Data-driven decisions: Artificial intelligence-based experimental validation of ocean ecosystem services scale

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ABSTRACT

Several studies address the main topic of research, ecosystem services. It is also proven that decision-making in organizations generally involves a decision-maker, who assumes internal responsibility for the results. However, when the decision is collective, we need to think about the context of governance. How can we increase the sustainable decisions of ocean ecosystem services governance? When this decision is applied to ocean ecosystem services, in particular, we need a parameter. Therefore, the proposed scale is an initial guide for support key decision-makers decisions on the governance of ocean services ecosystems. The scale proposal with validation through classical linear regression, and supported by an artificial neural network, demonstrates the main variables that influence the decision and contribute to possible risk mitigations in terms of decisions.

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1. INTRODUCTION

In the literature, the “ecosystem services” have been researched a long time for diferents applications. Futhermore, the “ecosystem services” in the “decisions science” field has been growing since 2005 with a several studies. However, the number of studies in “ecosystem services” developed with “decision making” approach are considering inefficient because decision making processes envolved multiple techniques to solve the problem or provide the solutions. Its means that its not a sing solution.

Considering the approaches surrounding of ocean governance, this topic are complex and influenced by multiple factors and decision-makers with different worldviews and individuals [1]. Understanding how individual interests align with ecosystem services would allow for a better allocation of resources and possibly better governance in decision-making process [2]. While ecosystem service decisions are widely recognized as a useful approach for society, although they are controversial on the part of management, their assessment in the marine environment is considered to lag behind that of terrestrial ecosystems [3].

Recent studies on ecosystem services studies show that deep learning is changing the way of decisions are taking. As a result, it has been used in the studies like detection of rockfish in challenging underwater environments [4], detection of coastal erosion [5], and soil type prediction [6]. Additionally, the deep learning was used for various problems in the machine learning context, including predicting decisions, forecasting, and hybrid modelling approach [7]. Given this context, together with the need for ocean ecosystems to be adequate and effective in terms of management efficiency, we asked: how can we increase the sustainability of decisions in the context of governance? In addition, to support the study we adresse two questions: “what are the exact measurement factors for assessing sustainable governance decisions in ocean ecosystem services?" and "what is the relationship between the (six) decision variables in ocean ecosystem services?"

This document focuses on the growing interest in ocean service ecosystems directly involving governance in sustainable decision-making [8]. In contrast to these efforts, we developed and validated a scale to support key decision-makers in the governance of decision context. This scale is seen as a resource for adaptive governance to develop the capacity to carry out ecosystem management and is able to predictively assess the potential of decisions [9]. The scale proposal with validation through classical linear regression [7] and supported by an artificial neural network [8] demonstrates the main variables that influence the decision and contribute to possible risk mitigations in terms of decisions [9] in ocean governance ecosystems services.

It also allows the actors in the ecosystem to collaborate by interacting and evaluating individual interests, transforming them into collective interests [10]. In this way, scale helps to foster adaptive capacity as decisions change in different ocean contexts. It brings more value in terms of decision-making process and application in the future studies.

The document followed different sections. In the section 1 introduction, the literature review of the study and the questions were demonstrated. In section 2 method, the research and experimental procedure was conducted. In section 3 results, the experimental outcomes were presented. In the section 4 dicussion, the results were related to the literature review. Finaly, the section 5 conclusion, show the limitations, future research, and implications.

2. METHOD

The method of research and the experimental procedure was conducted following different sections. In the section 2.1, the concept and initial development of factors was introduced. After that, in the section 2.2, the procedure of measuring scale development was presented. In addition, in the section 2.3 the data collected process was described. The Figure 1 show the flow of development, analysis and measurement process (experimental setup).

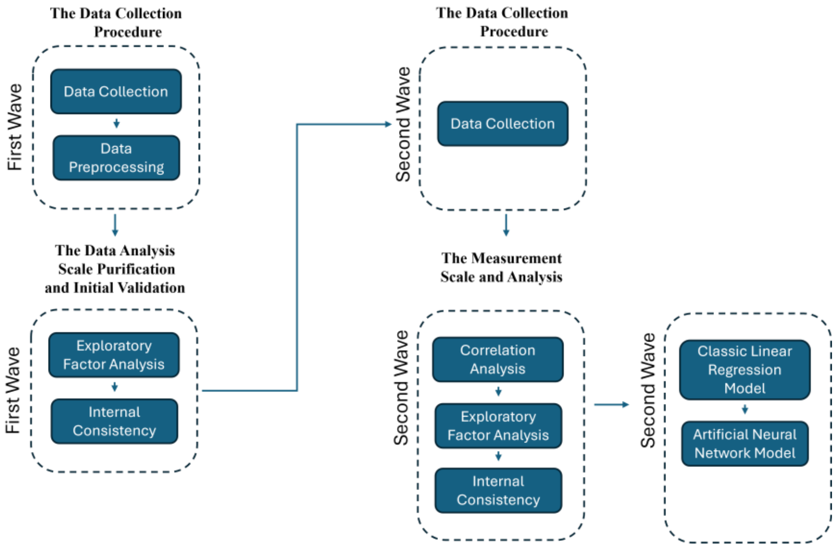

Figure 1. Picture of experimental setup

2.1. The concept and initial scale development process

The beginning of this scale development process started in (Study A), "Ecosystem services - challenges for future research applications" [forthcoming, 2025]. After that, the new paper (Study B) "Ocean ecosystem services: modeling a factor development process to create sustainable value for decision" [11], was developed based on the finds of (Study A). During this period, we followed the initial guidelines provided by [12] to develop three steps of the Delphi method: factor generation, factor reduction and factor refinement, including the domains (Study B). And, we followed the complementary steps provided by [13] to develop the constructs and procedures for validation. In this paper (Study C), "Data-driven decisions: artificial intelligence (AI)-based experimental validation of ocean ecosystem services scale" we validate a scale for sustainable governance decisions in ecosystem services management.

2.2. The procedure of measurement scale development

The factors were designed to follow multiple-item scales (likert scale/seven points). The measurement development process was conducted according to the “factor generation”, “factor reduction” and “factor refinement” (Study B) and included procedures of validation: i) “data collection”, “exploratory factor analysis” and “Cronbach’s alpha”; ii) “data collection”, “correlation analysis”, exploratory factor analysis”, “Cronbach’s alpha”, regression model and artificial neural network” [14]. The steps help us to support the two waves of data collection procedure: first questionnaire and second questionnaire.

2.3. The data collection procedure

To collect the empirical data, our study employed a professional research company to collect the required data from stakeholders involved in the ecosystem services field. The invitation was sent to a random sample of stakeholders [15] (Study B). The data were collected at two different time points. In addition, we selected respondents who were demographically similar to the population to reduce bias in the sample [14]. Finally, the IP address was used to check and validate a unique respondent and prevent responses from the same stakeholder.

In the first wave, a total of 1,200 stakeholders accessed the link, an online survey, with 480 responses to the variables described in Study B. After that, we removed the missing data, and 442 responses were considered valid for future analysis. Its help us to move to the second wave.

In the second wave, after three weeks, the same respondents were invited to complete the second questionnaire again. A total of 328 respondents were valid for analysis, for a gross response rate of 74%. The unit of analysis of our study was several organizations connected with the ecosystem services field. The respondents should be knowledgeable about the business and key-decision maker profile. The statistical package for the social sciences (SPSS) software (v.29) was used on the analysis [16].

3. RESULTS

3.1. Analysis of the first wave (scale purification and initial validation)

3.1.1. Exploratory factor analysis

The Kaiser–Meyer–Olkin (KMO) test was used to the sampling adequacy to reduce the redundancy of the constructs to show their validity. The results (.947*) present a number of measures higher than 0.5 (communalities), indicating that factor analysis can be useful for the variability of the variable. In terms of the high correlation between the variables, Bartlett´s test of sphericity shows a significant impact on the number of variables suitable for factor analysis (>5/Sig.<,001) [17]. The factor loading for each construct ranged between 575 and 903, indicating good validity of the constructs. The total variance explained was 78%. Finally, principal component analysis and the varimax with Kaiser normalization show that the 14 interactions converged in terms of rotation [18]. The factors GOV11 and GOV12 were excluded from the analysis. After the factors were retested in the “analysis of second wave” section [19].

3.1.2. Internal consistency reliability analysis - cronbach´s test

Internal consistency refers to the reliability of a summated scale in which several items are summed to calculate a total score. The internal consistency results (.975) according to the value of Cronbach´s test (α>.7) [20]. The final constructs are summarized in Table 1.

3.2. Analysis of the second wave (measurement scale and analysis)

3.2.1. Correlation analysis

The second wave was dedicated to representing a construct-to-factor measure scale [21]. We proposed the factor correlation (item-to-total) method to measure construct validity [22]. The results indicated that the correlation analysis was positive, from moderate to strong and significant for all the following constructs: governance (R: 1), people (R: +.605*), planet (R: +.750*), cultural (R: +.642*), and spatial (R: +.603*). The confidence interval was 95%, and the estimation was based on Fisher's r-to-z transformation with bias adjustment [23].

3.2.2. Exploratory factor analysis

The KMO results (.952*) present the number of measures higher than 0.5 (communalities), indicating that factor analysis can be useful for the variability of the variable. Bartlett´s test of sphericity revealed a significant impact on the number of variables suitable for factor analysis (>5/Sig.<.001) [24]. The factor loading for each construct ranged between 581 and 908, indicating good validity of the constructs. The total variance explained was the same, at 78% [17].

Table 1. Scale properties of the measurement model

Variable	Factors
GOVERNANCE	GOV1: Successful adaptation entails steering processes of change through institutions, in their broadest sense.
	GOV2: The governance of adaptation is concerned with issues of equity in the outcomes of environmental decision-making.
	GOV3: Comprehensive understanding is achieved by open, shared information sources that fill gaps and facilitate integration.
	GOV4: Cross-sectoral analysis identifies emergent problems and integrates policy implementation.
	GOV5: Flexible and responsive to change.
	GOV6: Focused holistically on social–ecological interactions.
	GOV7: Well, informed by a diversity of perspectives.
	GOV8: Reflective in decision-making.
	GOV9: Innovative in problem-solving.
	GOV10: Collective aspects related to fishing behavior and attitudes that influence fishermen's involvement in local management.
	GOV13: Governance is polycentric and horizontal, with broad stakeholder participation.
	GOV14: Adoption of dynamic cooperation agreements that adapt to the changing needs of governance.
PEOPLE	PEP1: We have individual leadership and stakeholder dialogue$2 with a focus on social transformation.
	PEP2: I talk to my colleagues from population registry, regarding where new people have moved in.
	PEP3: Employ a mix of collaborative tools and spaces that considers the skillsets and competences of different target audiences.
	PEP4: Ensure that adequate training and support are in place to tackle existing barriers to inclusive cocreation processes.
PLANET	PLT1: The measurable and perceived impacts of development on subsistence harvest of fish.
	PLT2: Fishermen are flexible to changes in the community and/or to new rules defining use and access to the resources.
	PLT3: Predictable and unpredictable impacts of climate change are expected to affect marine systems and have direct effects on fish species.
	PLT4: The impact of change on species on the coast.
PROFIT	PRFT1: Financial resources are diversified using a broad set of private and public financial instruments.
	PRFT2: Better infrastructure leads to higher flexibility and learning generating economic alternatives.
	PRFT3: Introducing measures for mitigating resource scarcity issues and ensuring the human, financial, and technological resources needed at the municipal level to support governance.
CULTURAL	CULT1: Promote a culture of (open) innovation and experimentation in the public sector.
	CULT2: Make the decision-making process more visible through the use of reports.
	CULT3: Develop standards and technical regulations for ecosystem services.
	CULT4: Engage with local and supralocal knowledge-sharing networks that facilitate the acquisition and dissemination of key lessons on governance decisions.
	CULT5: Manage innovation partnerships by replacing (when possible) bureaucratic control measures with trust-based mechanisms.
	CULT6: Ensure political commitment and public sector leadership throughout the different phases of smart city transitions.
	CULT7: Introduce innovative procurement methods, such as long-flexible contracts, that fit with the implementation requirements of ocean ecosystem services projects.
	CULT8: Nurture an innovative culture and experimentation in the public sector.
SPATIAL	SPAT1: Employ a space that considers the skillsets and competences of different target audiences.
	SPAT2: Discuss decisions with different neighborhoods in terms of impact.
	SPAT3: Identify several key capabilities that facilitate the application of geographic decisions.
	SPAT4: Avoid fragmentation of local policies for the governance of ecosystem services.
	SPAT5: Discuss the impact of being together in specific spaces with different approaches.
	SAPT6: Promote analyses focused on the role of area, place, and location.
	SPAT7: Develop standards and technical regulations for ocean ecosystem services data collection.
	SPAT8: Provide information about the spatial location for sharing decisions.
	Total of items: 39

3.2.3. Internal consistency reliability analysis

The internal consistency results (.976) according to the value of Cronbach´s test (α>.7) [18]. Also, the test presents good reliability for the constructs. Then, help us to test the factors in the classic linear regression model.

3.2.4. Classic linear regression model

A classical linear regression model was used to assess the constructs [25]. The model estimation was developed using ordinary least squares regression (OLS) [26]. Before the OLS was applied, the normality of the data was confirmed using a P-P plot with the Kolmogorov–Smirnov (K–S) test [27]. The results showed a normal distribution and no outliers (-3,0 minimum and 2,5 maximum). The model presented the variables entered (spatial, planet, profit, people, and cultural) as independent variables and (governance) as the dependent variable. All the requested variables were entered. The independence diagnosis (nonautocorrelated residuals) was tested using the Durbin-Watson test and showed a significant difference between 1,5 and 2,5 and near 2,0 (1,660, Sig<.001). The R2 indicated that the variation was (672) or 67%. Following the homoscedasticity diagnostic test, the results show homoscedasticity, with a sequence of random variables [28]. In terms of multicollinearity [29], the results were consistent with those of the variance inflation factor (VIF) and tolerance analyses: people (VIF 2,379/tolerance, 420); planet (VIF 1,913/tolerance, 523); profit (VIF 2,262/tolerance, 442); cultural (VIF 3,718/tolerance, 269); and spatial (VIF 3,734/tolerance, 268). The constructs that best represented the model in terms of explanatory importance (β) were planet, profit and culture.

3.2.5. Artificial neural network model

The model was developed to confirm the second time the constructs were assessed [25]. A multilayer perceptron (MLP) was used as a technique. In a neural network, the variables are randomly selected for training and testing [30]. The summary of case processing was composed of 228.69.5% (training) and 100.30.5% (testing), for a total of 328 valid responses (100%). The network was built based on several characteristics. The input layer was composed by five variables: people, profit, planet, cultural, and spatial. The output layer represents the model's dependent variable, Governance. The model was approached by hiding the bed and the hyperbolic tangent acting on the activation function, interval (1,1). The neural network was measured by the error function [29]. The synaptic weights that explain the variables associated with the appropriate neural network settings are shown in Figure 2. Additionally, a mathematical description of an artificial neural network is presented in the following formula:

$$Y=f^{(o)}(W^{(L)}\cdot f^{(L-1)}\ (f^{(2)}\ (W^{(2)}\cdot f^{(1)}(W^{(1)}\cdot X+b^{(1)})+b^{(2)}))+b^{(L)})$$

where X is the input data, L is the number of layers, $W^{(i)}$ represents the weight matrix for the connections between the ith and $(i-1)$th layers, $b^{(i)}$ the bias vector for the ith layer, $f^{(i)}$ is the activation function applied at the ith layer, and Y is the utputdata.

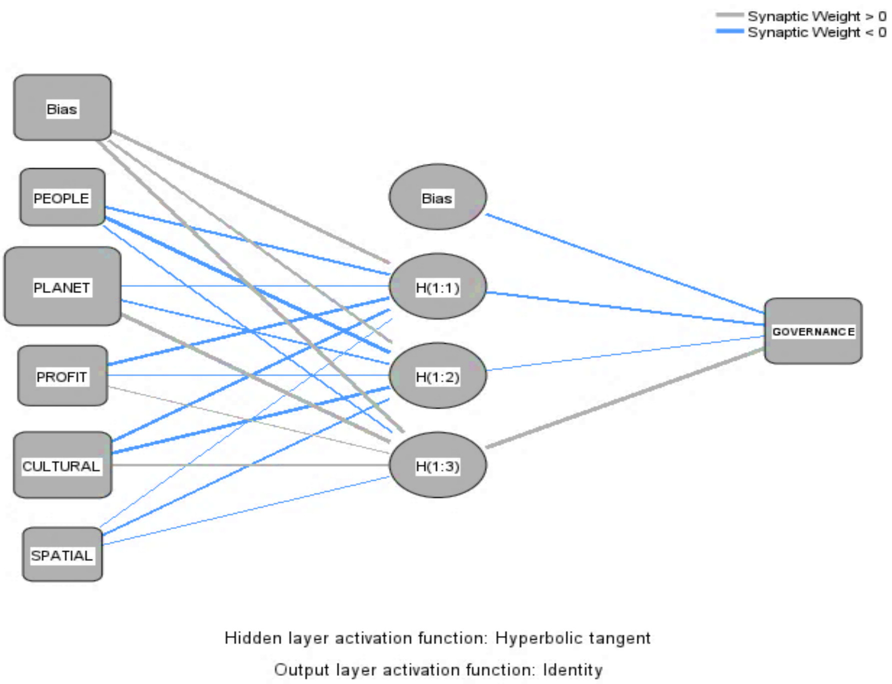

Figure 2. Flowchart of the AI-based models and experimental methods applied

The Table 2 show the results of the predicted mode. The predicted input layer values were processed using a standardized approach between -1 and 1, an association value. In terms of the predicted error, the model assumes a value of 355 (35%), which, in addition to being considered relatively low, demonstrates how the artificial neural network significantly predicts the Governance variable. For the validation of the model presented, Figures 3 and 4 show the behavior of the predicted value, taking into account the residual value. The linearity of the predicted values to the observed values can be seen in Figure 3, according to the linear arrangement of the points.

Table 2. Synaptic weights (parameter estimates) of the predicted modes

Predictor	Forecast			
	Hidden Layer 1			Output Layer
Input Layer	H(1:1)	H(1:2)	H(1:3)	GOVERNANCE
(Bias)	.613	.440	.649	
PEOPLE	-.415	-.673	-.267	
PLANET	-.116	-.278	.962	
PROFIT	-.538	-.238	.113	
CULTURAL	-.527	-.551	.268	
SPATIAL	-.087	-.283	-.003	
Hidden Layer 1				
(Bias)				-.300
H(1:1)				-.310
H(1:2)				-.038
H(1:3)				.963

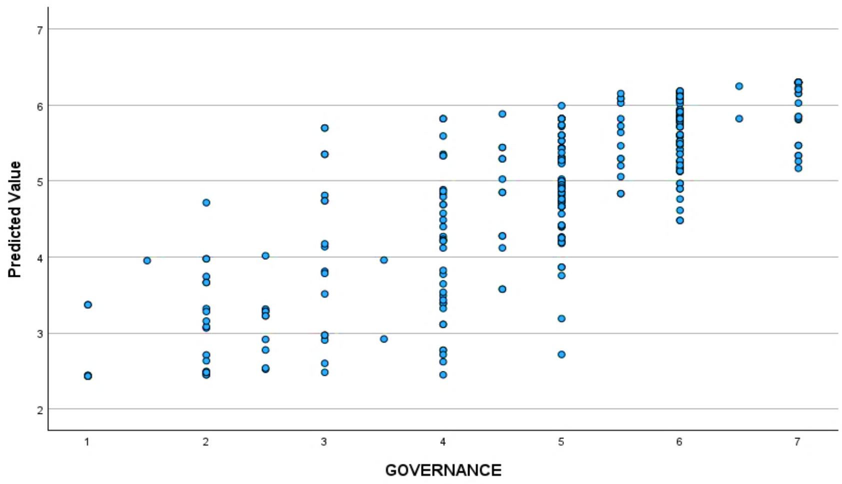

Figure 3. Diagram of predicted values

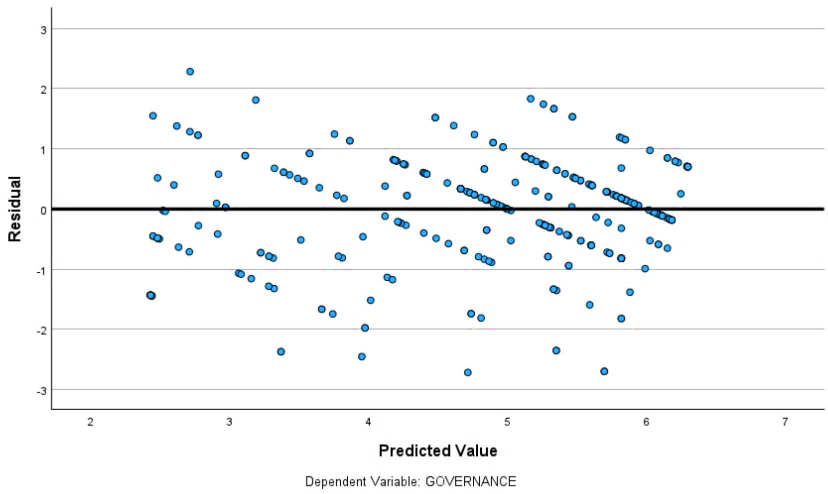

Figure 4. Diagram of the residuals per prediction

Considering the contribution of the independent variables to the model construction, the planet construct is the most representative of the network in terms of predictability, with a value of .491 (49%), followed by cultural, with a value of .255 (25%); profit, with a value of .145 (14%); people, with a value of ,088 (8%); and SPATIAL, with a value of ,021 (2%). With regard to the relevance of the dimension for the model, the training and test values show that the PLANET construct was 100%. While the other constructs were used as follows: cultural (51.9%), profit (29.6%), people (17.9%), and spatial (4.2%).

4. DISCUSSION

Recent studies on ecosystem services studies show that deep learning is changing the way of decisions are taking. This study investigated how can we increase the sustainable decisions of ocean ecosystem services governance. White recent studies focused on detection of rockfish in challenging underwater environments [4], detection of coastal erosion [5] and soil type prediction [6], they have not explicitly addressed its support the governance of ocean ecossytems services increase the value of decision-making processes.

We found that relationships between six variables and factors measurement sustainable governance decisions in ocean ecosystem service. The variables correlated, explain, and validate six constructs, like governance, people, planet, profit, cultural, and spatitial. We found five independent variables and one dependent variable (governance).

The proposed methods show that the same variables are correlated in terms of results. Its mean that, the results in artificial neural network present the variables "planet", "cultural", and "profit" as the main contribution. While in classical linear regression, the importance of variables was "planet", "cultural", and "profit". The others change in terms of sequence, but the variables still the same in both techniques applied. Its help to governance of ocean ecosystems be adequate and effective in terms of management efficiency to sustainable decisions.

Future studies may explore the scale in different applications of ecosystem services. In addition, a model with scale and factors could be development to measure the decision-making process in other countries in Europe or outside. In addition, studies can include a new variable create other approaches. Finally, the solutions proposed could be tested with another artificial intelligence technology.

5. CONCLUSION

The use of artificial neural networks (deep learning) combined with classical linear regression helped to validate the decision scale for ocean ecosystem services, guaranteeing a solution for governance in terms of future decisions. Ensuring the reliability of the scale became a concern due to the number of factors and the complexity of the process, from its initial phase dedicated to constructing the factors. In addition to considering the feasibility of scaling through deep learning associated with the classic linear regression technique, this study reinforces the importance of predicting decisions, creating a predictive approach to forecast possible outcomes based on the decisions of various key decisions-makers. The application of decision scaling to ocean ecosystem services can be considered a useful way of increasing the assertiveness of decisions, as it can significantly reduce the time invested in decision-making discussions by governance.

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