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A global meta-analysis of the economic values of provisioning and cultural ecosystem services

Abstract

Despite a growing demand to integrate ecosystem services into sustainability decision-making, our understanding of the global distribution of the economic value of ES is scarce. We extracted information from provisioning and cultural ecosystem services (PCES) from The Economics of Ecosystems and Biodiversity (TEEB) database using a meta-analytical approach. We then employed geostatistical methods to analyze the relationship between economic values and environmental and socio-economic predictors. Here we show that anthropogenic related factors such as accessibility, spatially explicit gross domestic product and ecosystem services scarcity explain global trends of PCES economic values. We observe higher PCES values in agricultural areas of strong human presence such as the British Isles, Southwest of Brazil and India and lower values in less disturbed natural areas. These findings highlight the decisive role that human systems play in the economic realization of PCES and caution that single-criterion sustainability and conservation policies aimed at maximizing the economic returns of PCES may not overlap with wild nature.

Keywords: ecosystem services; natural capital; mapping; sustainability.

1. Introduction

Economic development has come at the expense of the natural environment. The most pressing global issues of the 21st century include climate change, biodiversity loss and large-scale modification of nutrient cycles (Rockström et al., 2009). Ecologists have identified this period as Earth's sixth mass extinction event (Barnosky et al., 2011).

The unsustainable destruction of nature brings with it the loss of the goods, services and cultural benefits that nature provides to humanity ("ecosystem services" (ES)) (Millennium Ecosystem Assessment, 2005). Knowing how the value of ES is distributed across space can help identify strategies to mitigate this loss. There have been attempts to estimate global ES values (Costanza et al., 1998; de Groot et al., 2012). The first global attempt on a global scale was by Costanza et al. (1997), who assumed a constant value per hectare of ecosystem type. This approach did, however, not account for within-biome variations and differences in local conditions (Nelson et al., 2009). Moving beyond constant ES values within biome, Batker et al. (2008) incorporated expert opinion on the local context and Nelson et al. (2009) used spatially explicit analyses together with direct benefit transfer to estimate regional ES values. de Groot et al. (2012) utilized meta-analytical models to estimate aggregate values of global ES value but, like Costanza et al. (1997), these were not spatially explicit. On the other hand, Ghermandi & Nunes (2013) and Carrasco et al. (2014) used spatially explicit meta-analytical models to estimate spatially explicit global ES values but only of coastal recreation and of tropical forests, respectively. Global maps of ES values for terrestrial ES that account for the heterogeneity of values across space, to our knowledge, are however lacking.

Understanding the values of ES across space is also important to evaluate potential trade-offs with biodiversity. If the economic value of ES were spatially congruent with biodiversity, policies aimed at protecting the economic value of ES would also help protect biodiversity, allowing for win-win solutions. On the other hand, if they were not spatially congruent, trade-offs would emerge. This would imply that conservation policies based on the economic value of ES, competing with biodiversity conservation policies for the same budgets, could even be detrimental for biodiversity (Wilcove and Ghazoul, 2015). To date, however, large-scale trade-off analyses have focused more on ES supply rather than actual demand and resulting economic value. Among these, studies have concentrated on trade-offs between biodiversity and carbon containment and sequestration services (Ferreira et al., 2018; Reside et al., 2017) or on carbon, pasture and water supply services (Lin et al., 2018; Naidoo et al., 2008). Studies of trade-offs between the economic value of ES and biodiversity have, on the other hand, been limited to national case studies or the tropical forest biome (Balmford, 2002; Carrasco et al., 2014; Law et al., 2015).

Given these gaps in the literature, here we aim to carry out a spatially explicit meta-analysis of terrestrial provision and cultural ES (PCES) globally to: (i) understand what factors explain the economic value of ES; and (ii) produce global maps of economic values for terrestrial PCES. We considered an analysis of multiple PCES combined and individual analyses for single ES: food provision, raw materials and recreation.

2. Methods

2.1 Overview

The study dataset comprised observations of economic value of ES and potential predictors of value. We restricted the observations to PCES. We focused on PCES for two reasons. First, supporting ES were excluded to avoid double counting (Boyd and Banzhaf, 2007; Smith et al., 2011).Second, we excluded regulating services because the spatial relationships between supply and demand for regulating services are quite different from those in PCES. For regulating services, the relative location of supply and demand could renage from not being importnat at all (e.g. carbon sequestration) or depending in complex directional ways that are hard to capture with just accessibility (e.g. water flood reduction follows hydrological systems rather than distance to cities).

Accessibility is however a good proxy for PCES that involve beneficiaries moving to the supply to obtain a benefit (e.g. recreation or wild fruits collection from the forest). Four main analyses were considered: (i) the values of multiple PCES were analyzed together and (ii) food, (iii) raw materials, and (iv) recreation ES values were considered in separate analyses. Each of the analyses involved fitting 60 models generated using an information-theoretic approach. Models were selected using the Akaike information criterion corrected for small sample size (AICc). The selected models were used to generate predictions of economic values globally and assessed for their mean accuracy using leave-one-out cross validation. ArcGIS v10.3.1 (ESRI, 2016) and R statistical environment v3.3.2 (R Development Core Team, 2015) were used for spatial data and statistical analyses respectively.

2.2 Variables and data collection

The variables considered included study design variables, biotic variables, abiotic variables and socio-economic variables (Tables S1 and S2 indicate the rationale for inclusion of the variables, their data sources and descriptive statistics). The response variable was the economic value of PCES. This was obtained from The Economics of Ecosystems & Biodiversity (TEEB) dataset that contains 1310 observations of ES values distributed globally (Van der Ploeg and de Groot, 2010).

The various ES were grouped into two higher hierarchical categories, as per the ES framework by the Millennium Ecosystem Assessment (2005) and TEEB (Van der Ploeg and de Groot, 2010): provisioning services and cultural services. The reason for doing this is that without this clustering there would not be enough observations per ES type (but see below the criterion to run individual ES analyses). For a similar reason, the valuation methods were grouped into three higher hierarchical categories: market valuation, revealed preferences, and stated preferences.

Observations were excluded from the TEEB dataset because of various reasons (Figure S1): 457 observations that were obtained using the benefit transfer method did not represent independent valuation studies; 207 observations corresponded to marine ecosystems; 191 observations were excluded because they were regulating services and habitat or supporting services; 18 observations were regional studies and so their ES values could not be pinpointed to a specific location; and 146 observations had missing or incomplete information. In total, this left 291 observations of PCES for analysis (Figure S1 describes the number of observations excluded under each criteria and Table S3 contains the final dataset).

Currencies of PCES values were standardized to international dollars of 2016 (I$) using exchange rates and purchasing power parity conversion factors from the Penn World Table v7.1 (Heston et al., 2012) and deflator values from the U.S. Government's CPI inflation calculator (Bureau of Labor Statistics, 2016).

We included the following explanatory variables (Table S2): *study design variables*: year of publication, PCES category, and valuation method category. *Socio-economic variables*: spatially explicit population density, spatially explicit GDP, and accessibility. *Abiotic variables*: area of PCES, global land cover, elevation, annual mean temperature, annual mean precipitation, and above-ground and below-ground biomass. *Biotic variables*: bird species richness, amphibian species richness, mammal species richness and vascular plant species richness. Species richness for several taxa (birds, amphibians, mammals and vascular plants) were used as proxies for biodiversity which has also been linked to ecosystem function.

Using the geographic coordinates form each PCES value observation, we extracted values from the dependent variables using ArcGIS v10.3.1 (ESRI, 2016). We checked the extracted values for missing data. For continuous variables, observations with missing data were inputted using the mean value of the adjacent cells and, if not available, the closest cell with data. Missing values in PCES supply area were inputted using the median of non-missing values of all observations. The generated PCES value dataset was further verified by extracting the biome corresponding to each study location with the biome reported in the original study. 26 observations presented mismatches between global land cover values and reported biomes. These mismatches were solved by modifying the assigned land cover values according to those present in the reported location.

2.3 Statistical modeling

All independent variables were fitted to a linear model and tested for multicollinearity using variance inflation factors, showing no problems of collinearity.

The explanatory variables were refitted to a generalized least squares (GLS) model and diagnosed for spatial autocorrelation. A bubble plot, a semivariogram and directional variograms were created (Figures S2, S3 and S4). Spatial autocorrelation structures were added to the GLS model to account for spatial autocorrelation and compared to a model without spatial structures using the Akaike information criterion (AIC). The lowest AIC value was used as the model selection criterion showing that there were not problems of heteroscedasticity, non-normality and the spatial structures did not improve the model (Figure S5, Table S4).

Because observations from the same country or continent may present sources of non-independence, we refitted the independent variables to linear mixed-effects (LME) models with one candidate random effect each (country and continent). The lowest AIC value was used as the model selection criterion and country was chosen as the random effect (Table S5).

Using the information-theoretic approach, 60 LME models including the global model (a model with all independent variables used in this study) were proposed and fitted with the chosen random effect using the maximum likelihood method for parameter estimation. The 60 LME models had different combinations of the 16 independent variables, which had theoretical basis from the literature on ES (Table S1). All models were forced to contain the independent variables ES category and valuation method category.

The models were weighted using the MuMIn package and the models with the lowest and next-lowest values in AICc were refitted using the restricted maximum likelihood method for parameter estimation. Diagnostic plots were created for the final models and inspected for violations of the assumptions of normality and homoscedasticity. R^2 values were calculated to assess explained variance by fixed effects (marginal R^2) and both fixed and random effects (conditional R^2) (Nakagawa and Schielzeth, 2013).

This model selection process was conducted for four groups of analyses: multiple PCES, food ES, raw materials ES, and recreation ES. These three single ES types were analyzed because they each had at least three times the number of observations compared to the maximum number of variables in the study for reliable parameter estimation. The multiple ES scenario utilized all 291 observations in the study dataset, and the three single ES scenarios utilized a subset of the study dataset each containing 84, 89 and 49 observations, respectively. Diagnostic plots were created for the final models and inspected for non-normality and heteroscedasticity.

2.4 ES mapping and predictive error

We created a point grid of cell size 0.25 decimal degree covering all terrestrial areas of the world thorough prediction of the most supported models. Similar to the study dataset, the variables used for prediction were extracted from all datasets into the point grid to generate a dataset for prediction. Bilinear interpolation of values was enabled for all raster datasets except for accessibility and global land cover.

The levels ‘needle leaved deciduous forest’ and ‘regularly flooded forest, freshwater and brackish’ of the factor global land cover were aggregated with levels ‘needle leaved evergreen forest’ and ‘regularly flooded forest, saline water’, respectively in the study and prediction datasets. This was because the levels of this factor were present in the prediction dataset but absent in the study dataset. When observations in the prediction dataset did not present values for all variables the mean of each variable was inserted as a proxy for missing values. For countries present in the prediction dataset but not in the study dataset, their country values were replaced with a country present in the study dataset of random effect closest to zero.

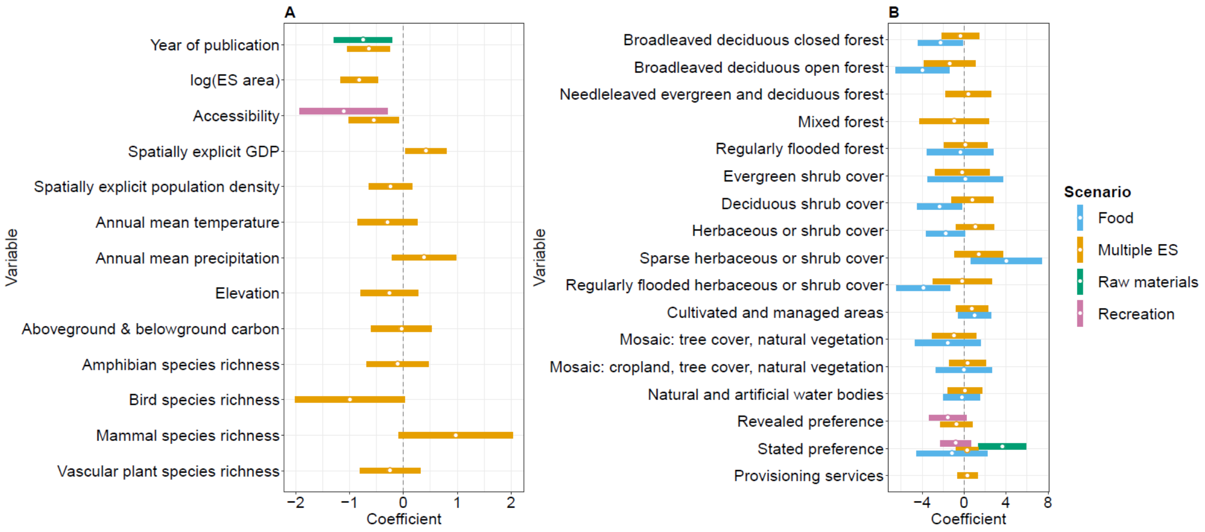
All models that were used for prediction in the previous section were assessed for their accuracy using leave-one-out cross validation. The mean absolute percentage error (MAPE) was used as the criterion to assess prediction errors of the models.

To ascertain the representativeness of the models when extrapolating to create global maps, we compared the distribution of the values of the explanatory variables in the dataset used to fit the models and the dataset used for prediction.

3. Results

For the multiple PCES analysis, the global model with all 16 independent variables was the most supported (Table S6). Among significant variables, year of publication, PCES area and time to travel to a city (accessibility) were negatively correlated to PCES economic value (Figure 1) while spatially explicit gross domestic product (GDP) was positively correlated (Figure 1).

Figure 1. Coefficients of all the independent variables in the best-supported models for the four analyses. The bars represent the 95% confidence interval. Coefficients of the continuous variables are standardized. Land use types are compared against broadleaved tropical evergreen forests. Valuation methods are compared against market valuation. Ecosystem service type is compared against provisioning services. A: continuous variables in the model; B: categorical variables in the model.



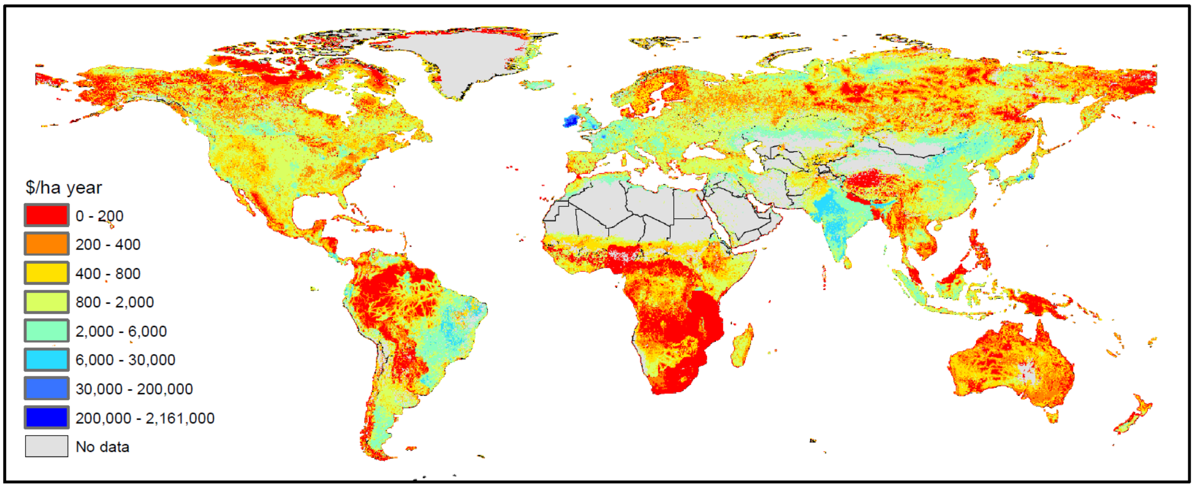
This model was able to explain 61% of the variance and represented improvements in predictive power with respect to direct benefit transfer of 46% (Table S6). The largest positive random effects by country (higher PCES values on average across a country) were for Ireland, Israel, India, Ecuador and Brazil. The highest negative random effects were however for Nepal, Malaysia, Zambia and Mozambique (Table S7).

In the food ES analysis, the model with global land cover had the most support (broadleaved deciduous closed and open forests, deciduous, sparse and regularly flooded herbaceous or shrub cover had lower value than broadleaved tropical evergreen forest). In the raw materials ES analysis, year of publication had a negative relationship with value and valuation method had a significant influence on value. In the recreation ES analysis, time to travel to a city (accessibility) had a negative relationship with recreation value (Table S6). These models explained from 49 to 73% of the variance but the most supported models presented substantially higher prediction errors than direct benefit transfer (30%, 250% and 400% for food, raw materials and recreation ES analyses, Table S6).

Predictions from the most supported multiple PCES analysis model showed that higher PCES values generally occurred in North America, South America, Europe and Asia. The highest PCES values occurred in wealthy ‘global’ cities in these four continents, such as New York, London, and Tokyo.

This is explained by small ES area, high accessibility and spatially explicit GDP, i.e. these are areas where the level of beneficiaries of PCES per unit of area of ecosystem is very high. Other regions with high value included eastern Brazil, eastern China, northwestern and southern India, Western Europe, and central Japan. Generally, areas with low PCES values coincided with large tracts of relatively undisturbed ecosystems despite their high ecological value, such as the Amazon rainforest, the national parks of Africa, northern Canada, and most parts of Russia (Figure 2).

Figure 2. Prediction output of the best-supported model by AICc for the multiple PCES scenario. The map shows spatially explicit economic values of final PCES across the world, in units of 2016 international dollars per hectare per year. The data needed to reproduce the map are available in Table S8.



The dataset used for the meta-analysis presented certain spatial biases that made it unlikely to be representative of regions in high latitudes (e.g. Russia, Canada, Figure S6). For instance, the dataset presented higher coverage of tropical and subtropical regions (Figure S6, Table S9). This was reflected by higher median temperature, precipitation and carbon aboveground than the dataset used to populate the global map (Figure S7).

4. Discussion

The results of this study highlight the important role that anthropogenic factors play in determining economic values of PCES at the global scale. Biotic factors, by contrast, were not found to be significantly correlated with PCES values. These results agree with Ghermandi & Nunes (2010) and de Groot et al. (2012) for ES area and GDP, and Carrasco et al. (2014) for ES area and year of publication. The results do not agree with de Groot et al. (2012) for population density but this could be due to the inclusion of accessibility in our models absorbing the variance previously explained by population density.

We found that species richness of mammals, birds, amphibians and vascular plants were not significant predictors of PCES value. As noted in the predicted global maps of PCES value (Figure 2), this could point towards a potential incompatibility between biodiversity conservation and PCES realization, i.e. humans and infrastructure need to be present for the economic value of PCES to be fully realized while this, in turn, leads to habitat disturbance that impacts biodiversity negatively (Carrasco et al., 2014; Carrasco et al., 2017; Wilcove and Ghazoul, 2015). This is expected given how sensitive is biodiversity to small levels of disturbance from forest use (Barlow et al., 2016). In other words, the fact that an ecosystem presents a high volume of PCES supply related to biodiversity or ecosystem functioning does not necessarily translates in realized PCES (or service used by beneficiaries) and eventually into economic value. Other possible reason for these results is that species richness may not be a useful measure to relate the contributions of organisms in an area to ecosystem functioning. The relationship of species richness with ecosystem functioning, although previously identified to be positive and then saturate with number of species , is still an area of active research (Loreau et al., 2001).

Notwithstanding the possibility that species richness could have been a poor measure of ecosystem functioning and PCES supply levels, we clearly found anthropogenic factors to be more important than biotic factors in determining PCES values. This ties in well with recent studies that have started to recognize the importance of human capital in supplying and delivering ES to people (Burkhard et al., 2014; Jones et al., 2016; Remme et al., 2014; Tallis et al., 2012). For instance, rather than viewing humans merely as beneficiaries of ES, Jones et al. (2016) argues for an integrated social-ecological framework where humans can also play other roles, for example, as co-producers of ES and contributors to ES. In this framework, ES are subdivided into potential ES and realized ES. Realized ES is a function of potential ES, users of the ES, and the efficiency with which users extract value from the ES (Jones et al., 2016).

Applying this framework can provide some insights into why some of the socio-economic and abiotic factors in our results were significant. Since most of the economic values of PCES from the TEEB dataset we used corresponded to use values with domination by provisioning services, the maps likely show realized values. This being the case, it is possible that accessibility came out as a significant predictor of PCES value because it is a proxy for the efficiency of PCES value extraction by humans (de Groot et al., 2010). Areas with higher accessibility can increase realized ES value because they represent areas with higher investments in transport infrastructure (e.g. roads) or because of ease of access, both of which increase PCES value by increasing the maximum efficiency of ES extraction or utilization.

For spatially explicit GDP, areas with higher GDP could represent higher demand for PCES thereby increasing ES values because a larger fraction of potential ES values are realized (Schröter et al., 2005). As for ES area, the results support the consensus among meta-analyses of ES values that economic or monetary values of ES increases as ES area decreases (de Groot et al., 2012; Ghermandi et al., 2010). A small ES area (e.g. small forest) may represent a low supply of ES. If that low supply is combined with high demand for the service (e.g. near a city), it will lead to scarcity of the ES which would, in turn, increase the value of the ES. For a given demand level, a small ES area can also be interpreted as having little or no substitutes for a particular natural resource which will affect the well-being of local resource users more if that natural resource base is degraded (Ghermandi et al., 2010). We should caution however that ES area was a variable with several missing values that required imputation.

Given these results, policymakers need to be aware that economic values of PCES are likely to represent the realized values of ES more so than their maximum potential values. ES values that are likely to be under-represented in realized ES values include insurance value (e.g. presence of species with the capacity to adapt to diseases or climate change) and non-use value of ecosystems, which current valuation methods have difficulty quantifying (Thampapillai and Sinden, 2013). In other words, land-use strategies focusing on realized economic values of PCES risk leaving behind biodiversity.

That PCES economic values are determined by anthropogenic factors is, however, not surprising since the concept of ES valuation relates back to human well-being and ES have no value if they are not benefitting humans (Millennium Ecosystem Assessment, 2005). Similar to human-manufactured products and services, humans also have the ability to create and destroy or to increase and decrease ES value through their actions in terms of land use, ecosystem management and rate of utilizing or extracting ES (de Groot et al., 2010; Jones et al., 2016). Recognizing the role of anthropogenic factors will allow policymakers to account for changes in economic PCES values caused by human actions in addition to changes in the intrinsic characteristics of ecosystems. The human dimension of ES means that biodiversity conservation priorities may not always align with goals to maximize economic ES values (Naidoo et al., 2008). Therefore, governments, conservationists and land use managers must be aware that PCES-centered policies may not align with biodiversity.

The analyses presented several assumptions and limitations. Firstly, it is important to note that our analyses focused exclusively on PCES. We preferred not to include regulating services because the spatial relationship between supply and demand is different to that of PCES. These spatial relationships can range from no spatial relationship between supply and demand (e.g. carbon sequestration) to spatial directional relationship that follows hydrological and air circulation systems. For instance, in South America, 70% of available water in the Rio de la Plata Basin depends on evapotranspiration from the Amazon forest (Van der Ent et al., 2010). It is thus expected that the maps of economic value of regulating ES would be quite different to those we obtained for PCES. Future research should aim at producing such maps for comparison. As such, the reader needs to be mindful of the limited scope of the article, which focuses on PCES alone. Related to the issue of distant telecouplings between ES supply and demand, our benefit transfer exercise implicitly assumes that PCES demand within each grid cell was met by PCES supply generated within each grid cell. This may not be true, especially for cities and heavily urbanized areas which draw natural resources from its periphery and from other parts of the world through international trade (Chang et al., 2016). Future work can improve by adding material flows from rural areas to cities and trade between countries when modelling supply and demand of ES, i.e. ES embedded in trade (Chang et al., 2016). Data paucity was also an issue in this study, especially for the analyses of single ES for which 49 to 89 observations were only available. This led to unreliable predictions for models of single ES, making them less reliable that simpler direct benefit transfer. Although these models are insightful in understanding the contribution of specific ES to the composite analysis, the high predictive errors suggest that these models may be overfitted and unreliable to construct maps of individual ES. This is likely the result of lower sample sizes. If more data were available, they could be added to the study dataset and this study repeated to check for any change in the relationships previously found. The combined model, despite a reasonably high R^2 and good performance during cross-validation, should be treated with caution when translated into the final map. Our analysis of representativeness shows that the figures for very high latitudes, for instance, would need to be treated with special care. Another limitation, common to ES meta-analytic studies, is that we did not deduct the co-production costs in human and manufactured capital necessary for ES to be realized. For instance, for recreational angling ES to be realized, investments in roads for accessibility, boats and fishing equipment are necessary (Palomo et al., 2016). These co-production costs are however rarely reported in ES valuation studies, making their incorporation into the meta-analysis non-viable. Finally, functional diversity may be a better measure of ecosystem functioning than species richness (Lefcheck et al., 2015), and thus a better predictor of ES value which should be considered in future research.

5. Conclusions

We have produced a global meta-analysis of economic values of terrestrial PCES. Although the resulting map could be useful for global-scale conservation planning and policies in areas where training data were most available, we find the main role of the meta-analysis is to highlight the importance that humans play in the determination of PCES economic values. Because of this dominant human dimension, trade-offs between environmental conservation and economic values of PCES could occur. Our results thus demonstrate that economic PCES values are likely to only represent the realized benefits of PCES and not the maximum potential benefits of ES and the insurance value of biodiversity.

Conflict of interest

The authors declare no conflict of interest.

Data availability

The data used for the study are available in Table S3.

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Author contributions

S.H.S.T. and L.R.C. designed the study. S.H.S.T. carried out data collection. S.H.S.T., H.S., W.S. and T.P. carried out data analysis. W.S., H.S. and T.P. provided information and reagents. S.H.S.T. and L.R.C. wrote the article.

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