management unit and vice versa. Hovering over a management unit with the cursor triggers a pop-up that displays the density and the background density of the management unit. As we only declared four of the six determinant covariates as being subject to management and manipulation, the remaining two determinant covariates contributed to the background density, which is the minimum pigeon density the management unit can reach when exhaustive use is being made of all four covariates to be managed. We selected four management units with a relatively high pigeon density (average of ~9 pigeons per hectare) and set out to reduce the density below three pigeons per hectare. We uploaded the cost file of unit management costs and hit the ‘Submit’ button to initiate the cost-effectiveness computation.

In the end, CEAMEC produced an optimal management plan that entails a cost of SGD10 400 to achieve the management target that reduces pigeons to fewer than three per hectare within 24 months across the four management units. We downloaded the kml file and the Excel file (the first tab) to view the detailed management suggestions for each management unit (Fig. 3a and b). In the subsequent tabs of the Excel file, CEAMEC provided a comparison between the best management suggestion and other, financially less optimal combinations of management methods (Fig. 3c) for every management unit selected.

Discussion

CEAMEC provides a framework allowing for the integration of hierarchical modelling of species abundance with the management of resources, creating a promising application for cost-effective resource-based animal management. CEAMEC accommodates hierarchical modelling results from the most widely used sampling methods, such as distance sampling (Buckland et al. 2005), repeated counts sampling (Dorazio 2007), double observer sampling and removal sampling (White 1982). Programmed in the R language, CEAMEC integrates ‘unmarked’ (Fiske and Chandler 2011), one of the

(b)

Scenarios	Costs	Pre-mana	Post-mani	BS	EE	FI	OP	layer
best	3625	12.35167	2.931972	5	0	15	0	2838
best	1250	4.549284	2.868805	6	0	3	0	2839
best	1875	6.049285	2.850263	7	0	6	0	2840
best	3650	13.49408	2.992936	6	0	15	0	2935

(c)

Scenarios	Costs	Pre-mana	Post-mani	BS	EE	FI	OP
BS+0+0+0	150	12.35167	9.609716	6	0	0	0
0+EE+0+0	75600	12.35167	10.72718	0	105	0	0
BS+EE+0+0	75750	12.35167	8.096099	6	105	0	0
0+0+FI+0	4700	12.35167	2.298544	0	0	21	0
BS+0+FI+0	4850	12.35167	1.501622	6	0	21	0
0+EE+FI+0	80300	12.35167	1.793401	0	105	21	0
BS+EE+FI+0	80450	12.35167	1.162254	6	105	21	0
BS+0+0+OP	150	12.35167	9.609716	6	0	0	0
0+EE+0+OP	75600	12.35167	10.72718	0	105	0	0
BS+EE+0+OP	75750	12.35167	8.096099	6	105	0	0
0+0+FI+OP	4700	12.35167	2.298544	0	0	21	0
BS+0+FI+OP	4850	12.35167	1.501622	6	0	21	0
0+EE+FI+OP	80300	12.35167	1.793401	0	105	21	0
BS+EE+FI+OP	80450	12.35167	1.162254	6	105	21	0
best	3625	12.35167	2.931972	5	0	15	0

Figure 3. Results from the demonstration run of CEAMEC. (a) screenshot of the kml file opened in Google Earth, (b) summary table of optimal methods and (c) per management unit table of methods comparisons.

most popular programs for abundance estimation, which has been cited over 1,900 times, and can be used by those who wish to derive downstream applications from abundance estimates. Accounting for populations' natural growth rates and the spatial distribution of environmental resources that contribute to a species' density distribution, CEAMEC provides relatively realistic suggestions on the combinations of methods for managers to achieve their targets.

Managers routinely collect baseline population data of species that require active management. However, we recommend that managers additionally collect geospatial data of natural and anthropogenic resources that may impact the density of target species. If resource-based covariates are identified to substantially contribute to a population's density in hierarchical modelling, CEAMEC allows managers to design specific methods based on the manipulation of these resources. CEAMEC does so by running a cost-effectiveness computation across all different management combinations to allow managers to assess whether to apply resource-based approaches over non-resource-based approaches (e.g. culling or neutering).

CEAMEC is based on the assumptions that target populations have reached their carrying capacity and are low in mobility. Therefore, ideal management targets for CEAMEC users should be species that are highly anthrodependent (well-established invasive species and feralized domesticated species) and those which are known to breed fast and have small home ranges (Hulme-Beaman et al. 2016). Even though 'unmarked' is capable of hierarchical modelling in populations that are open to temporary emigration or other more complicated demographic processes (Royle and Nichols 2003, Chandler et al. 2011, Dail and Madsen 2011), CEAMEC is less ideally suited to many management scenarios involving native wildlife with low detectability that may be subject to complicated environmental dynamics.

The current version of CEAMEC only allows users to input one set of pre-management population densities. As population management is typically a continuous effort that involves constant monitoring and census work, future upgrades of CEAMEC are planned to allow re-calibrations of hierarchical models with sampling data as management proceeds. Such model re-calibrations would allow for flexibility by accounting for a species' resilience to management (Nelson et al. 2007), e.g. switching to alternative food sources (Newsome et al. 2014, Doherty et al. 2015, Stofberg et al. 2019, Soh et al. 2021). As the emergence of such resilience is highly case-specific, follow-up studies are required to provide detailed parameters and test cases to guide CEAMEC upgrades.

CEAMEC is designed for the management of over-abundant invasive species or human commensals in anthropogenic environments, where reductions in a species' density and changes in environmental capacity are easy to achieve and there are few concerns regarding trophic cascades and the stability of the ecological community (Miller and Rudolf 2011). Therefore, the currently available version of CEAMEC is only able to assist in the cost-effective reduction of a target species via the manipulation of its environmental capacity. We still see the potential to implement CEAMEC's capability to evaluate strategies for the cost-effective manipulation of the environmental capacity to boost the density of a target species of conservation concern. However, increases in the number of individuals of a species through the introduction of additional resources may lead to instability of trophic systems in the natural environment (Tylianakis 2010). Future updates of CEAMEC which cater to conservation needs would therefore require an incorporation of complex ecosystem models to specifically account for the equilibrium between the target species and other species in the trophic system, and the stability of the entire ecosystem (Haerter et al. 2016, Lurgi et al. 2018, Geary et al. 2020).

To cite CEAMEC 1.0 or acknowledge its use, cite this Software note as follows, substituting the version of the application that you used for 'version 1.0':

Tang, Q. et al. 2022. CEAMEC 1.0: a 'Shiny' application for cost-effective animal management via environmental capacity. – Ecography 45: 1–8 (ver. 1.0).

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Author contributions

Qian Tang: Conceptualization (equal); Funding acquisition (supporting); Software (equal); Writing – original draft (lead). **Yanyun Yan**: Investigation (lead); Software (equal); Writing – original draft (supporting). **Malcolm C. K. Soh**: Investigation (supporting); Writing – review and editing (supporting). **Frank E. Rheindt**: Conceptualization (equal); Funding acquisition (lead); Writing – review and editing (lead).

Transparent peer review

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Data availability statement

The program is available online on 'Shiny' Cloud: https://qt37t247.shinyapps.io/CEAMEC/. Source codes, user manual and example datasets are available on the GitHub: https://github.com/qt37t247/CEAMEC (Tang et al. 2022).

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