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A global spatial meta-regression analysis of mangrove valuation studies

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ABSTRACT

Meta-regression analyses of environmental valuation studies often reveal spatial dependence, which must be addressed to properly explain and predict variation in valuation estimates. This paper develops meta-regression models that explicitly incorporate spatial dependence using a dataset of mangrove ecosystem service (ES) values, comprising 506 estimates from 106 primary studies extracted from the Ecosystem Services Valuation Database (ESVD).

We first estimate conventional aspatial models with explanatory variables accounting for multiple sources of heterogeneity and autocorrelation. Subsequently, we specify and estimate a series of spatial regression models that integrate spatial processes directly. Different spatial weighting matrices are tested, based on geographic distances and attribute-based similarity reflecting socioeconomic and biophysical characteristics of study sites. In addition, hybrid matrices are developed to combine these spatial dimensions and to relax the assumption that identical spatial processes affect all components of the model.

After selecting the best aspatial and spatial models, we evaluate their predictive performance using in-sample and out-of-sample validation. Results show that the random-effects model, which clusters observations by site, offers a theoretically sound framework that effectively captures latent spatial dependence. However, Moran's I tests applied to OLS residuals reveal remaining spatial autocorrelation, indicating that explicit spatial modelling is still needed to uncover underlying spatial processes.

Among the alternative spatial specifications, the Spatial Autoregressive Combined (SAC) model performs best, as it allows distinct spatial processes to influence both the dependent variable and the error term, also through correlations captured by hybrid matrices. While spatial dependence does not substitute the explanatory contribution of site-level heterogeneity, it marginally improves out-of-sample predictive accuracy. This suggests that spatially explicit meta-regression models can yield more reliable and spatially consistent predictions for benefit-transfer applications.

1. Introduction

Decision-makers in environmental management increasingly rely on economic valuation evidence to justify conservation investments and prioritise ecosystem interventions. However, primary valuation studies are costly and not always feasible, especially in data-scarce regions, making benefit transfer a necessary tool for policy support. When transfers are based on values drawn from heterogeneous contexts, errors can arise, compromising the reliability of policy decisions.

In this context, meta-analysis provides a systematic way to synthesise existing valuation evidence and derive transferable value functions. Over the past two decades, the economic literature on the value of ecosystem services (ES) has expanded dramatically, providing a wealth of information on the contribution of natural capital to human well-being (Dasgupta, 2021). As this literature grows, there is a need for research synthesis techniques to aggregate information and identify common determining factors (Bal and Nijkamp, 2001; Stanley, 2001; Smith and Pattanayak, 2002; Bateman and Jones, 2003; Havránek et al., 2020). Meta-analysis was first proposed as a research synthesis method by Glass (1976) and has since been developed and applied in many fields of research, including environmental economics (Nelson and Kennedy, 2009). Meta-analysis is a method of synthesizing the results of multiple studies that examine the same phenomenon by identifying a common effect, which is then 'explained' using regression techniques in a meta-

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regression model (Stanley, 2001). In the context of ES valuation, the common effect is generally measured in monetary units and quantified as a metric of human welfare. In addition to identifying consensus in results across valuation studies, meta-analysis is also of interest as a basis for estimating values for unstudied policy sites, i.e. for value or benefits transfer (Rosenberger and Phipps 2007; Brander et al., 2012; Moeltner, 2019; Johnston and Bauer, 2020).

In the field of ES valuation there are now a plethora of meta-analyses that synthesize values for a wide array of ecosystems, including wetlands (Brander et al., 2006; 2013; Ghermandi et al., 2010; Moeltner et al., 2019), coral reefs (Brander et al., 2006; Londoño and Johnston, 2012), and mangroves (Brander et al., 2012; Salem and Mercer, 2012; Getzner and Islam, 2020; Su et al., 2021; Kanan et al., 2024).

A key development in the literature on meta-regression analysis of environmental valuation studies is the incorporation of spatially variable determinants of value, such as the availability of substitute and complementary resources and the number and characteristics of beneficiaries (Brander et al., 2012; Johnston et al., 2017). Results, in general, show an improvement of the explanatory power of meta-regression models and in the accuracy of value transfer applications. Such analyses, however, have not attempted to measure any spatial relationships among the data using spatial econometric models. Only recently, Moeltner et al. (2023) used locally weighted meta-regressions and demonstrated that this approach brings substantial gains in predictive efficiency for benefit transfer applications.

A further and less investigated spatial dimension of concern in meta-analysis is the presence of spatial dependence in the data,[1] which may arise when multiple primary valuation studies are conducted in the same area (Nelson and Kennedy, 2009; Lopez-Rivas and Cardenas, 2024).

LeSage and Pace (2009) and Elhorst (2010) identify three potential spatial components of autocorrelation: *i*) the spatial lag of the dependent variable; *ii*) the spatial lag of the independent variable(s) – the so-called "Durbin" component; and *iii*) the spatial lag of the error term. In the context of ES values, spatial autocorrelation could affect all these three components (Brander et al., 2010; De Salvo and Signorello, 2015; Bu and Rosenberger, 2014; Schägner et al., 2018). The first component measures the influence of the economic value of ES at one site on the value of the same service at neighbouring study sites. This effect could arise because sites are complex ecosystems that are not isolated from each other. Ecological interconnections could imply the existence of spatial patterns in the provision of ES and, therefore, in corresponding economic values (Legendre and Fortin, 1989). Moreover, the economic value of ES also depends on how the ecological value of a site relates to the landscape and other contextual features, and on how it is perceived and valued by the beneficiary population. Such aspects could also show spatial patterns and, therefore, it is possible to identify a second spatial "Durbin" component in meta data on ES values that could represent the influence of characteristics of beneficiaries, but also the landscape and other features, at neighbouring sites on the value of services at a specific site (Mahan et al., 2000; Bin and Polasky, 2004; Boyer and Polasky, 2004; Brander et al., 2006). Finally, the third component could reflect the presence of omitted spatially correlated variables, such as landscape or socio-economic characteristics shared by neighbouring study sites that significantly affect ES value estimates but are not included among the regressors (Brander et al., 2010).

These three spatial processes could all be present in ES valuation data, although the mechanisms underlying variable correlations may be difficult to identify with any theoretical prior and may extend beyond geographic conceptualizations of proximity. Ignoring spatial correlation in ES welfare estimates can lead to biased and inefficient estimates of ES values and increased error in benefit transfer (Bu and Rosenberger, 2014).[2] Moreover, a deeper understanding of the spatial processes that shape the economic value of natural resources and the potential spillover effects across areas is crucial for policymakers. Such knowledge supports the design of more spatially informed and effective intervention measures, enabling decision-makers to account for interdependencies between regions and to target conservation or restoration efforts where they can generate the greatest ecological and economic returns. The application of spatial econometric methods could provide a potentially valuable means to control for spatial autocorrelation (Anselin, 2010; Anselin et al., 2013). However, determining the appropriate specification to capture the spatial processes that affect the data remains a challenging task.

A further challenge to implementing spatial econometric methods in meta-regressions is the need to define a relevant weight matrix representing the structure of "neighbouring" value observations. Often this matrix is defined by geographical distance; however, other attributes can be used to define neighbour relationships, such as environmental or ecological distance (Dormann et al., 2007), social distance (Doreian, 1980), or economic distance (Conley, 1999). Another potentially useful approach is to combine one or more distance attributes with the geographical distance to create hybrid spatial weight matrices (Duncan, 2017). Models that include multiple spatial parameters typically employ the same weight matrix to represent different spatial processes. However, the weight matrices associated with distinct spatial dependence parameters may differ and can also be based on non-geographical criteria, such as ecological or socio-economic distance. Although the traditional approach is preferred for its practical simplicity and ease of implementation, it may also limit the model's ability to accurately distinguish among distinct spatial mechanisms, especially when economic, social, or environmental interactions follow different spatial structures.

The motivation for considering weight matrices based on non-geographical criteria is that, in the context of ES valuation, biophysical comparability is not limited to spatial contiguity but also depends on the functional similarity of ecosystems. For this reason, we also consider ecological distance derived from biodiversity similarity. Higher biodiversity similarity between mangrove sites is likely to reflect comparable ecological functioning, similar bundles of ES, and analogous resilience and habitat quality attributes, which, in turn, shape both the magnitude of ES values and the types of valuation methods applied in primary studies (Barbier, 2019; Brander et al., 2012). While geographic distance captures potential ecological spillovers, biodiversity-based proximity captures functional ecosystem similarity, which is particularly relevant for regulating and habitat services such as nursery functions, nutrient retention, or storm protection. Therefore, two sites may be geographically distant but ecologically similar in terms of species composition and ecosystem functioning, implying greater comparability in both biophysical service provision and valuation contexts than would be

[1] Haining (1990) highlights the importance of applying spatial analytical methods to observational data, such as those commonly used in *meta*-analyses. Because *meta*-analytic datasets typically draw on studies conducted in different locations and contexts, they are subject to several methodological challenges, including inherent biases and heterogeneity among study sites. Unlike experimental data, the explanatory variables in *meta*-analysis are not under the direct control of the analyst, and only observed events can be modelled or predicted. This often results in confounding relationships among explanatory variables and complicates the interpretation of findings. Moreover, measurement errors—particularly in independent variables—tend to be more pronounced, while sample sizes are constrained by the availability of studies. In such contexts, incorporating spatial analytical techniques can help mitigate biases and improve model performance, especially when standard statistical assumptions (e.g., independence of residuals) are violated due to spatial autocorrelation in the dependent or explanatory variables.

[2] If the spatial process affects the dependent variable and/or the explanatory variables, regressing effect sizes on moderators will yield inconsistent coefficient estimates. Moreover, if spatial correlation in the residuals is not properly accounted for, the estimated coefficients will be inefficient (Kopczewska, 2021).

predicted by geographic distance alone. In parallel, socio-economic distance captures institutional, cultural, and income-related convergence in valuation preferences and study design choices, as the value transfer literature suggests that transfer errors arise not only from biophysical heterogeneity but also from contextual socio-economic mismatches between study and policy sites (Navrud and Ready, 2007; Johnston et al., 2015a). In this respect, the use of non-geographical weight matrices can also be interpreted as an explicit attempt to address the issue of commodity consistency in value transfer. By defining proximity in ecological or socio-economic terms, the model explicitly accounts for heterogeneity across study sites that affects both the biophysical characteristics of the environmental goods valued and the contextual factors shaping individual preferences. In practice, non-spatial matrices do not replace the need to control for commodity consistency; instead, they provide a structured and model-based way to account for biophysical and contextual differences between study and policy sites, thereby improving the comparability and reliability of transferred ES values (Boyle and Bergstrom, 1992; Johnston et al., 2015b; Vedogbeton and Johnston, 2020).

To account for all these phenomena simultaneously, we conceptualize spatial dependence as a hybrid, multidimensional process in which geographic distance accounts for spatial clustering, biodiversity-based distance captures functional ecological similarity, and socio-economic distance represents convergence in valuation contexts and methodological design. This trial geographical-ecological–socioeconomic rationale aligns with recent evidence suggesting that meta-regression residuals often reflect unobserved socio-spatial clustering that is not purely geographical (Klaiber and Phaneuf, 2010). Therefore, a hybrid matrix defined across these dimensions allows us to approximate a more realistic proximity structure driving both spatial autocorrelation in observed ES values and residual dependence linked to methodological convergence across studies and biological similarity across sites.

To the best of our knowledge, there are no meta-analyses in the environmental valuation field that account for more than one spatial process and investigate potential effects related to the definition of the weight matrix (Johnston et al., 2018). Brander et al. (2010) and Bu and Rosenberger (2014) are the only meta-analytic applications in the field of ES valuation that account for spatial autocorrelation in the data. In these (unpublished) papers, the authors propose the use of simple spatial lag models in which spatial dependence is modelled only on the dependent variable or the error term. Brander et al. (2010) define neighbour relationships among sites through a matrix based on a first-order neighbour connectivity structure using Thiessen polygons. Bu and Rosenberger (2014), instead, constructed and tested multiple threshold distance matrices, and applied matrices based on geographical distance, ecological similarity, and economic similarity criteria.

As highlighted by Bu and Rosenberger (2014), however, when spatial models are implemented to estimate a meta-regression function, it is crucial to verify that spatial dependence is not confused with between-study or within-study[3] dependence, which typically affects meta-analysis results when the unbalanced panel nature of data is not considered (Nelson and Kennedy, 2009). Databases for meta-analysis, in fact, generally include multiple observations provided by the same study, given the use of different valuation methods. Moreover, different studies could refer to the same site or estimate the value of more than one ES provided by the study site. These circumstances could imply correlation in errors, violating the assumption of independent observations, leading to biased standard error estimates unless the correlation is accounted for.

Avoidance and aspatial regression-based methods have been proposed in the literature to address potential data-dependency phenomena (Vista and Rosenberger, 2013). In the avoidance approach, data dependency is faced by reducing the metadata to a single estimate per study, drawing a single estimate or computing the average value of multiple estimates per primary study. However, regression-based methods are generally preferred, especially in environmental economics meta-analyses, because they are more efficient, do not involve information or degree-of-freedom loss, and provide unbiased estimates of the partial effects of moderator variables (Bijmolt and Pieters, 2001). Aspatial regression-based methods make use of Weighted Least Squares (WLS) models (Mrozek and Taylor 2002; Nelson and Kennedy 2009; Borenstein et al. 2010), Fixed Effects (FE) and Random Effects (RE) panel data models (Jeppesen et al., 2002; Rosenberger and Loomis, 2000), and Hierarchical/Multi-Level (ML) models (Bateman and Jones, 2003; Johnston et al., 2018). Testing for the presence of spatial autocorrelation in the residuals of such models, after other sources of autocorrelation have been addressed, would strengthen the evidence for spatial lags in the data and steer the estimation process towards spatial econometric models.

The main purpose of this paper is to address spatial dependencies in the metadata of mangrove ES values and to use suitable econometric approaches to model spatial dependence. To pursue this objective, we proceed in several steps. Firstly, we implement aspatial regression-based models to verify whether our primary valuation dataset is affected by spatial correlation. Secondly, as spatial correlation can arise from multiple sources, we identify the best spatial model specification by testing the effects of including one or two spatial lags in the regression. In this task, we follow Elhorst's (2010) approach and estimate a General Nesting Spatial (GNS) model. To define spatial similarity among observations (neighbours), we build weight matrices based on geographical and non-geographical distances, as well as weight hybrid matrices combining matrices based on geographical, ecological, and socio-economic distances. These matrices are incorporated into the spatial models under two alternative assumptions: one in which spatial relationships are constant across different spatial processes, and another in which they are allowed to vary, capturing potential heterogeneity in spatial interactions across model components.

Finally, we test the predictive power of the best-fitting spatial models using the in-sample (Rosenberger and Loomis, 2000) and the out-of-sample (Shrestha and Loomis, 2003) validation procedures.

The rest of the paper is structured as follows: Section 2 describes the metadata; Section 3 details the estimation process of the econometric analysis; Section 4 illustrates and discusses the results; and finally, section 5 provides conclusions.

2. Data description

The data set used in our empirical analysis is drawn from 106 primary valuation studies on ES across 155 mangrove areas worldwide (see Fig. 1). The data contain 506 separate value estimates for 17 ES types identified in the Economics of Ecosystems and Biodiversity classification (TEEB, 2010). The data were extracted from the Ecosystem Services Valuation Database (ESVD), a publicly available global database of monetary value estimates for all biomes and ES (Brander et al., 2024; Brander et al., 2024). The extracted mangrove ES values were reviewed by a member of the research team to assess the interpretation of the primary valuation studies and the accuracy of the coded information. Studies included in the ESVD are identified through a systematic literature search following the PRISMA-P 2015 protocol for conducting formalized systematic reviews (Moher et al., 2015). To enable comparability and synthesis of value observations, estimated values are standardized to a common currency, year of value, spatial unit, temporal unit, and beneficiary unit. In the ESVD, the standardised units are Int.$

[3] Between-study correlation arises when primary studies are drawing from the same data source or using the same study location, functional form, or explanatory variables. Within-study correlation, instead, arises when primary studies report more than one estimate (Vista and Rosenberg, 2013).

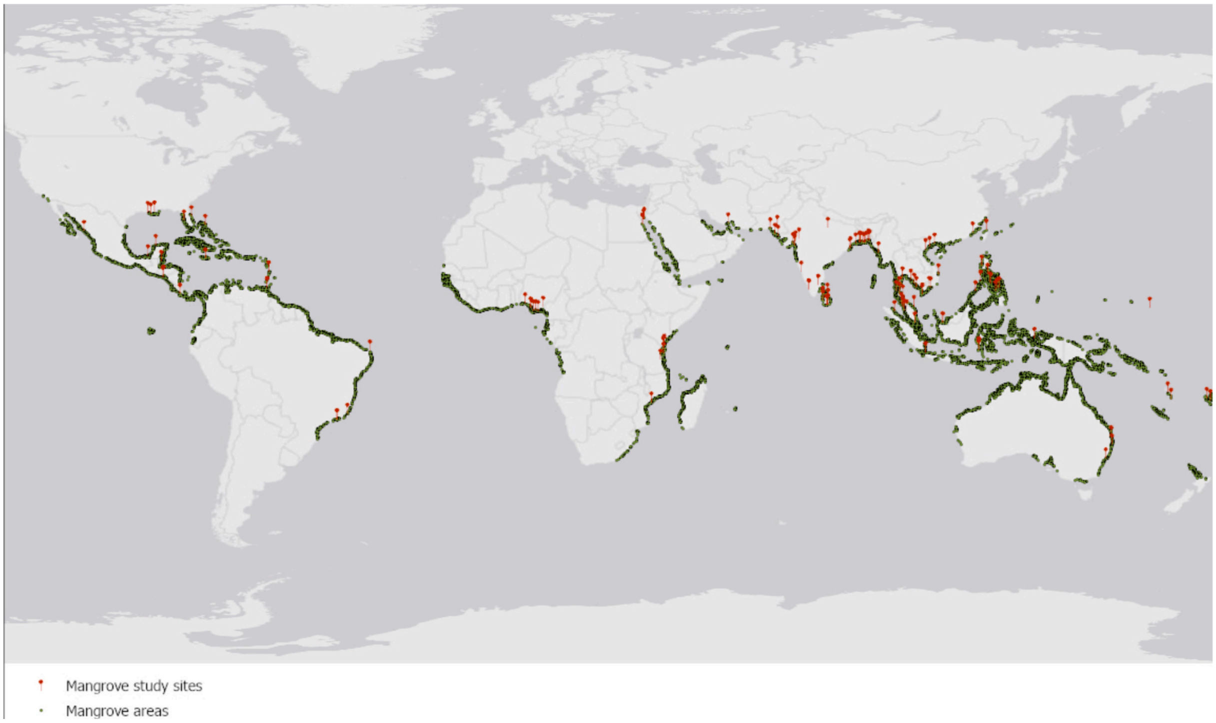


Fig. 1. Spatial distribution of mangrove study sites.

(i.e., USD adjusted for differences in purchasing power across countries) per hectare and per year for the total number of relevant beneficiaries at the 2020 price level.[4] The total number of relevant beneficiaries for a mangrove ES is obtained from the underlying primary valuation studies. Value estimates that are not reported for the total number of relevant beneficiaries (e.g., per visitor, person, household) are aggregated using the relevant total beneficiary population reported in the study. When the study does not report the relevant number of beneficiaries, no standardised value is computed, and the estimate is not included in the analysis.

We note three common challenges in the meta-analysis of ES values present in the data used in our analysis. The first is that the data are from multiple ES, which raises questions about commodity consistency and whether it is valid to compare values across different ES (Brander et al., 2013; Vedogbeton and Johnston, 2020). Aside from the expectation that different ES have different values, which can be modelled in the analysis, the values of different ES may be influenced by different determinants, or even by factors that have opposing effects on values across different ES. One proposed solution is to focus on individual ES or groups of ES deemed similar. In the present analysis, however, we aim to provide a comprehensive assessment of mangrove values and conceptualise the commodities being compared as mangrove assets (defined in spatial units per hectare), for which variation in annualised values can be explained by the ES the assets provide. The second challenge is that the data do not contain information on the scope of ES provision or change in scope in the case of marginal valuations (Bergstrom and Taylor, 2006; Johnston and Wainger, 2015; Boyle and Wooldridge, 2018). This source of heterogeneity in the data is challenging to account for, and the definition of quantitative or categorical variables for this purpose is problematic. The ESVD currently includes only a text description of the (change in) scope of the asset or ES that is valued. The third challenge is that the value estimates are for different measures of value (Bergstrom and Taylor, 2006; Johnston and Moeltner, 2014). This source of heterogeneity is also challenging to account for, and the source database that we used does not contain categorical variables for different value measures that could be used for this purpose. The best available approximation is the valuation method, which is closely related but not perfectly aligned with the value concept being estimated. We acknowledge these challenges in the data, but do not expect them to negate the comparison of alternative spatial and aspatial model specifications.

The full list of 106 primary studies is reported in the Supplementary Materials, Table A1. This Table also provides further details, such as the number of estimates obtained from each study and the number of valued sites and ES. The number of study sites with more than one value estimate is 109 (70.3%). In these cases, the number of estimates for the same ES range from 2 to 14.

Table 1 reports summary statistics for the economic value (in Int. USD 2020, per hectare, per year) of mangrove ES for each ES category. Figs. 2 and 3 display, respectively, the frequencies of primary value estimates by ES type and valuation method. Most estimates relate to food provisioning services (i.e., fisheries, 197 estimates, 39%) and, to a lesser extent, to the provisioning of raw materials (111 estimates, 21%). The most frequently applied methods are Market Prices/Gross Revenue (MP: 250 estimates, 49%), Net Factor Income (Residual Value; Resource Rent) (FI: 79 estimates, 16%), and Contingent Valuation (CV: 50 estimates, 10%).

For each observation (value estimate), we define three main categories of independent variables: *i*) the valuation method, *ii*) the type of ES, and *iii*) the bio-physical and socio-economic characteristics of the study site. All variables related to the first two categories are dummies and are extracted from the ESVD. Variables associated with the third category of predictors are predominantly continuous and were obtained from multiple sources. In the Supplementary Materials, Tables A2-3 provide details on unit of measurement, labels, reference year, sources, and summary statistics for all variables.

3. Econometric analysis

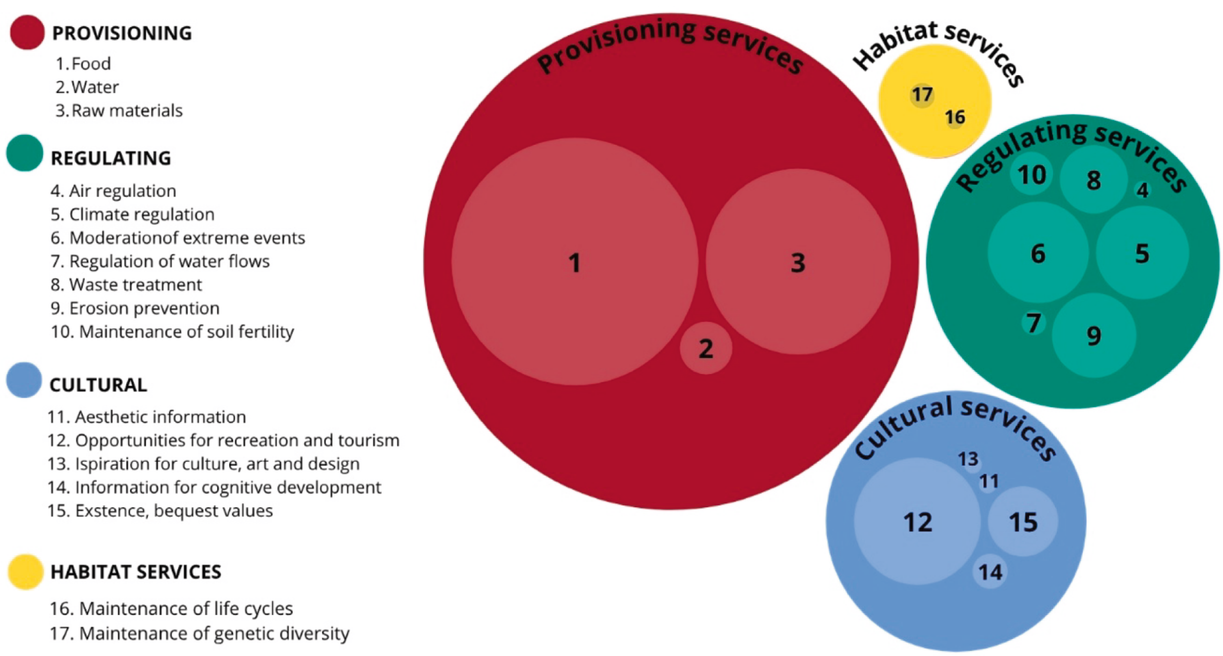
Fig. 4 illustrates the stages in the econometric analysis.

[4] More details on value standardization can be found in Brander et al. (2024), paragraph 2.3.

Table 1
Economic values of ES of mangroves per TEEB category.

Ecosystem service			n.	%	Economic values (2020 USD per hectare per year)			
					Mean	Standard deviation	min	max
1	Provisioning services	Food	197	38.93	13.493	61.071	0.02	710.660
2		Water	9	1.78	610	647	27.94	1.833
3		Raw materials	111	21.94	10.629	78.023	0.01	804.507
4	Regulating services	Air quality regulation	1	0.20	2.094	–	2093.82	2.093
5		Climate regulation	28	5.53	5.771	17.749	0.03	91.236
6		Moderation of extreme events	33	6.52	14.655	55.039	0.38	266.839
7		Regulation of water flows	2	0.40	1.89	2.164	0.36	3.42
8		Waste treatment	15	2.96	4.078	7.018	1.45	26.879
9		Erosion prevention	23	4.55	6.651	12.252	1.87	47.631
10		Maintenance of soil fertility	6	1.19	5.333	11.214	103.82	28.147
11	Cultural services	Aesthetic information	1	0.20	668	–	668.07	668
12		Opportunities for recreation and tourism	52	10.28	19.954	123.416	0.04	890.477
13		Inspiration for culture. art and design	1	0.20	3.889	–	3889.53	3.889
14		Information for cognitive development	4	0.79	1.429	1.450	69.46	3.038
15		Existence. bequest values	16	3.16	2.269	5.357	0.22	21.402
16	Habitat services	Maintenance of life cycles	1	0.20	3.726	–	3726.28	3.726
17		Maintenance of genetic diversity	2	0.40	1.307	1.815	23.14	2.590
18	Unknown		4	0.79	1.396	2.177	52.38	4.617

Source: our elaborations.

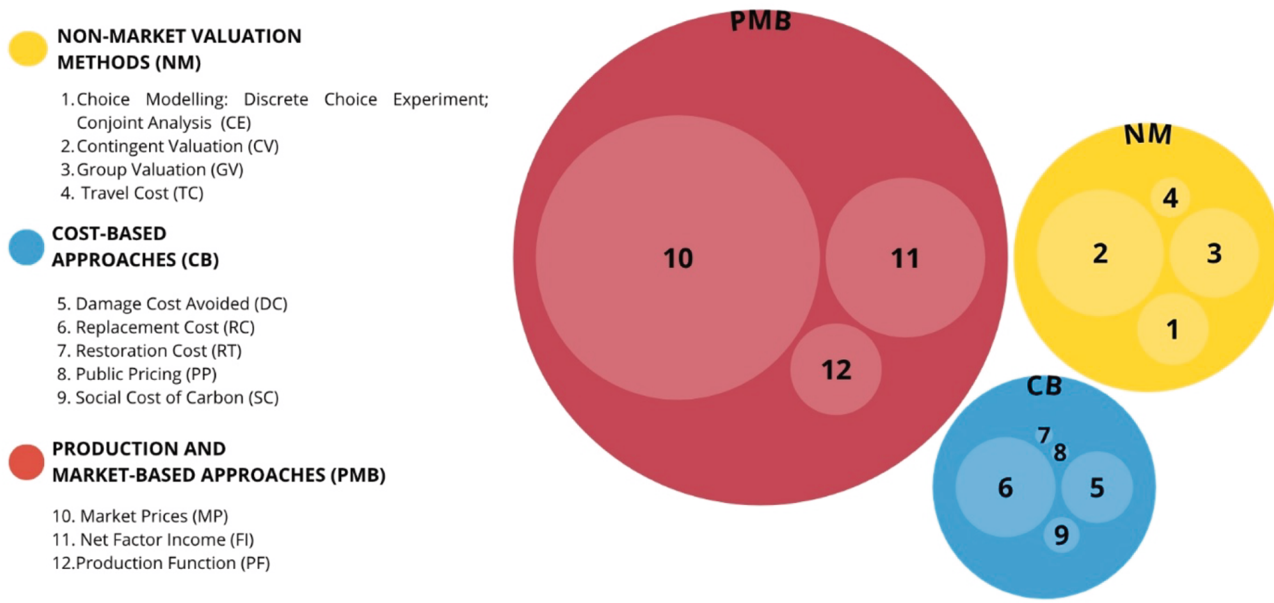


Source: our elaborations.

Fig. 2. Distribution of value estimates per ES. .
Source: our elaborations

Preliminary analysis focused on distributions, dependency, and multicollinearity issues, and the selection of variables. For some explanatory variables, we used logarithmic transformations to approximately normalize the distribution (Schägner et al., 2018). We also tested the use of different scales for defining spatial variables by applying buffers ranging from 10 to 50 km. The best results were obtained for variables measured within buffers with a radius of 10 km. A stepwise procedure assuming $p < 0.20$ (Efroymson, 1960) was used to identify the predictors listed in Table 2. These variables were not affected by multicollinearity.

In the next step, we estimated a standard OLS regression model with the logarithm of the ES value (USD 2020 per ha per year) as the dependent variable and the valuation method, type of ES, and the biophysical and socio-economic characteristics of the study site as explanatory variables. The OLS model was specified as follows:



Source: our elaborations.

Fig. 3. Distribution of value estimates per valuation method. .
Source: our elaborations

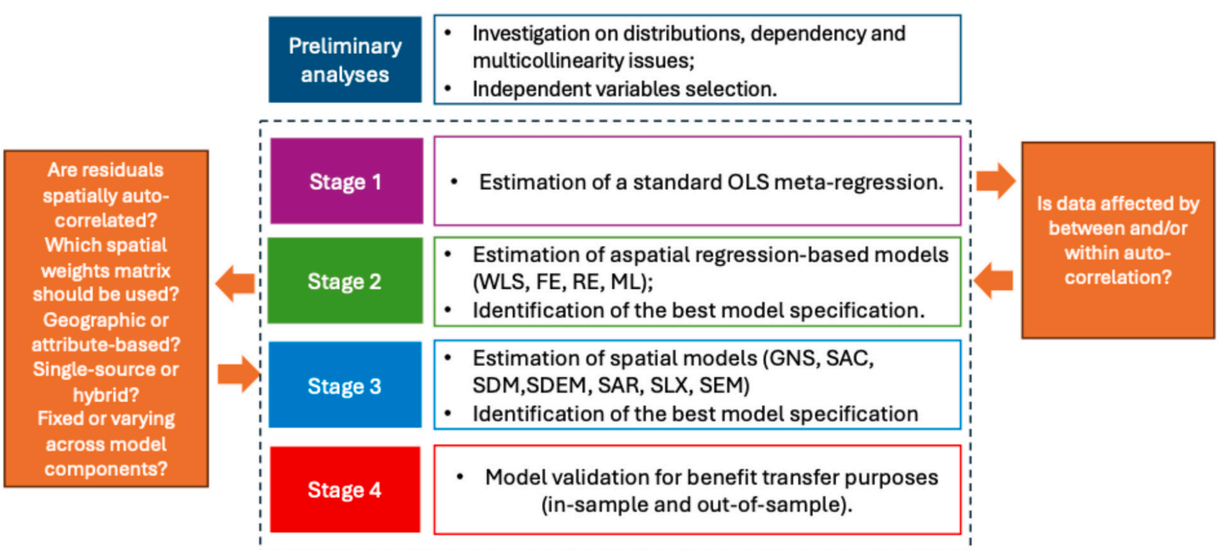


Fig. 4. Stages in the econometric analysis.

$$y = \boldsymbol{X}\beta + \varepsilon \tag{1}$$

where:

- y is an Nx1 vector consisting of one observation on the dependent variable for every unit in the sample (I = 1, …, 506);
- $\boldsymbol{X}$ Denotes an N × K matrix of exogenous explanatory variables, with the associated parameters β contained in a K × 1 vector
- ε is the idiosyncratic error term.

With consideration to the unbalanced nature of the dataset, we also estimated a Weighted Least Squares (WLS) model based on the following specification:

$$y = \boldsymbol{X}\beta w_S + \varepsilon \tag{2}$$

where w_S is the weight imposed on each observation and equals the

Table 2
Dependent variable and predictors.

Variable	Label	Mean	Standard deviation	Min	Max
Dependent variable: ES value*	*cat_ln*	5.874	2.714	0.01	13.700
Predictors:					
Provisioning services: food	*es_food*	0.377	0.485	0.00	1.00
Provisioning services: water[a]	*es_water*	0.018	0.132	0.00	1.00
Provisioning services: raw materials[a]	*es_raw materials*	0.219	0.414	0.00	1.00
Regulating services: Air quality regulation[a]	*es_air_quality*	0.002	0.044	0.00	1.00
Regulating services: Climate regulation	*es_climate*	0.055	0.229	0.00	1.00
Regulating services: Moderation of extreme events	*es_extreme*	0.061	0.240	0.00	1.00
Regulating services: Regulation of water flows	*es_flows*	0.004	0.063	0.00	1.00
Regulating services: Waste treatment[a]	*es_waste*	0.029	0.170	0.00	1.00
Regulating services: Erosion prevention[a]	*es_erosion*	0.045	0.208	0.00	1.00
Regulating services: Maintenance of soil fertility	*es_soil*	0.012	0.108	0.00	1.00
Regulating services: Maintenance of life cycles[a]	*es_species*	0.002	0.044	0.00	1.00
Regulating services: Maintenance of genetic diversity [a]	*es_diversity*	0.004	0.063	0.00	1.00
Cultural services: Aesthetic information[a]	*es_aesthetic*	0.002	0.044	0.00	1.00
Cultural services: Opportunities for recreation and tourism	*es_recreation*	0.093	0.29	0.00	1.00
Cultural services: Inspiration for culture, art and design[a]	*es_art*	0.002	0.044	0.00	1.00
Cultural services: Information for cognitive development	*es_cognitive*	0.008	0.089	0.00	1.00
Cultural services: Existence bequest values	*es_existence*	0.032	0.175	0.00	1.00
Method: Cost-based Approaches	*method_cb*	0.105	0.306	0.00	1.00
Method: Not available[a]	*method_na*	0.004	0.063	0.00	1.00
Method: Production and Market-Based Approaches	*method_pmb*	0.701	0.458	0.00	1.00
Method: No-Market (SP and RP)	*method_mn*	0.189	0.392	0.00	1.00
Distance to nearest city (>100.000 population)*	*dist_city_ln*	3.897	1.274	0.00	7.71
Population density: buffer 10 km*	*popd_10_ln*	2.193	2.575	0.00	10.3
Mangrove abundance: buffer 10 km*	*man_16_10_ln*	5.338	3.561	0	11.26
Road length*	*road_10_ln*	3.005	1.825	0.00	5.120
Surface area	*cat_area_1*	7.882	2.864	1.100	15.75
Continent. Africa	*continent1*	0.142	0.350	0.00	1.00
Continent. Asia[a]	*continent2*	0.676	0.468	0.00	1.00
Continent. North America	*continent3*	0.099	0.299	0.00	1.00
Continent. South America[a]	*continent4*	0.041	0.199	0.00	1.00
Continent. Oceania[a]	*continent5*	0.030	0.170	0.00	1.00
Protection status: partially protected	*protected1*	0.314	0.465	0.00	1.00
Protection status: totally protected	*protected2*	0.142	0.350	0.00	1.00

* Logarithmic transformation.
[a] included in the constant term.

inverse of the square root of the number of estimates reported in the corresponding study (Mrozek and Taylor 2002; Nelson and Kennedy 2009; Borenstein et al. 2010).[5]

Further, we estimated other regression-based models commonly used to account for dependency structures in meta-analysis, including FE and RE panel-data models and ML regression models. These models were specified as follows:

$$\text{FE}: \ y = \boldsymbol{X}\beta + \alpha_r + \varepsilon \tag{3}$$

$$\text{RE}: \ y = \boldsymbol{X}\beta + \alpha_r + \delta_r + \varepsilon \tag{4}$$

$$\text{ML}: y = \boldsymbol{X}\beta + \alpha_r + \delta_r + u_{study} + u_{site} + u_{ES} + \varepsilon \tag{5}$$

The notation differs across the three equations. In Eq. (3), α_r is the fixed effect parameter. In Eqs. (4) and (5), α_r and δ_r are respectively the central tendency and the dispersion of the intercept, which is assumed to be randomly distributed. Finally, in Eq. (5) $u_{(.)}$ is the variance for each strata assumed to be relevant in the hierarchy of ML models.

We tested different grouping variables for FE and RE panel data models: the first was the number of underlying studies (N = 106), the second was the site (N = 155), and the third was the valued ES (N = 17). Regarding the ML models, we estimated two specifications, assuming three strata (study-site-ES) and two strata (study-site). Table 3 reports the number of groups for each grouping variable.

To determine the most appropriate panel specification, a series of diagnostic and specification tests was conducted. A Breusch-Pagan Lagrange Multiplier test for random effects, based on the null hypothesis that the residual variance equals zero, was applied to compare the RE and pooled OLS models. A Hausman specification test was then performed to assess whether the coefficients estimated by the FE estimator differ systematically from those obtained with the RE estimator, thus verifying the orthogonality assumption between individual effects and regressors. Additionally, an F-test was used to compare the FE and pooled OLS specifications, and the Wooldridge test was used to detect serial correlation in the residuals. The Breusch–Pagan test was used to assess heteroskedasticity, and likelihood-ratio (LR) tests were used to compare hierarchical RE structures. Finally, alternative model specifi-

Table 3
Grouping information for the ML models.

		Observations per group		
Group variable	n. of groups	Minimum	Average	Maximum
ID_Study	106	1	4.7	40
ID_Site	155	1	3.2	14
ID_ES	17	1	28.1	197

[5] The other symbols assume the same meaning as in equation (1).

cations were evaluated using information criteria (AIC, BIC, AICc and CAIC)[6] to identify the most parsimonious and statistically adequate formulation.

In the next step, plausible sources of dependence across the observations were investigated using standard approaches. We performed a Moran's I test to assess the presence of significant spatial autocorrelation in the residuals from the standard OLS model and the best aspatial model. To implement Moran's I test, we specified a weight matrix (***W***) to represent the spatial relationship across observations. Given that ***W*** is exogenously determined and leads to specification problems (Florax and Rey, 1995), we built and tested different weight matrices that define the neighbourhood relationships among study sites. We first used the standard geographic criterion and then extended the approach by assuming that other dimensions can describe relationships among study sites. In particular, we considered that mangroves sharing similar biological or socio-economic characteristics may provide comparable ES and respond similarly to contextual factors, even when located far apart. Accordingly, we developed non-geographical and hybrid weight matrices based on biological and socio-economic similarity, following Doreian (1980), Case et al. (1993), Conley and Tsiang (1994), Conley (1999), and Bu and Rosenberger (2014). Biological distance was calculated using the Shannon and Simpson diversity indices (Magurran, 1988), while socio-economic distance was based on the Planetary Pressures–adjusted Human Development Index (PHDI) (Conceição, 2020) and the Night Light Development Index (NLDI) (Elvidge et al., 2012). Summary statistics for these variables are presented in Table 4.

We estimated both symmetric (inverse-distance) and asymmetric (K-nearest neighbours, K = 4–8) spatial weight matrices (Kopczewska, 2021). All matrices were constructed using great-circle (Haversine) distances or standardized attribute distances, applying inverse-distance weighting (IDW) and row-standardization (rows sum to one). To remove scale effects, attribute-based distances were computed from z-score-standardized variables before calculating the absolute differences (|Δ attribute|) and their corresponding weights.

After constructing all spatial weight matrices (geographical, biological, and socio-economic/attribute-based), we implemented a systematic selection procedure to identify the best-performing specification within each dimension. For each matrix, we estimated a consistent set of single-component spatial models (SAR, SLX and SEM) each incorporating spatial dependence on only one process at a time: on the dependent variable, on the explanatory variables, or on the error term. This step provided empirical guidance on which distance criteria were more appropriate for capturing each spatial process separately. For every estimated model, we computed information criteria (AIC, BIC, AICc, and CAIC) together with Moran's I test on model residuals. Specifications with significant residual autocorrelation in the residuals ($p < 0.05$) were discarded, as residual spatial dependence indicates that the spatial process has not been adequately captured, implying model misspecification, biased or inefficient parameter estimates, and unreliable inference due to underestimated standard errors. Among the admissible models, we ranked the remaining specifications primarily according to information criteria. We then constructed hybrid "union" matrices across dimensions (Geographical ∪ Biological, Geographical ∪ Socio-economic, Biological ∪ Socioeconomic, and the triple union) by merging, for each observation, all neighbours appearing in any of the individual matrices. For each connected pair of sites, we computed the average weight across the matrices in which the connection was present. Finally, each hybrid matrix was row-standardized to ensure that the weights in every row sum to one.

Table 4
Statistics of variables used to define non-geographical distances.

Variable	Symbol	Mean	Standard Deviation	Min	Max
Shannon index	Shannon	0.3289	0.3492	0.00	1.22
Simpson index	Simpson	0.7980	0.2203	0.32	1.00
Planetary Pressures–adjusted Human Development Index	PHDI	0.6704	0.0716	0.45	0.80
Night Light Development Index: buffer 10 km	NLDI	10.6792	11.6409	0.00	50.51

[6] The AIC is generally used for model comparison when the sample size is large, while the corrected version (AICc) is preferred for smaller samples to reduce bias. The CAIC applies a stricter penalty for model complexity, making it a more conservative criterion. In contrast, the BIC is typically preferred when model selection is conducted within a Bayesian framework or when the objective is to ensure consistency in identifying the true model as the sample size increases..

The best matrices (plus their hybrid versions) were then used to estimate the whole set of spatial models. To select the best spatial model specification, we followed the "general to specific" modelling approach suggested by Elhorst (2010). According to this approach, we first estimated the Manski model, also named General Nesting Spatial (GNS) model (Manski, 1993). The GNS model assumes the relevance of all the three spatial lags:

$$y = \rho \boldsymbol{W_y} y + \alpha + \boldsymbol{X}\beta + \boldsymbol{W_x} X\theta + \lambda \boldsymbol{W_\varepsilon}\varepsilon + \varepsilon \tag{6}$$

where:

- $\rho \boldsymbol{W_y} y$ denotes the endogenous interaction effects that depend on $\boldsymbol{W_y}$, an N × N nonnegative matrix describing the arrangement of the units in the sample, and on ρ that is the spatial lag parameter;
- α is the constant term;
- $\boldsymbol{W_x X}\theta$ represents the exogenous interaction effects, depending on $\boldsymbol{W_x}$ and on θ that is the spatial Durbin parameter;
- $\lambda \boldsymbol{W_\varepsilon}\varepsilon$ indicates the interaction effect among error terms, depending on $\boldsymbol{W_\varepsilon}$ and on λ that is the spatial error parameter.

The GNS model is a generalized model. By imposing restrictions on the value of spatial terms, it is possible to generate other models that assume two or one spatial components. Generally, in the spatial econometric analysis, a satisfactory target is a model with two spatial factors, given that GNS often suffers from overspecification problems (Elhorst, 2014). Table 5 illustrates how many reduced forms can be derived from the GNS by constraining the value of specific spatial term (s) to zero. These restricted models are the Spatial Autoregressive Combined (SAC) model (also known as the Spatial Autoregressive model with Autoregressive disturbances, SARAR; or Kelejian–Prucha model, Kelejian & Prucha, 1998), the Spatial Durbin Model (SDM), the Spatial

Table 5
Estimated spatial models.

Basic cross-sectional models	Spatial lag (ρ)	Durbin component (θ)	Spatial error (λ)
General Nesting Spatial (GNS) or Manski model	≠ 0	≠ 0	≠ 0
Spatial Autoregressive Combined (SAC)	≠ 0	= 0	≠ 0
Spatial Durbin Model (SDM)	≠ 0	≠ 0	= 0
Spatial Durbin Error Model (SDEM)	= 0	≠ 0	≠ 0
Spatial Auto-Regressive (SAR) or spatial lag model	≠ 0	= 0	= 0
Spatial Lag of X (SLX) model	= 0	≠ 0	= 0
Spatial Error Model (SEM)	= 0	= 0	≠ 0
Ordinary Least Squares (OLS) model	= 0	= 0	= 0

Source: adapted from Elhorst (2010).

Durbin Error Model (SDEM), the Spatial Autoregressive (SAR) model, the Spatial Lag of X (SLX) model, and the Spatial Error Model (SEM). The GNS model collapses to the OLS model when all spatial factors are fixed at the zero level.

For models with multiple spatial lags, the literature typically recommends using the same spatial matrix to simplify the analysis. In this paper, however, we test the use of different spatial matrices to better capture and distinguish the various correlation patterns across mangrove sites.[7] Starting from the reduced set of spatial weight matrices (the three best ones for each dimension, plus their hybrid versions), we assigned them in triple roles: one matrix for spatial dependence on the dependent variable (W_y), one for spatial dependence in the error term (W_ε), and one for the spatial lags of the covariates (W_x). This configuration resulted in 343 possible combinations (7 matrices in total: 3 base and 4 hybrid matrices, combined as 7^3). For each combination, we harmonize the data to ensure the same subset and ordering of observations, applying row-standardization. For each harmonized dataset, we estimate the full set of spatial models. This procedure yielded a total of 2,401 estimated spatial models (343 combinations of spatial matrices, each used to estimate 7 model specifications). Spatial models were estimated by means of the Maximum likelihood estimator using RStudio (Versione 2024.12.1+).

For each model, we compute information criteria (AIC, BIC, AICc, CAIC) and identify the best-fit model within each triplet. To further evaluate the adequacy of the selected models, Moran's I test was applied to the residuals of each best-fitting model using the corresponding error-weight matrix (W_ε). This procedure generated a single summary record for each combination of spatial matrices, reporting the selected model type, its AIC/BIC/AICc/CAIC values, the Moran's I statistic and associated p-value, and the number of observations included in the estimation.[8]

Finally, the models were compared and ranked according to four complementary criteria. First, we required spatial parameters to be statistically significant at the 10% level, indicating that spatial dependence was meaningfully captured. Second, among those models, we prioritized specifications showing the lowest residual spatial autocorrelation, as indicated by a high p-value in Moran's I test.

Third, we evaluated overall model fit and selected the models with the lowest AIC/BIC/AICc/CAIC values. Finally, when multiple models exhibited similar performance, we favoured those with a larger number of statistically significant explanatory variables ($p < 0.10$), reflecting greater explanatory robustness.

Since meta-regression functions are also used for benefit transfer, we finally estimated the predictive power of the best spatial model specification using both in-sample and out-of-sample approaches to assess transfer error (Johnston et al., 2015b). The out-of-sample validation was implemented using a Leave-One-Group-Out (LOGO) cross-validation procedure rather than a simple Jackknife or random data-splitting approach. In the LOGO procedure, observations are grouped by study site, and at each iteration, all observations in a group are omitted from the estimation sample. The model is then estimated on the remaining groups, and the estimated parameters are used to predict the omitted group's observations. This approach is particularly appropriate for meta-regression analysis, where multiple value estimates are derived from the same primary study or site. By excluding entire groups rather than single observations, LOGO explicitly accounts for the intra-group correlation that typically characterizes meta-analytic data and avoids artificially inflating predictive performance due to within-group similarity. Compared to the traditional Jackknife, which omits one observation at a time, the LOGO method provides a more conservative and realistic assessment of the model's predictive power and transferability. It better mimics the benefit transfer context, where the goal is to predict values for an entirely new site using information from other locations.

The transfer error was measured in terms of Absolute Percentage Error (APE) (Kaul et al., 2013; Rosenberger 2015; Boyle and Wooldridge, 2018)[9]:

$$APE_i = \frac{|\hat{y_i} - y_i|}{y_i} * 100 \tag{7}$$

where y_i is the observed value of the dependent variable, and $\hat{y_i}$ is its predicted value.

We first calculated the Mean Absolute Percentage Error (MAPE), the most used accuracy index in meta-analytical applications, because of its intuitive interpretation and reliance on the full distribution of prediction errors. However, when APE distributions are positively skewed and include extreme values, MAPE tends to overstate the population forecast error (Ghermandi and Nunes, 2013; Zhou et al., 2020). To overcome this limitation and provide a more robust assessment of benefit transfer accuracy, we complemented MAPE with several additional measures that capture different characteristics of the error distribution (Montaño Moreno et al., 2013).

Specifically, we examined both central tendency and variability by computing the median APE (MdAPE), the first and third quartiles (Q1 and Q3), and the interquartile range (IQR), which reflects the distribution's spread. To reduce the influence of outliers, we followed the procedure suggested by Schwertman et al. (2004) and implemented by Kaul et al. (2013), removing observations whose errors fell outside the interval defined by 1.5 times the IQR. We also estimated alpha-trimmed MAPEs, obtained by excluding fixed percentages (1%, 5%, and 10%) of the largest and smallest APEs in the ordered distribution (Vista and Rosenberger, 2013), and a cleaned MAPE (MAPE_IQR_clean) based on the filtered distribution.

In addition, we calculated robust M-estimators, specifically, Huber's, Tukey's Biweight and Hampel's, which assign decreasing weights to extreme deviations while still considering the entire distribution of errors (Montaño Moreno et al., 2013). These estimators provide a more stable measure of prediction accuracy when the error distribution is heavy-tailed or contaminated by outliers.

Finally, we assessed the practical reliability of benefit transfer results through acceptability thresholds, measured by PAR10 and PAR25, which represent the percentage of "good" predictions with an APE below 10% and 25%, respectively.

Together, these indices offer a comprehensive and nuanced evaluation of predictive performance, capturing not only the central tendency of the error distribution but also its variability, robustness, and practical acceptability for benefit transfer applications (see Table 6).

Table 6
Prediction error indices.

Category	Calculate indices	Purpose
Central / Mean Errors	MAPE, MdAPE	Overall prediction accuracy
Distribution Metrics	Q1, Q3, IQR	Variability of prediction errors
Filtered (Robust) Errors	MAPE_IQR_clean, mape_trim_	Outlier cleaning and robustness improvement
Robust M-Estimators	M_Huber, M_Tukey, M_Hampel	Accuracy with downweighting of outliers
Acceptability Thresholds	PAR10, PAR25	Share (%) of acceptable or 'good' predictions

[7] We are grateful to one of the anonymous reviewers for this valuable and constructive suggestion..

[8] These additional results are omitted for brevity but can be provided upon request.

[9] This metric is also known into literature as absolute Percentage Transfer Error (|PTE|) (Rosenberger, 2015).

4. Results and discussion

Fig. 5 provides a synthesis of the main results, while detailed tables for each analytical step are presented in the supplementary materials.

Results from stages 1 and 2 indicate that the random-effects model clustering observations by site (*RE_site*) provides a theoretically more appropriate specification for the data structure. Although the RE model with study-level grouping (*RE_study*) shows a slightly better BIC (2278 vs. 2317), information criteria (AIC = 2180 vs. 2220; CAIC = 2301 vs. 2340) and diagnostic tests reveal only marginal differences between the two specifications (detailed results reported in supplementary materials, Table A4). Given the spatial nature of the data, the site-level grouping captures the most relevant source of dependence across observations, reflecting the ecological and geographical similarities among sites within the same study area (Boyle and Wooldridge, 2018). Moreover, the dataset shows substantial overlap between studies and sites: 89 of 106 studies (approximately 84%) report estimates for a single site, while 17 studies cover multiple sites. This structure implies that most of the observed variation occurs at the site level, reinforcing the rationale for grouping random effects by site rather than by study. Considering this ecological and spatial rationale, the *RE_site* model is preferred, as spatial proximity and shared environmental conditions are likely to generate correlation among observations within the same site rather than within the same study. This specification better reflects the spatial clustering typical of ES data and ensures that unobserved spatial heterogeneity is appropriately captured at the site level.

The Breusch–Pagan Lagrange multiplier test confirms that the variance of the random effects is significantly different from zero ($p = 0.0001$), whereas the Hausman specification test shows no significant differences between the fixed- and random-effects estimates for either the study-level ($p = 0.1836$) or site-level ($p = 0.1696$) models, supporting the use of a random-effects specification. Diagnostic tests further reveal the presence of first-order autocorrelation (Wooldridge test, $p = 0.0116$) and heteroskedasticity (Breusch–Pagan test, $p = 0.0419$); consequently, robust standard errors were employed to ensure consistent inference. The comparison between hierarchical specifications also supports this choice, as the two- and three-level mixed models do not significantly improve model fit compared to the simpler random-effects specification (Likelihood Ratio test, $p = 1.000$) (see supplementary materials, Table A5).[10]

Estimates of Moran's I test indicate the presence of a highly significant positive spatial autocorrelation in the OLS residuals, regardless of how the spatial weights matrix (W) is specified ($p < 0.0001$). This result suggests that the OLS model fails to account for the data's spatial structure, leading to clustered residuals and potentially inefficient coefficient estimates. Conversely, Moran's I test performed on the residuals of the *RE_site* model consistently indicates the absence of spatial autocorrelation, demonstrating that the inclusion of random effects at the site level successfully captures the latent spatial dependence among observations. As a result, the *RE_site* specification provides robust and unbiased estimates of the coefficients.

Nevertheless, while this model effectively controls for spatial dependence through random grouping, it does not explicitly model how spatial processes influence the magnitude or distribution of ES values across space. In contrast, spatial econometric models can explicitly quantify spatial spillovers and feedback effects, offering deeper insights into the spatial dynamics underlying ES valuation patterns.

Focusing on the outcomes of Moran's I test applied to OLS residuals (reported in supplementary materials, Table A6), the results suggest that weight matrices based on geographical distance exhibit the most substantial spatial dependence. In these matrices, the share of variability explained by the spatial structure ranges between 5.4% and 13.8%. This proportion is notably lower for matrices constructed on socio-economic proximity (Nightlight: 0.7%–6.1%; PHDI: 0.3%–1.0%) and for those based on biological similarity (Shannon: 1.5%–4.3%; Simpson: 1.7%–2.6%). However, it is essential to emphasize that the variability explained by the spatial structure, approximated here by the square of Moran's I, should be considered a heuristic, non-robust indicator. Moran's I is not directly comparable to a coefficient of determination (R2), and its squared value only provides a rough comparative measure of spatial dependence across different weighting schemes (Kopczewska, 2021). Therefore, while these results highlight meaningful differences in spatial dependence across different definitions of spatial relationships, a more detailed spatial econometric analysis would be required to characterize the underlying dependence structure in the data fully.

For this reason, the next stage of the analysis involved estimating SAR, SEM, and SLX models using all the identified spatial weighting matrices to determine which specification performed best in addressing the suspected spatial correlation: whether in Y (the logarithm of the ES economic value), in the X variables (contextual factors), or in the residuals.

The selection procedure for the most appropriate spatial weight matrix for each dimension confirms that geographical proximity is the dominant source of spatial dependence in the data (see supplementary materials, Table A7). The SAR model estimated using the geographical distance matrix with inverse distance weighting (*geo_band_idw*) achieves the lowest information criteria values (AIC = 2238.34; BIC = 2335.55) among all specifications, indicating that spatial dependence is most effectively captured through spatial interaction in the dependent variable (Y).

For the socio-economic dimension, the SEM model with the nightlight-based matrix (*nightlight_band_idw*) performs best (AIC = 2278.91; BIC = 2376.12), slightly outperforming both the SAR and SLX alternatives, as well as the PHDI-based matrices. This suggests that spatial patterns in economic activity proxied by nightlight intensity are more relevant than those captured by human development indicators (PHDI) when modelling spatial dependence.

Within the biological dimension, the SEM model with the Shannon-based matrix (*shannon_band_idw*) achieves the lowest AIC and BIC values (AIC = 2280.37; BIC = 2377.58), marginally outperforming the Simpson-based specification. This finding implies that biodiversity-related heterogeneity, as measured by Shannon's index, provides a slightly better representation of ecological spatial relationships.

Overall, the best-performing models operate within the SAR and SEM frameworks, capturing unobserved spatial processes in both the dependent variable and the error term. The consistent superiority of distance- and nightlight-based matrices underscores the central role of geographical and economic proximity in explaining spatial dependence patterns in ecosystem service values.

The three selected matrices were then used to construct their hybrid versions and to estimate more complex spatial models.

Among all the estimated spatial models (2401) and for each combination of the three matrices, the best-performing model is the SAC, which combines spatial dependence in both the dependent variable and the error term. The latter model assumes the existence of a significant "global" spatial dependence, meaning that spillover effects, the impact of changes in explanatory variables in a particular unit *i* on the dependent variable values in another unit *j* (*i*), are global in nature. As Anselin (2003) clarifies, this means that a change in an explanatory variable at any location is transmitted to all other locations, even if two locations are assumed to be unconnected in the respective weight matrix.

The model's classification procedure identified two optimal configurations of the SAC model (see supplementary materials, Table A8). The first assumes that the same weighting scheme governs all spatial processes, which, for the SAC, include the spatial lag of the dependent variable and the spatial structure of the error term ($W = W_y = W_\varepsilon$). It is the matrix named *geo_band_idw*.

The second configuration, which allows for a more nuanced representation of spatial dependence by relaxing this assumption, employs

[10] Coefficient estimates for these models are available on request.

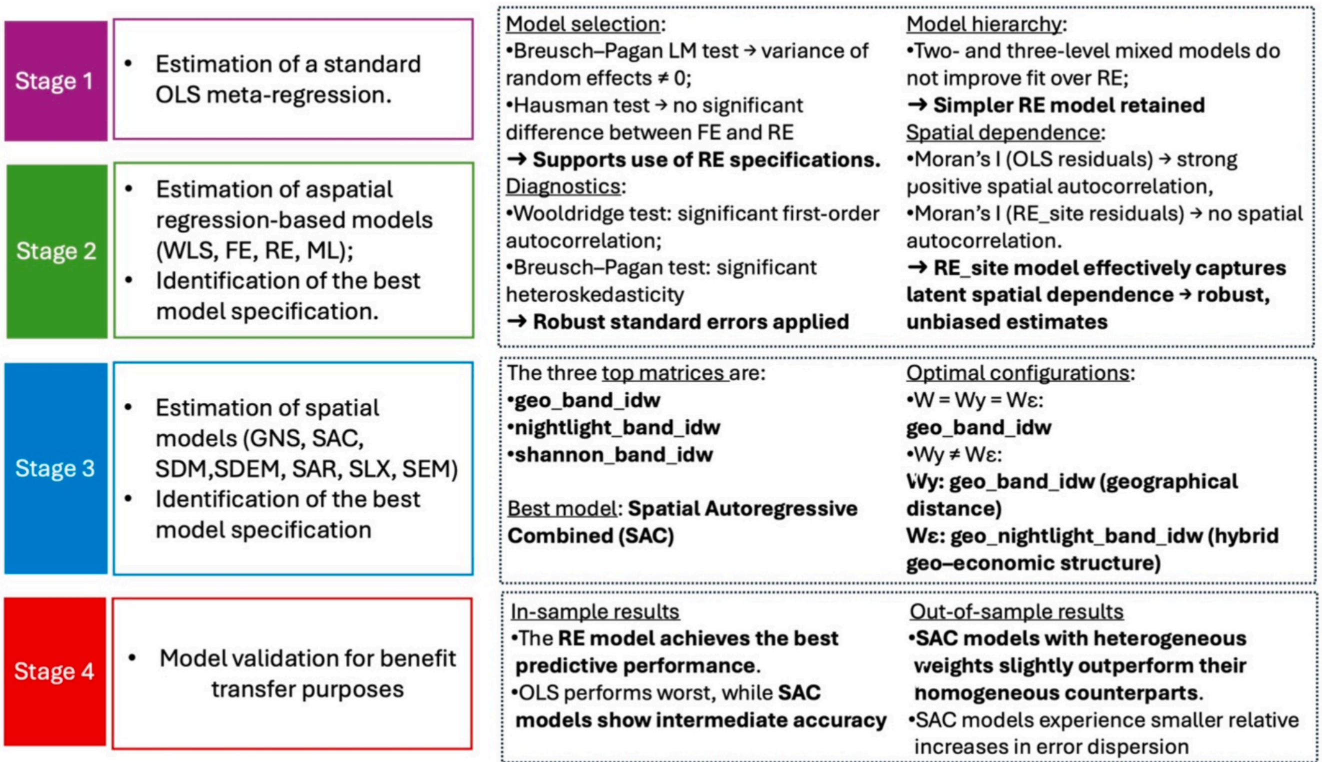


Fig. 5. Main results.

differentiated spatial matrices for the spatial lag Y and for the spatial structure of the error term ($W_y \neq W_\varepsilon$). In this case, the spatial correlation of Y is estimated from the matri *geo_band_idw*, while the spatial lag of ε is modelled through the hybrid matrix *geo_nightlight_band_idw*. This result confirms that direct spatial interactions among the economic values of ES occur primarily through physical proximity, consistent with the idea that ecosystem benefits and local preferences tend to be territorially contiguous. However, residual correlations not explained by the model reflect a shared socio-economic component. In particular, areas with similar levels of economic development or nightlight intensity exhibit comparable patterns in ES valuation, even when they are not geographically adjacent.

Table 7
Aspatial and spatial models coefficient estimates.

	OLS			RE_siteid			SAC $W = W_y = W_\varepsilon^a$			SAC $W_y \neq W_\varepsilon^b$		
	estimate		SE	estimate		SE	estimate		SE	estimate		SE
(Intercept)	11.0760	***	1.8769	10.7807	***	1.6794	4.8870	**	1.5791	5.1923	**	1.6024
es_food	1.4279	***	0.2603	1.3197	***	0.2054	1.2497	***	0.2198	1.2794	***	0.2214
es_recreation	0.9213	*	0.4135	0.9377	**	0.3359	0.6607	*	0.3317	0.7114	*	0.3384
es_climate	1.5901	**	0.4888	0.8281	*	0.3946	1.2074	**	0.3875	1.2118	**	0.3939
es_extreme	−0.5437		0.5051	−0.2288		0.4125	−0.4599		0.4054	−0.4648		0.4144
es_existence	−0.9931		0.6569	−0.1304		0.6059	−0.5430		0.5082	−0.6848		0.5188
es_flows	−3.9074	*	1.7579	−2.9388	*	1.4540	−3.3719	*	1.4444	−3.2411	*	1.4639
es_cognitive	1.4369		1.2114	1.2780		0.9281	1.1267		0.9757	1.0980		0.9969
es_soil	0.9961		1.0089	0.8247		0.8152	0.5174		0.7793	0.5782		0.8146
cb	0.0324		1.7750	0.6113		1.3893	0.2516		1.4023	0.1741		1.4416
pmb	−1.9865		1.7644	−1.3112		1.3844	−1.4447		1.3957	−1.5356		1.4322
nm	−1.0437		1.7757	−1.3243		1.4144	−0.7701		1.3995	−0.9024		1.4379
continent1	−1.3245	***	0.3218	−0.6754		0.5226	−0.6232	**	0.2212	−0.7089	**	0.2379
continent3	1.3103	**	0.3993	1.9642	***	0.5448	0.7121	**	0.2727	0.6809	*	0.2802
protected1	0.3557		0.2702	0.2418		0.3659	0.2146		0.1810	0.2072		0.1931
protected2	−1.4208	***	0.3370	−0.5557		0.4519	−0.6184	**	0.2357	−0.6426	**	0.2462
cat_area_1	−0.3414	***	0.0429	−0.4461	***	0.0670	−0.1515	***	0.0339	−0.1592	***	0.0347
popd_10_ln	−0.0759		0.0480	−0.0614		0.0615	−0.0485		0.0313	−0.0514		0.0325
man_16_10_ln	−0.0870	**	0.0307	−0.1020	**	0.0374	−0.0485	*	0.0204	−0.0483	*	0.0218
dist_city_ln	−0.1314		0.0904	−0.1700		0.1319	−0.0274		0.0586	−0.0188		0.0614
road_10_ln	−0.0950		0.0687	0.0060		0.0804	−0.0353		0.0447	−0.0294		0.0473
rho							0.5757	***	0.0556	0.3533	***	0.0477
Lambda							−0.2837	**	0.1031	0.2231	**	0.0865

Legenda:. $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
a: W = geo_band_idw;
b: W_y = geo_band_idw; W_ε = named geo_nightlight_band_idw.

Table 7 reports the estimated coefficients (β_k) obtained from the OLS model, from the random effects by site model (*RE_siteid*), and from the two versions of the spatial autoregressive combined model (SAC). The results confirm that the economic values associated with ES vary substantially across service types. In particular, the coefficient for food provision (*es_food*) is positive and highly significant across all models, indicating that provisioning services receive the highest economic value. Climate regulation (*es_climate*) also shows positive, statistically significant coefficients, though with weaker significance compared to food provision. Recreation services (*es_recreation*) retain a positive effect but with reduced importance in the spatial specifications, suggesting that some of the previously attributed variation for this service may be due to spatial effects. The coefficient associated with flow regulation services (*es_flows*) is negative and significant across all models, indicating that these services are systematically associated with lower economic values than other ES categories. Cognitive development services (*es_cognitive*) show a positive but non-significant effect, suggesting that their perceived contribution varies more heterogeneously across sites.

Regarding contextual variables, population density (*popd_10_ln*) is not statistically significant across specifications. In contrast, mangrove cover (*man_16_10_ln*) is negative and significant ($p < 0.05$), suggesting that areas with greater vegetation cover may be associated with lower ES values, possibly due to lower human pressure or accessibility. Distance to the nearest city (*dist_city_ln*) and road density (*road_10_ln*) are not significant in the spatial specifications, suggesting that accessibility effects are weak or absorbed by the data's spatial structure.

Among the categorical variables, relevant differences emerge: *continent1* (Africa) shows negative, significant coefficients in the OLS model but loses significance in the spatial specifications, whereas *continent3* (North America) maintains a positive, statistically significant effect across all models, indicating higher average ES values in this region. Fully protected areas (*protected2*) exhibit negative, significant effects, suggesting that strictly protected sites are associated with lower economic values, likely due to limited accessibility or use restrictions. Furthermore, area size (*cat_area_1*) is strongly negative and highly significant, indicating that as area size increases, the economic valuation per unit of surface tends to decrease. Variables related to the valuation method (*cb, pmb, nm*) are not significant in any specification, suggesting that the applied valuation technique does not systematically influence the estimated economic values.

Finally, the spatial dependence parameters (ρ and λ) are highly significant in both versions of the SAC model, confirming the presence of strong spatial autocorrelation in both the explanatory variables and the errors. In both specifications, ρ is positive and highly significant, ranging between 0.35 and 0.58. This indicates a moderate to strong spatial autocorrelation in the dependent variable, meaning that the economic values of ecosystem services in one site tend to resemble those of neighbouring sites. A ρ of about 0.57 (first specification with a constant W) is relatively high for this type of analysis, suggesting a marked direct spatial dependence, while in the second specification ($W_y \neq W_\varepsilon$) the strength of dependence weakens but remains significant ($\rho = 0.35$). In summary, the spatial lag process is important but not dominant, consistent with ecological and socioeconomic phenomena characterized by medium-range spatial correlation.

Regarding the spatial error coefficient, λ is significant and of moderate magnitude in both model versions: in the first, it is negative (–0.28), suggesting local compensation among neighbouring residuals, while in the second, it is positive (0.22), indicating moderate positive spatial autocorrelation among adjacent areas. Both values are realistic and consistent with environmental and economic data, where the unobserved component tends to spread across space but with lower intensity than the spatial lag effect on the estimated value. The change in the sign of the parameter λ (from negative to positive) between the two SAC model versions suggests that the nature of the spatial dependence in the errors varies with the imposed spatial weight matrix structure. In the first SAC model, where the same contiguity matrix (W) is assumed to govern both the spatial lag process (W_y) and the error process (W_ε), a negative λ indicates negative spatial autocorrelation in the errors. In other words, residuals tend to offset each other among neighbouring areas: a site with a positive error is surrounded by sites with negative errors, and vice versa. This may reflect a spatial competition or substitution effect among nearby sites, where higher economic values in one area are associated with lower values in adjacent areas (a local saturation effect). When the assumption $W_y = W_\varepsilon$ is relaxed, allowing the spatial interaction processes in the dependent variable and the error term to follow different structures, λ becomes positive and significant. This implies that once the distinct nature of the two spatial processes is properly specified, positive spatial autocorrelation in the errors emerges: geographically proximate areas tend to share similar unobserved components (common effects, for example, due to environmental, institutional, or socioeconomic characteristics not included in the model).

Overall, the SAC specifications provide a more accurate representation of the phenomenon, revealing that a substantial portion of the variance previously attributed to local factors is, in fact, spatially structured.

Fig. 6 reports the estimated direct and spillover effects for variables significant at least at the 10% level in both models. Compared with the baseline SAC model, its extended specification, which assumes $W_y \neq W_\varepsilon$ and employs a hybrid error structure, generally produces higher spillover effects. It also reveals greater variability in both direct and indirect estimates, indicating improved sensitivity to spatial heterogeneity. In particular, ES variables (*es_flows, es_food, es_recreation*) exhibit more substantial spillover effects. In contrast, socioeconomic and locational predictors (*dist_city_in*) remain relatively stable across specifications. Overall, the extended SAC model captures more complex spatial

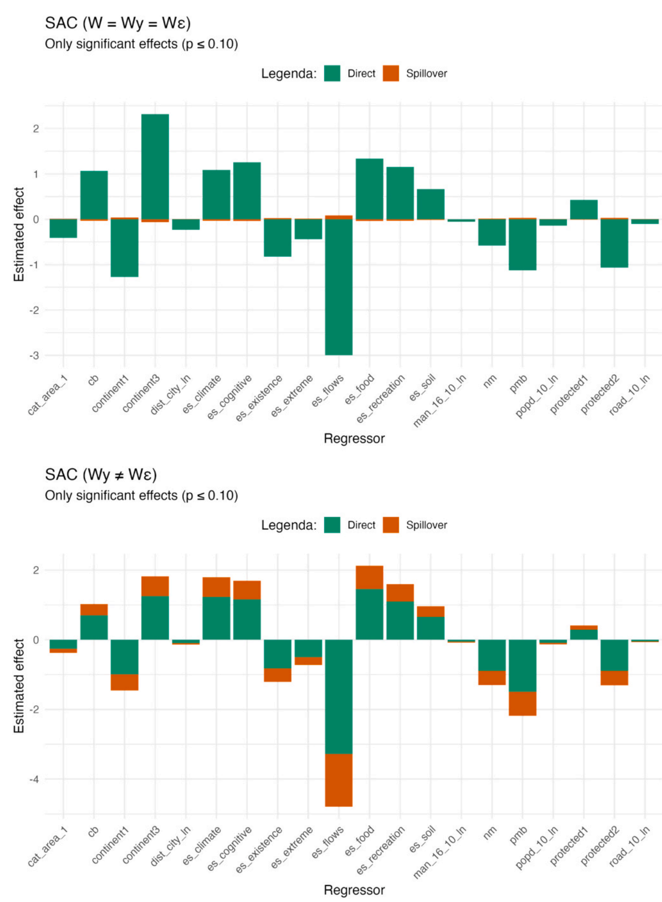


Fig. 6. Comparison of estimated direct and spillover effects under two SAC spatial specifications.

dependencies, highlighting stronger cross-regional propagation of both beneficial and adverse effects.

Fig. 7 displays the relationships between observed and predicted values across the four models. Each graph shows the point cloud, the trend line and its equation, and the correlation coefficient between observed and predicted values. The RE model exhibits the highest explanatory power, as indicated by the largest R^2 value (0.70), suggesting that variability across sites is the dominant component in explaining the observed differences. The spatial SAC models perform better than the simple OLS specification ($R^2 = 0.27$) but do not reach the predictive strength of the RE model. This is likely because they capture the spatial interdependence among nearby observations but fail to account for the broader structural heterogeneity across sites or groups. The version with a differentiated spatial weights matrix provides a slightly better fit ($R^2 = 0.44$) than the one assuming the same matrix ($R^2 = 0.41$), indicating that the strength of spatial dependence is not uniform across the study area. In summary, spatial effects are clearly present, but cross-site variability remains the main driver of the observed levels of the dependent variable.

Table 8 reports summary statistics for the in-sample and out-of-sample APE distributions across the four estimated models. Overall, the table shows consistent improvements in predictive accuracy when moving from OLS to RE and SAC models, though differences emerge between in-sample and out-of-sample results.

For the in-sample analysis, the RE model achieves the best predictive performance, with the lowest mean absolute percentage error (MAPE = 163.40) and median absolute percentage error (MdAPE = 16.11). These results confirm the strong explanatory power of the RE specification, as observed in the R^2 comparison, and highlight the importance of accounting for unobserved heterogeneity across sites. In contrast, the OLS model shows the weakest predictive ability, with a MAPE exceeding 380 and a MdAPE of 25.75, reflecting its inability to capture either spatial or hierarchical structure in the data. The SAC models, which explicitly incorporate spatial dependence, perform better than OLS but remain less accurate than RE, with median APEs around 22%. The introduction of spatial effects thus reduces prediction errors, but not as effectively as modelling cross-site heterogeneity directly.

Dispersion indicators, such as the interquartile range (IQR), confirm these patterns: the RE model exhibits the narrowest IQR (22.37) compared with the OLS (33.21) and SAC (31.0–31.3) specifications, indicating more stable, less dispersed prediction errors. Robust measures such as trimmed means and M-estimators (Huber, Tukey, and Hampel) display the same hierarchy, with the RE model consistently producing the lowest values (e.g., M_Huber = 19.70; M_Tukey = 15.78). These results suggest that outliers exert a limited influence once random site-level variability is explicitly modelled.

When applying the outlier-cleaning procedures (IQR-based filtering and alpha trimming), the relative differences among models persist. The MAPE_IQR_clean remains lowest for the RE model (16.89) and highest for OLS (26.13), while the SAC variants lie in between (22–24). Trimmed means confirm the robustness of these patterns: removing 10% of extreme values, the mean absolute percentage error drops to 20.66 in the RE model, compared to 28–31 in SAC and 31.67 in OLS. The overall reduction in variability further supports the stability of the RE-based predictions.

The out-of-sample evaluation, which tests the transferability of model predictions, produces higher error levels across all specifications, as typically observed in the literature (Lindhjem and Navrud, 2008; Chaikumbung et al., 2016). Mean errors (MAPE) increase by approximately 50–60% relative to in-sample results, confirming the expected loss in predictive precision outside the estimation sample. Nonetheless, the relative ranking of models remains consistent: the RE model continues to outperform all others (MAPE = 447.84 in OLS vs. 382.16 in SAC, with RE = 408.92), and the SAC models with heterogeneous weights slightly outperform their homogeneous counterparts, indicating that allowing spatial processes to vary across the study area yields a modest but meaningful improvement in transfer accuracy.

Robust estimators (M_Huber, M_Tukey, M_Hampel) converge to similar conclusions: although all models experience a deterioration in predictive accuracy in the out-of-sample setting, the SAC models

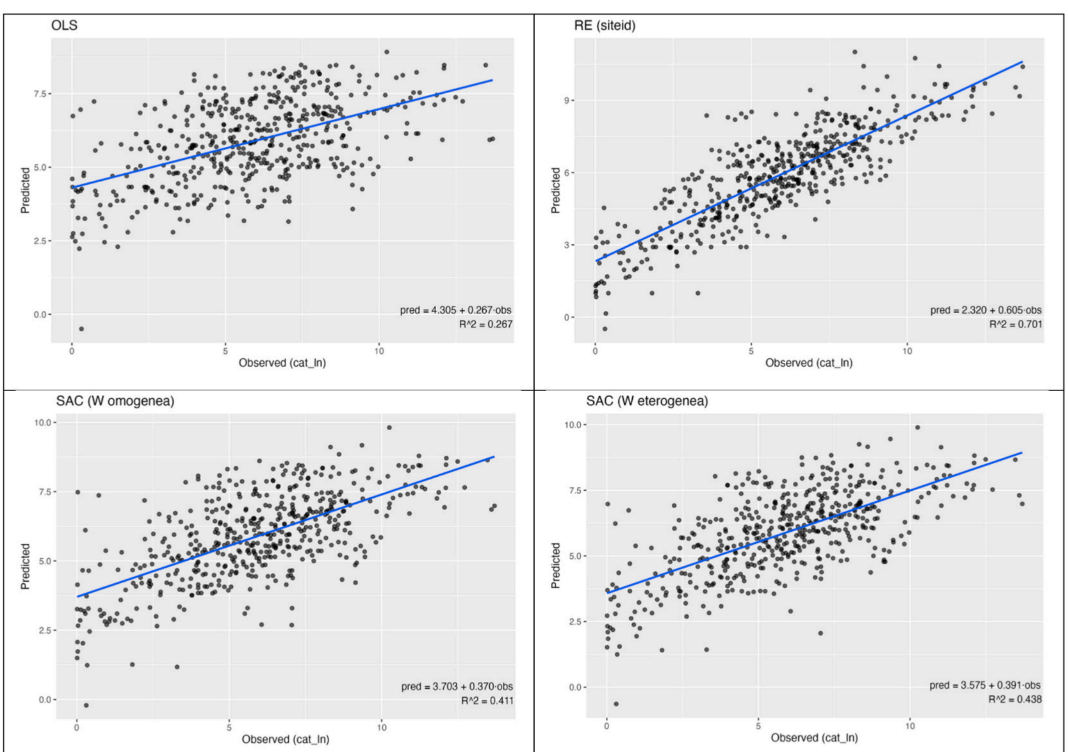


Fig. 7. Correlations between observed and predicted values across models.

Table 8
Summary statistics of APE (in%).

	In-sample				Out-of-sample			
	OLS	RE	SAC $W_y = W_\varepsilon^a$	SAC $W_y \neq W_\varepsilon^b$	OLS	RE	SAC $W_y = W_\varepsilon^a$	SAC $W_y \neq W_\varepsilon^b$
MAPE	381.52	163.40	296.49	276.24	408.92	447.84	382.16	382.16
MdAPE	25.75	16.11	22.40	22.16	28.62	28.34	29.40	29.40
Q1	12.61	7.66	11.13	10.85	13.42	13.01	15.17	15.17
Q3	45.83	30.03	42.15	42.16	48.55	47.45	50.28	50.28
IQR	33.21	22.37	31.01	31.31	35.13	34.44	35.11	35.11
MAPE_IQR_clean	26.13	16.89	24.01	22.96	28.23	27.65	29.67	29.67
mape_trim_1p	118.36	59.08	94.61	89.79	129.81	143.47	121.76	121.76
mape_trim_5p	38.50	24.30	34.51	33.44	41.71	42.17	42.31	42.31
mape_trim_10p	31.67	20.66	28.87	28.09	34.24	34.05	34.86	34.86
M_Huber	30.23	19.70	27.52	26.78	32.56	31.98	33.66	33.66
M_Tukey	25.03	15.78	22.48	21.87	27.05	26.53	28.49	28.49
M_Hampel	28.57	19.21	26.53	25.75	30.70	30.11	31.40	31.40
PAR10	19.37	32.02	22.13	22.92	18.38	17.59	16.80	16.80
PAR25	48.42	68.77	55.73	54.74	44.86	45.26	41.70	41.70

(especially with heterogeneous weights) show smaller relative increases in error dispersion. These results suggest that spatial effects capture a portion of systematic variation that is transferable across contexts, while the RE model's strength lies more in fitting site-specific structures.

Finally, the predictive accuracy ratios (PAR10 and PAR25) offer additional insight into model performance at lower error thresholds. In-sample, the RE model correctly predicts values within ±10% for 32% of cases and within ±25% for nearly 69%, both the highest proportions among all models. In the out-of-sample setting, these shares decline for all specifications, yet SAC models maintain slightly better performance at the 10% and 25% thresholds (e.g., PAR25 = 41.7 for SAC vs. 44.9 for RE). This pattern suggests that spatial models, though less precise in-sample, may exhibit greater relative robustness when applied to new spatial contexts.

5. Concluding remarks

The main motivation of this article arises from the observation that, although existing meta-regression studies in environmental valuation often account for dependence among estimates from the same primary study and control for spatial heterogeneity in explanatory factors, they still tend to overlook the role of spatial autocorrelation.

Such autocorrelation may arise when the dependent variable and/or explanatory variables are geographically clustered, potentially biasing parameter estimates and reducing the reliability of benefit transfer.

This study contributes to filling this methodological gap by exploring and comparing a range of spatial meta-regression models capable of capturing the spatial processes underlying environmental valuation data. Using a global dataset of mangrove ecosystem service (ES) values, including 506 estimates from 106 primary studies, we identified and modelled the sources of spatial dependence and assessed variations in model performance under alternative spatial specifications.

To this end, we developed multiple spatial weight matrices capturing different neighbour relationships among study sites, based on geographical, ecological, and socio-economic distances, as well as hybrid matrices that integrate these dimensions.

Our analysis departs from the traditional assumption of identical spatial structures across processes in two- or three-way spatial models, allowing a more flexible representation of spatial patterns in the data.

The spatial econometric results and Moran's I tests confirm the presence of significant spatial dependence in the dataset. Although the random-effects (RE) model, which clusters observations by site, provides the best overall fit, effectively capturing latent spatial dependence and yielding robust, unbiased coefficient estimates, it does not provide explicit insights into the spatial processes that shape valuation outcomes. In contrast, the Spatial Autoregressive Combined (SAC) model, particularly when estimated with heterogeneous and hybrid spatial weight matrices, captures both spatial interactions in the dependent variable and spatial dependence in the error term. This SAC specification performs slightly worse in-sample TE. Still, it exhibits superior out-of-sample TE robustness compared to OLS and RE models, suggesting greater predictive reliability for benefit transfer purposes.

From a practical standpoint, these findings underscore the importance of explicitly modelling spatial structure in meta-regression analyses of ES values. For researchers and policymakers relying on meta-regression for benefit transfer, accounting for both site-specific heterogeneity and spatial dependence is essential to produce reliable policy values, especially when new primary valuation studies are infeasible.

The SAC model, which combines a spatial lag component based on geographical proximity with an error structure defined by a hybrid matrix that integrates both geographical and socio-economic distances, offers a deeper understanding of the spatial dynamics underlying environmental valuation data. This configuration reveals the coexistence of two distinct spatial processes. On one hand, the similarity of estimated values among geographically proximate sites reflects spatial diffusion mechanisms driven by shared ecological conditions or regional valuation practices. On the other hand, the hybrid error structure captures the influence of unobserved contextual similarities, such as comparable levels of economic development, governance quality, or cultural attitudes, among sites that are geographically distant yet socio-economically alike.

From this perspective, the spatial distribution of mangrove ES values cannot be explained solely by physical proximity. Instead, the transferability of values also depends on how comparable the socio-economic contexts are across study sites. This finding suggests that benefit transfer exercises should account not only for geographical distance between donor and policy sites but also for their contextual similarity, which can play an equally important role in determining the reliability of transferred estimates.

Beyond the statistical and econometric implications, this study also offers practical guidance for applied researchers and decision-makers. Those working with meta-regression models, whether for benefit transfer or other valuation purposes, are often confronted with databases characterised by firm site-specific heterogeneity. This paper shows how spatial modelling tools, available in many statistical software packages (such as R, Stata, or GeoDa), can be used to control for biases that may otherwise arise when spatial dependencies are ignored.

In our analysis, the best-performing spatial weights were those that incorporated both geographical and socio-economic distances. However, researchers working in other ecological or policy contexts should also consider testing models that include measures of ecological distance, which may exert a stronger influence in different settings. Although accounting for spatial autocorrelation entails several additional analytical steps beyond conventional meta-regression, these steps can markedly reduce transfer errors and, ultimately, enhance the quality and policy relevance of the information available to decision-makers involved in the management and conservation of ecosystem services.

Nevertheless, the analysis also reveals certain limitations. Ecological distance, as proxied by the Shannon index, did not significantly enhance model performance, possibly because this biodiversity metric does not adequately capture the ecological processes underlying value formation. Future research could explore alternative measures of ecological proximity, such as trait-based functional diversity or ecosystem condition indicators, to assess whether ecological similarity plays a more substantial role in other valuation contexts.

Overall, this study offers a methodological roadmap for addressing spatial econometric challenges in meta-analyses of environmental valuation. It illustrates how distinct spatial processes can be identified, modelled, and compared through alternative and hybrid weighting schemes. Integrating spatial econometrics into meta-regression frameworks enables a more realistic representation of how spatial spillovers and contextual dependencies influence the economic value of ecosystem services, thereby enhancing both the robustness and policy relevance of benefit transfer applications.

CRediT authorship contribution statement

Maria De Salvo: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Validation, Supervision. **Laura Giuffrida:** Data curation, Visualization, Investigation. **GIovanni Signorello:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Luke M. Brander:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2026.101815.

Data availability

Data will be made available on request.

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