An Intelligent Environmental Plan for Sustainable Regionalisation Policies: The Case of Ukraine

Abstract
This paper introduces an environment-driven, artificial intelligence model for sustainable policymaking in European countries, with a focus on Ukraine. It develops regional clusters using artificial neural networking; then, it dynamically optimises budgeting allocations. It is a hybrid, environment-driven model that clusters regionalised-data using Kohonen's self-organising map and optimises budget allocations using the simplex-modified distribution method (U-V MODI). Model benefits focus on regional public policies, environmental development, and core-periphery balanced growth. Results reveal an innovative plan that activates the participation of environmental stakeholders in public policymaking, reforms regions based on set sustainability criteria, and optimises regional funding.

Keywords: Environmental planning, sustainable public policy, environment-driven regional policies, artificial neural network methodology

1. Introduction

Politically biased regionalisation employs a unilateral hierarchical distribution of resources that strengthens centralised economic policies. Such comprehensive public policies jeopardise horizontal patterns of environmental governance in the European Union (EU) (Dąbrowski, 2014). It is important to consider sustainable infrastructure organisation that is focused on a transparent, environment-driven diffusion of capital resources (Wren, 2009). In the current EU austerity era, a sustainable approach to environmental planning is motivated by the depletion of natural resources, the lack of regional funding (Martinez-Garcia and Morales, 2019), and existing socioeconomic imbalances in Ukraine and other European countries (Gløersen et al, 2019). These three motivational indicators have caused significant national and international shifts toward centralisation in public policies regarding environmental planning. Ukraine has suffered from non-transparent administrative public policies. Currently, sub-optimal socioeconomic practices in regional public administration and post-Soviet environmental policies still form an obstacle to sustainable Ukrainian growth (Pokutsa & Burak, 2016).

New planning tools and methodologies should reform the on-going difficulties regarding EU cohesion policies. Planning models should provide a scalable process of decision-making for implementing environmental public policy (Knights et al., 2014). Public policy planning with sustainable design should integrate the economic, environmental, and social dimensions and consider many different decentralised forms of development (Ezcurra & Rodríguez-Pose, 2013). Biased environmental planning is limiting the diversity of managerial perspectives regarding green spaces, nature, hydro resources, air quality, and rural well-being (Burak, 2015). Therefore, by emphasising the knowledge domain of environment-driven planning and public policymaking, this paper focuses on essential sustainability cluster indicators that diverge from current regional planning processes.

The aim of this paper is to explore the dynamic relationship between budget-constrained regionalisation and environment-driven development. It formulates an innovative policymaking model, adopting artificial neural networks (Lein, 2009) and self-organising map algorithms (Konohen, 1989) to form new sustainable regions. Then, it optimises regional funding using a simplified simplex method (U-V MODI) (Limbore, 2013). As a result, it limits the negative environmental effects of current budget constraints, aiming to preserve the EU's regional public policy.

Historically, several environmental and economic studies relate to this paper's research aim. Many of these studies focus on European micro- and macro-economic policies, which are endangering the Europeanisation process (Broadhurst, 2018). Contemporary research indicates that regional resource availability and flexibility in environmental planning are the most important factors for sustainable development (Gløersen et al., 2019). In alignment with our artificial intelligence (AI) model, we also examine contemporary studies of interactive relations among the 'triple bottom line' parameters for a sustainability framework (Breslow et al., 2018). In addition, Kyriacou et al. (2017), investigate general regional inequalities regarding the transition from bureaucratic to post-bureaucratic public policies. They argue that European countries' economic development is pursued mainly through downsizing measures for fiscal stabilisation (Cepiku & Mititelu, 2010). Similarly, other studies shift the focus from the centralisation to the localisation of environmental development (Mykhnenko & Swain, 2010; Pike et al., 2017). Finally, other core-periphery models by Rauscher (2009) and Catalano et al. (2016) investigate regionalisation through the lens of environmental pollution and its impact on the economy.

Our environment-driven regionalisation model is innovatively different from the aforementioned models. Using AI, it aims to form novel, environmentally focused clusters and redistribute national funding accordingly. It differs from the existing models by deviating from the original Tulsian algorithm (2006), the Angenent algorithm (2003), and the Reeb and Leavengood (2018) algorithms. By combining the artificial neural network (ANN) and self-organizing map (SOM) algorithms, also employed by Chaudhary et al. (2014) and Faezy and Shadloo (2016), we prioritise regional funding policies to provide an innovative solution to environmental and socioeconomic obstacles. Similar to Tiwari (2006), we take a completely different approach to regionalisation policies by integrating environmental development with the funding of socioeconomic schemes.

The advantage of the proposed model for academic research is the co-existence of AI and a form of simplex method. Simultaneous adoption of intelligent neural networking and liner programming solves current obstacles to regionalisation policies by re-distributing central funding. By doing so, we sustainably optimise the regional budgeting of the newly formed clusters. In relation to policymaking, the model’s advantage is the implementation of impactful environmental indicators for sustainable regional policies. As a result, our model advances clarity regarding the "rules of the game" for all stakeholders, budget distribution transparency for environmental planning, and dynamic interaction among regional stakeholders and natural resources.

Since the early 1990s, Ukraine's revolving national budget deficits have led to systemic micro- and macro- socioeconomic blockages and centralised public policies (Tsimbos et al., 2011). This budget allocation policy preserves centralism, limiting rather than strengthening sustainable regionalisation in central and eastern European (CEE) countries (Schmidt et al., 2018). In addition, such policies restrain current regional consumption levels of natural resources in favour of optimal economic valuations according to centralised public policies (Jung, 2018).

Reflecting on our study of hydro-economic imbalances in Ukraine, the trivial distribution of public funding has the potential to create ecological disasters for water supply networks (Papagiannis et al., 2018). Ukraine is a large country. In Ukrainian legislation, the term 'region' is frequently used to identify the territories of administrative areas centred on large regional cities (Pike et al., 2017; Constitution of Ukraine, Chapter IX: Territorial Structure of Ukraine, Article 143). Budget constraints confirm the status of each economic centre, reinforcing over-centralised core-periphery funding (Rodden et al., 2003, Hajkowicz, 2009). Recently, with the emergence of international economic crises, budget constraints raise the problem of inefficient regional policies and inadequate funding allocations (Singh & Zammit, 2006; Dabrowski, 2014; Kyriacou et al., 2017). Most of the CEE countries, including Ukraine, demerit environment-driven regional planning, primarily because national reforms entail a very broad public policy agenda (Matei & Andrei, 2009). CEE countries' agendas principally focus on the regional allocation of economic resources and competitive clusters, subject to national public policy thresholds (Isaksen, 2009). This is also evidenced by the concept of the ecological footprint (Nijkamp et al., 2004), which offers an alternative approach to the environmental development of Ukrainian regions.

In our paper, we develop an artificial inteligent two-phased, environmental model of sustainable development that is subject to the level of availability of regional-based natural resources. We prioritise environment-driven indicators, which include the land area of the natural reserves and national natural parks, green space areas for public use, air emissions, and raw water availability by region. We also incorporate economic indicators that include all capital-related investments for environmental protection. Finally, socially focused indicators include regional policy innovation with respect to the green economy and regional stakeholders' well-being.

The first phase of this model is to consider and normalise regional resources according to the environmental and socioeconomic indicators (see Table 1) in order to form sustainable clusters. This initial clustering phase classifies data from resource-based indicators into newly formed clusters that are subject to the constraints of local and neighbouring regional resources. More specifically, with the first phase of this model, we distribute the sustainable indicators, as vectors of similar characteristics, to all current neighbouring clusters to form a newly sustainable one. Similar multiple modelling approaches (Barrio et al., 2006) are used to predict the potential impacts of climate change on species' distributions.

The second phase of this model optimises the effects of the 'triple bottom line' of sustainability—environmental, social, and economic—within the newly formed clusters. As part of this, environmental indicators could intelligently contribute by balancing the availability of regional resources. Thus, we could potentially deviate from the current politically biased public funding policies (Pike et al., 2017). Our model results also highlight an environmental plan that hierarchically relates to diverse socioeconomic values.

The novelty of our environmental model is that our cluster formations are targeting simultaneously to regional socioeconomic policies and sustainability needs of the rural stakeholders. Our AI design for environmental planning provides an integrated public policy perspective based on regional indicators. Therefore, our model's innovative approach contributes to the active participation of regional stakeholders in policymaking and potential collaborations among European countries (Wilshusen & MacDonald, 2017). Our hybrid model is designed for efficient environmental planning that recognises the dynamics of socioeconomic well-being (Smetschka & Gaube, 2020).

In brief, the methodological contribution of this paper is to enrich the range of environmental science and policy methods, providing fertile grounds for sustainable growth optimisation based on a contemporary central government funding policy for CEE countries. The study's impact is also particularly important for current centralised environmental planning policies, where lack of regional coordination is prominent (Schmidt et al., 2018; Schmidt, 2013; Rodhe & Strahl, 1995).

Sustainable national thresholds in Ukraine should support a bilateral public policy system to preserve the environment and ensure 'safe' living conditions (Mykhnenko & Swain, 2010). Internationally, while the EU remains a centre of economic wealth, the nature of sustainable development reveals significant socioeconomic imbalances. A dynamic combination of environmental quality and socially responsible behaviour that values the sensible consumption of regional resources should underlie our research questions.

Therefore, we are motivated to an integrated environmental elevation, for all 24 Ukrainian regions, to the optimal sustainable national thresholds. The following are our research questions:

Research question 1: Are current public regionalisation policies best for environmental planning and sustainable development?

Research question 2: Is it possible to plan environment-driven sustainable development by clustering regions according to the availability of their natural resources?

Research question 3: Is it possible to optimise regional budgeting policies by coupling our environment-driven indicators to public budget constraints?

In short, we consider our model to be a hybrid, as the scientific methods adopted simultaneously enable linear algorithms and intelligent neural networking.

2. Methodology and Data

The research methodology is informed by our systematic approach, both qualitative and quantitative, and was developed by the authors through a lengthy and complex communication process. The data-input for our model parameterisation refers to the official data in the annual statistical digest ‘Environment of Ukraine’ (Statistical Yearbook: Environment of Ukraine, 2016). Figure 1 illustrates our research approach.

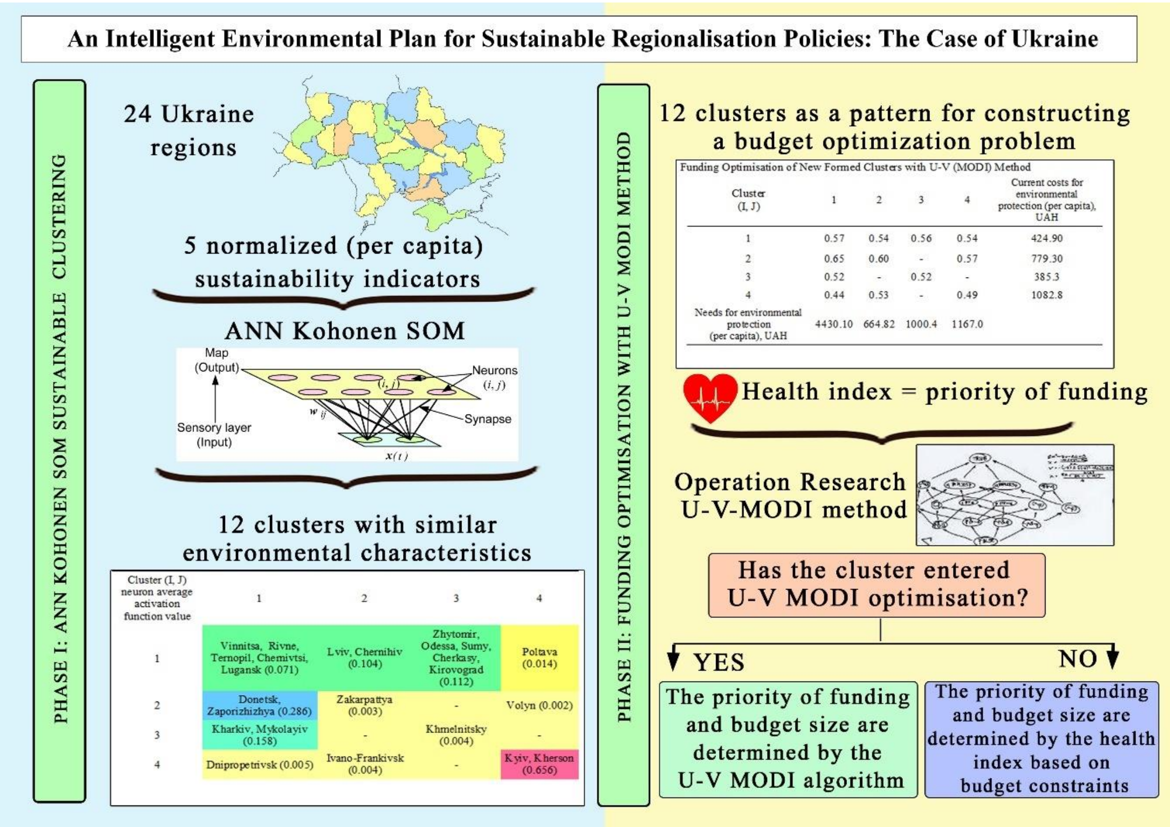

Fig. 1. The research approach

At model phase one, according to our first research question, we are employing an artificial neural network (ANN): Kohonen's self-organizing map (SOM) algorithm (Faezy Razi & Shadloo, 2016). An ANN is a computational methodology, which allows unsupervised learning and produces a low-dimensional, discrete representation of the training samples' input space. As a result, it identifies each neuron in a unique location (row, column) on a two-dimensional space forming a SOM map (Chaudhary et al, 2014). An important reason for selecting Kohonen's ANN methodology is that it features maximum transparency and objectivity. Therefore, the result of training depends only on the structure of the input data (e.g., environmental indicators), eliminating any externally biased policymaking (Rumelhart et al, 1986).

In our Ukrainian input data, from 2010 to 2016, we select generally accepted environmental and socioeconomic impactful criteria that include availability of: i) green spaces; ii) air purity; iii) water resources; and iv) natural reserves (Statistical Yearbook: Environment of Ukraine, 2016). We use as input data these selected regional criteria, focusing on the natural resources' availability level, to form optimal environmental and socioeconomic clusters. We normalise these seven-year-long input data, adjusting values measured on different scales to a notionally common scale, using the Statistica 12.0 software tool.

Thus, we produce a novel, multi-shape, output data-clustering map, which graphically represents our research analysis, according to SOM (Kohonen, 1982). The colour indicates the value's magnitude, relating to the specific weight component of a vector. The vector's weight is indicated from a neuron *(i, j)* that specifies a particular node on the SOM map (Kohonen, 1989). As a result, our input data defines the: i) topological relations; ii) activation function; and iii) number of neurons, which determine the scale, the colour or the granularity of the resulting model.

At model phase two, according to our second and third research questions, we optimise our clustering maps. This multi-nodal optimisation method aims to plan sustainable regionalisation, considering regional environmentally focused resources, as resulted from model stage one. Although, it is subject to two mutually inclusive algorithmic constraints. The first constraint refers to the multi-directional ‘movement’ of the spending of budget funds in SOM clusters. Contrary to the current core-periphery unidirectional budget allocation, SOM method allows multi-directional and multi-level budget allocation. The second constraint refers to the budget-constrained public policies’ approach that currently reflects the country’s economic plans. It allows budget allocation according to the selected environmental indicators (input data at phase one) lifting existing regional budget caps. Therefore, these two original model constraints form a type of transportation problem, which is common in linear programming (Reeb & Leavengood, 2018). Consequently, we employ a U-V MODI (modified distribution) method, which allows us to prioritise and determine the budgeting stages and the flow of funds (Dantzig, 1947; Limbore, 2013). Subject to the two constraints introduced in the phase two model, it enables dynamic interaction among our newly formed regional clusters. In addition, we adopted the U-V MODI method, rather than the simplex method, as it provides the optimal funding distribution numbers and the “stage-by-stage” order of their distribution. A step-wise methodological process is critical for environmental policymaking (Knights et al., 2014).

Therefore, in accordance with our second research question, we optimise budget costs for environmental funds distribution from a number of ‘supply’ sources to optimise a number of ‘demand’ destinations, subject to budgetary constraints (Tulsian, 2006). As a result, we multilaterally cluster the Ukrainian regions following a type of environmental funds ‘transportation route’. This ‘transportation route’, based on a type of simplex method (U-V MODI) (Tiwari, 2006; Reeb & Leavengood, 2018), identifies demand cells (e.g., cells with their required costs for environmental protection per capita), and supply cells (e.g., actual capabilities of regional budgets), thus breaking down the actual costs incurred for sustainability-driven regional policymaking.

Finally, in order to satisfy our third research question, we simultaneously set a new minimisation objective function. This linear function minimises the total budget expenditures of central government. It creates a budget surplus from central funding policies, which we re-direct to regional economies. Thus, we maximise regional development based on central funding availability. This methodological approach contradicts the existing normative one, where regional developmental policies derive solely from regional funding. For optimal central government budget allocation we now set the health index in neuron *C (i,j),* as the cluster's optimal distribution priority criterion. We formulate the objective minimisation function according to our U-V MODI algorithm (Babu et al, 2014). In this way, we are employing a linear function (see function 8) that aims to minimise the total expenditures from central government budgeting policies (Singiresu, 2009).

Our methodological approach innovatively reforms regional funding policies, as instead of selecting the lowest cost indicator in the formed clusters, it selects the lowest environmental and social indicators (e.g., average health index/region) that comply with our objective function of budget cost availability (see Table 4). In addition, we source the regional funding from a central surplus, which we methodologically form, based on our minimisation function. As a result, we prioritise novel clusters with low environmental indicators in an effort to satisfy the triple bottom line of sustainability (Wilshusen and MacDonald, 2017).

There are although certain limitations in our research. Firstly, there is an evident public policy need for wider and on time availability of environmental and social indicators in the Ukrainian regions to strengthen further our model. Secondly, the SOM scale selection is limited to the generalisation capability of the ANN algorithm and the SOM map produced. Thirdly, the SOM mapping juxtaposes generalisation and accuracy capabilities. Consequently, research studies (Kiang, 2001) recommend using the maximum possible number of neurons in the map, as the initial SOM radius of neuro-training greatly affects the capacity for generalisation. Our scientifically acceptable compromise focuses on the actual number of SOM nodes (e.g., 24 Ukrainian regions).

3. The Model

Our environment-driven model for all Ukrainian regions is a dynamically parameterised place-based design for regional policies. Unlike natural systems, regional and urban ecosystems are not self-regulating and self-reproducing. Therefore, central and regional public policies formulate and implement territorial balance and development through specific means of regulation. Our *two-phase* model engages in the first phase the Kohonen's ANN and SOM method. In the second phase, it engages the U-V MODI algorithmic method simultaneously introducing a minimisation function.

The *first phase* of our planning model employs an algorithmic logic that relates our input data to the clustering process. Table 1 includes the model's input data, which are the 5 prominent environment-driven indicators for the 24 Ukrainian regions. The 5 indicators are: i) ecological purity of the land area; ii) the green places for public use; iii) the quality of drinking water; iv) air pollution; and v) the environmental funding in the region.

More specifically, in this first phase we enter, as input data, these 5 indicators (see Table 1) to the Kohonen's SOM algorithm. We ensure normalisation by reducing the input data attributes' values to a confident interval of *Cij*. Consequently, this self-learning algorithm (SOM) through multiple iterations, introduces newly formed clusters of *Cij* data, according to the 5 environmental indicators introduced. Each newly formed cluster of *Cij* identifies a unique location, where row and column represent a two-dimensional space (see representation in Table 2). During creation and training, this self-learning intelligent algorithm forms a data array that includes the following input data attributes' values: i) neuron ID; ii) neuron location in the clustering map; and iii) the value of the activation function in accordance with the incoming data. The SOM training goes through the following three main processes in order to create the new clusters. The first process is *competition*, the second is *cooperation* and the third is *adaptation* (see SOM progress in Appendix A). The clustering results of this intelligent reformation are exhibited in Table 2.

Concluding the first phase of our model, we construct a neutral space to introduce the 12 newly formed clusters. These 12 clusters are created from the integration of two or more regions, according to the 5 environmental indicators introduced (see Table 1). Our AI clustering approach, according to Kohonen's SOM, defines space by the neurons' average activation function values (e.g., i, j). We display these 12 novel clusters in red-green-blue (RGB) colour in Table 2 and all summary clustering data in Table 5. Now, in Phase II these 12 environment-driven clusters enter the second and final reformation stage of optimisation. The optimally produced number of 12 clusters in Phase I is even. Therefore, in Phase II, we satisfy the U-V MODI method optimisation requirement for an even number of cells (see Table 3).

Through the prism of the current EU economic crisis, our economic optimisation in *phase II* can inform a constrained core-peripheral policymaking for reducing costs in regional budgets. Therefore, it eliminates non-optimal financial directions. Instead, it identifies priority areas for rural environmental development by simultaneously eliminating the budget gaps between the actual, extant budget costs and the required budget costs.

This formation is a variation of the transportation problem, where in logistics we simultaneously calculate the minimum transportation costs of goods and the optimal allocation of resources. It is a frequently adopted method in several scientific knowledge domains, including environmental engineering (Adhikari, 2014). This linear programming formulation is known as the Hitchcock-Koopmans problem (Singiresu, 2009). Thus, we engage the U-V MODI method to solve this optimisation problem. We already have 12 clusters based on the 5 environmental indicators, which we need to optimise. The optimisation criterion is formed from an additional 6^{th} indicator, which is the health index/region (see Table 6). It is the actual measurable result of the 5 environmental indicators forming our 12 clusters (see Table 2). Consequently, according to the annual healthcare report in 2016, the health index/region indicator reports the regional average healthcare condition (Ukrainian Ministry of Health, 2017). This 6^{th} indicator accumulates a value, which is pertinent to our 5 environment-driven indicators, and inversely proportional to regional malady status (*1/n*), where *n* is the average annual number of illnesses/region (Ukrainian Ministry of Health, 2017).

Therefore, we prepare an input data and clustering results (12 clusters) for our U-V MODI method in a matrix formation (see Table 3). In this second phase of our intelligent model, we consider *phase I* results as input data that facilitates the selection of regional priorities. A transparent creation of a financing policy that embraces the following mandatory requisites per regional cluster: i) current costs for environmental protection; ii) required budget costs for environmental protection (needs); and iii) optimisation criteria. As a result, among the 12 clusters, we prioritise for regional funding the clusters with the minimum health index.

In accordance with the U-V MODI method, we verify the economic optimality of the newly formed clusters (see Table 7) by introducing a linear programming function for prioritised funding in phase II. This function aims to eliminate the budget gaps between the current budget costs and the required budget costs, as follows:

$$f(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} X_{ij} \rightarrow min, X_{ij} \geq 0 \qquad (1)$$

where X_{ij} - the amount of funding from the budget in *i, j* cluster,

C_{ij} – an optimisation criterion for a cluster.

In accordance with the linear programming formula, variables: x_{11}, x_{12}, ..., x_{44} – denote the amount of funding from the budget in Xi,j cluster . Therefore, we have the linear formation of limitations on current budget costs, as follows:

$x_{11} + x_{12} + x_{13} + x_{14} \leq 424.90$ (for $i = 1$ clusters); $x_{21} + x_{22} + x_{23} + x_{24} \leq 779.30$ (for $i = 2$ clusters); $x_{31} + x_{32} + x_{33} + x_{34} \leq 385.3$ (for $i = 3$ clusters); $x_{41} + x_{42} + x_{43} + x_{44} \leq 1082.8$ (for $i = 4$ clusters).

Consequently, the clusters' budget funding is formed as follows:

$x_{11} + x_{21} + x_{31} + x_{41} \leq 4430.10$ (for $j = 1$ clusters); $x_{12} + x_{22} + x_{32} + x_{42} \leq 664.82$ (for $j = 2$ clusters); $x_{13} + x_{23} + x_{33} + x_{43} \leq 1000.4$ (for $j = 3$ clusters); $x_{14} + x_{24} + x_{34} + x_{44} \leq 1167.0$ (for $j = 4$ clusters).

Finally, we formulate, as follows, the target function considering the sole matrix cells, where there is cluster availability:

$$f(x) = 0.57x_{11} + 0.54x_{12} + 0.56x_{13} + 0.54x_{14} + 0.65x_{21} + 0.60x_{22} + 0.57x_{24} + 0.52x_{31} + 0.52x_{33} + 0.44x_{41} + 0.53x_{42} + 0.49x_{44} \rightarrow min \qquad (2)$$

More specifically, in cluster ID column we have the region of (1, 2) Lviv, Chernihiv. This region, as introduced in Table 7 and according to U-V MODI method, exhibits a value of 0.54 [424.90]. Therefore, in Table 3 the lowest average health values per cluster of Table 6: 0.44, 0.52, 0.54, 0.57 are prioritised as first funding priority in Table 3, including (1, 2) Lviv, Chernihiv that requests funding of 424.90 for environmental protection. Consequently, we aim to methodologically ensure optimal funding, for this prioritised group of four clusters in Table 7, indicating the redistributed funds in the following sign: '[ ]'. So, on the one hand we have these four priorities (1-4), including: (4,1) Dnipropetrivsk, (3,1) Kharkiv and Mykolayiv, (1,2), Lviv and Chernihiv, and (2,4) Volyn. On the other hand, we have clusters like (4,4) Kyiv, Kherson, which we eliminate through this U-V optimisation. The reason for that elimination is the funding surplus they currently receive (115.56%), as our threshold funding value is set to 100% (see Table 3).

The results of our environment-driven regionalisation model provide a series of interesting findings.

4. Results

Our findings provide overwhelming evidence that a mutually inclusive, balanced existence can be obtained by averaging sustainable cluster values according to our AI model. The U-V MODI algorithmic results reveal a sustainable regional design. The following are the model findings and results per phase:

Phase I Results.

As the algorithmic U-V MODI optimisation process pairs actual funding with requested funding, we notice a significant reformation. We find that the 24 Ukrainian regions (see Table 1) are integrated into 12 novel, environment-driven clusters. These are as follows: (4,1) Dnipropetrivsk (funding priority = 1); (3,1), which is a merger of Kharkiv and Mykolayiv (funding priority = 2); reformed (1,2), which is a merger of Lviv and Chernihiv (funding priority = 3); and reformed cluster (2,4) Volyn (funding priority = 4). The remaining clusters (5-12) are left out of the optimisation process, as these rule-based iterations selectively consider all table cells (see Table 7). Therefore, we ensure optimal regional sustainability by initiating the optimisation process with the smallest health index, 0.44, cluster (4,1) (see Table 6). Simultaneously, we redistribute funding as we set the minimum threshold a_i, or b_j that is paired with the corresponding cell to 100%, eliminating extra funding. In addition, cluster ranking with networked priority allows us to discover rural environmental leaders and those who are lagging behind.

Currently, the weakest regions in health index, like (4, 1) Dnipropetrivsk, receive funding for environmental planning at 514.60 UAH/per capita. Unfortunately, this is only 30.3% of what regional stakeholders require (1696.90 UAH/capita). Based on their health index of 0.44, which is the lowest in the country, their regional well-being clearly needs sustainable improvement (see Table 4). Our model with the U-V MODI optimisation algorithm prioritises this region's funding. It provides Dnipropetrivsk with funding in the amount of 1082.8 UAH/capita. This amount is more than twice its current funding, approaching 63,8% of its funding requirement. Correspondingly, the optimisation algorithm produces novel funding hierarchies for all 12 environment-driven clusters (see Table 4).

Phase II Results.

Entering phase II, we noticed that all of the reformed clusters that entered the optimisation process could potentially receive a maximum of 100% budget coverage, as we eliminated any regions with excess funding (more than 100%). Additionally, our model ensures current budgeting for all regions, besides their sustainability profile (see Table 6, changes in coverage column); we notice several regions receiving zero extra budgeting due to their low priority coefficient. As a result, we have minimised core-peripheral funding imbalances in Ukraine by eliminating overfunded regions like (4,4) Kyiv, Kherson, which includes Kyiv, the capital of Ukraine (see Table 6). In addition, we could further explore the progress of the final results with this indicative example: cluster (2,4) Volyn (see Table 7) receives 779.30 UAH/capita but only requires 109.80 UAH/capita (see Table 6, Volyn). Consequently, in accordance with our linear formation of limitations on actual budget costs, the 669.5 UAH/capita in excess funding (779.30-109.80 = 669.5 UAH/capita) $x_{21} + x_{22} + x_{23} + x_{24} \leq 779.30$ (for $i = 2$ clusters) is distributed among the two remaining clusters (see Table 3). These clusters are cluster (2,2) Zakarpattya and cluster (2,1) Donetsk, Zaporizhizhya. Cluster x_{23} is not in the pattern (see Table 3). Therefore, we allocate the first available budgetary funds to cluster (2,2) Zakarpattya (102.56 UAH/capita) and then cluster (2,1) Donetsk, Zaporizhizhya receives (669.5 - 102.56 = 566.94 UAH/capita, 764.4+566.94 = 1331.94 UAH/capita (see Table 4 results).

The results seem promising for sustainable policymaking, since, according to linear optimisation rules, any failing cluster that exits the process offers its funds to the existing participating clusters with environmental funding requirements. Therefore, clusters and regions that did not receive any funding while optimising (see Table 7) will receive funding on a residual basis, based on the *Phase I* environment-driven indicators and health index from 5-12 (see Table 4). Table 4 allows us to synoptically scrutinise our reformed U-V MODI process (see Tables 3 to 7). We graphically exhibit the impact of our intelligent model in percentage of budget covered in Figure 2.

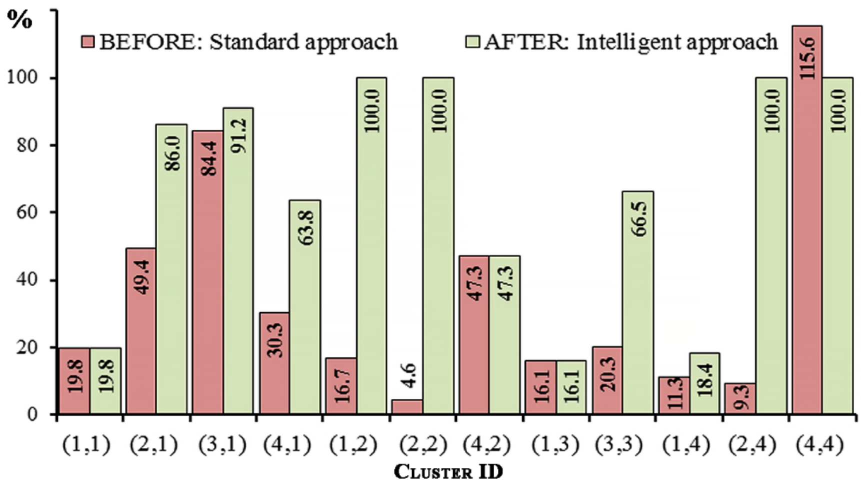

Fig. 2. Environmental planning: Before and after situation

Our model results exhibit the elimination of excess funding in certain regions, especially when others remain significantly underfunded. Therefore, as the results show, all regions secure 100% of their environmental funding. According to this planning approach, out of the 12 reformed regions, which were produced from the 5 environmental indicators, 9 increase their funding, 2 sustain their current funding, and only 1 receives less funding due to the excess funding (more than 100%) already received. Findings reveal a dynamic sustainable prioritisation, which encourages substantial changes in European and Ukrainian regional policies, based on the availability of impactful natural resource indicators (Qaderi & Babanezhad, 2017). Finally, the pre-eminent elements of this novel method's results and findings are graphically summarised in Figure 3.

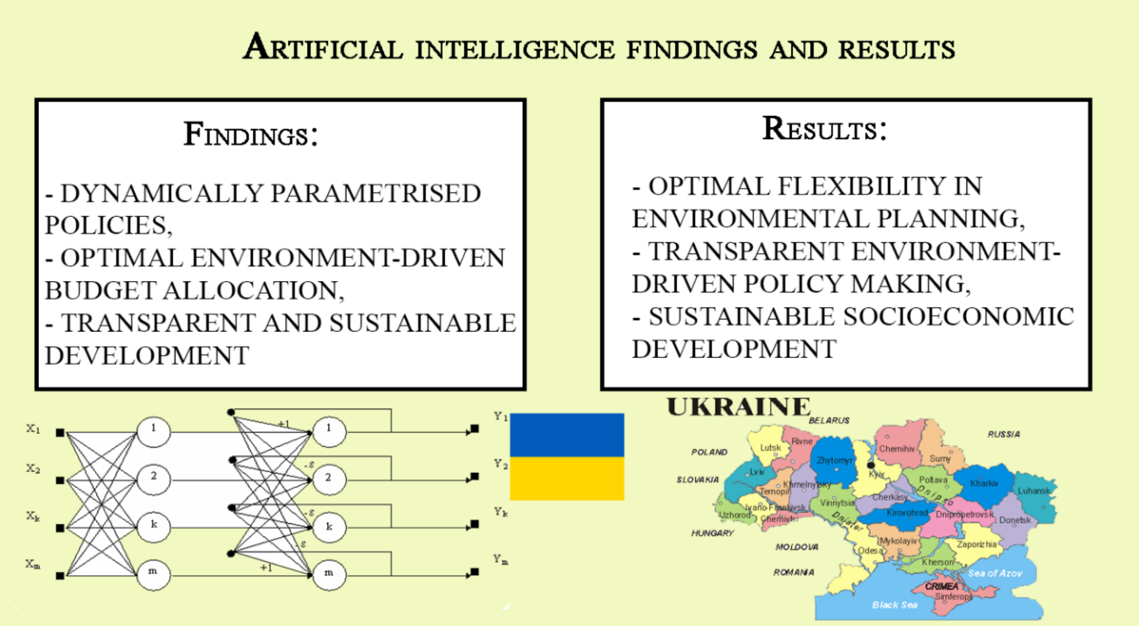

Fig. 3. Findings and results

Overall, our AI model findings and results go beyond current public policymaking, as they decentralise environmental conservation forces, leading the EU actors to adopt regionally differentiated values in a transparent setup (Bailey & Caprotti, 2014). Ultimately, they could transform public policymaking in the maintenance of natural resources and potentially calm on-going policymaking debates relating to regional autonomy and sustainability in the CEE countries (Mella & Gazzola, 2018).

5. Conclusion

Is this environmental planning contribution significant to current EU cohesion policies? Yes, as we have supported our second and third research questions and discarded question one. Our AI model reflects on 6 micro- and macro- indicators and achieves optimal sustainable policymaking, empowering regional environmental development. In addition, it allows us to inspire cross-border policymaking, which transitions toward a new European cohesion paradigm from smart cities to sustainable cities and regions (Young & Lieberknecht, 2018). Its intelligent approach could exclude subjective influencing factors, inspiring an objective view of sustainable public policies, not only in Ukraine, but also in the European Union.

In relation to our third research question, model results reveal that it is possible to optimise the regional budgeting of the 12 newly formed clusters. Its AI algorithmic logic systematically optimises macro- and micro- indicators of sustainability. As a result, it diverges from the CEE countries' centralised design, which unilaterally overwhelms regional policies. An economic increase for most of the newly formed clusters promotes environmental planning and sustainable policymaking. In addition, the simultaneous employment of ANN and optimisation algorithms multiplies the impact of the employed indicators, facilitating transparent regional innovation in public policies.

In conclusion, we introduce an intelligent environmental plan that resists the 'noisy' data, which lead to controversial public policymaking; ensures environmental funding flexibility, empowering regional stakeholders; and, facilitates intelligent learning. The model's innovative design can provide multilateral flexibility and transparency for environmental planning, potential collaborative policymaking among European stakeholders, and transferability potential to similar EU countries. Employed as a regional policy tool, our model could deliver place-based programming that respects regional differentiation, promotes sustainable development, and uses selective prioritisation as a leading indicator for multilevel policymaking.

The long-term benefits of this study focus on environment-driven equilibrium, flexible financing policies, and sustainable development. Our national paradigm also provides a developmental EU foundation that would increase European environmental cooperation. Finally, we would like to believe that our planning approach could signal a 'green' cultural orientation, increase independence in policymaking, and motivate diverse sets of stakeholders to converge toward international sustainability-driven alliances.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Acknowledgements

The authors are grateful to the anonymous reviewers for their insightful comments.

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Appendix A

SOM Process I: Competition

Step 1: Initialisation. For all the vectors of synaptic weights,

$$\mathrm{w}_j = [w_{j1}, w_{j2}, \ldots, w_{jm}]^T,\ j = 1,2,\ldots,l \qquad (1)$$

where *l* – is the total number of neurons, *m* – is the dimension of the input space, a random value from -1 to 1 is selected.

Step 2: Sub-selection. Choose the vector $\mathrm{x} = [x_1, x_2, \ldots, x_m]$ from the input space.

Step 3: Search for a winning neuron. We find the most suitable (winning neuron) *i(x)* at step *n*, using the minimum Euclidean distance criterion (which is equivalent to the maximum of the scalar multiplication $\mathrm{w}_j^T \mathrm{x}$):

$$i(\mathrm{x}) = \arg \min_j \|\mathrm{x} - \mathrm{w}_j\|, \quad j = 1,2,\ldots,l \tag{2}$$

SOM Process II: Cooperation

The winning neuron is located in the centre of the topological neighbourhood of the 'cooperating' neurons. The key question is: how to determine the so-called topological neighbourhood of the victorious neuron? For convenience, we denote it by the symbol: $h_{j,i}$, with the centre in the winning neuron i. The topological neighbourhood must be symmetrical with respect to the maximum point determined when $d_{j,i} = 0$, $d_{j,i}$ is the lateral distance between the winning i and the neighboring neurons j. A typical example satisfying the condition above, $h_{j,i}$ is the Gaussian function:

$$h_{j,i} = \exp(-\frac{d_{j,i}^2}{2\sigma^2}) \tag{3}$$

where σ – is the effective width. Lateral distance is defined as: $d_{j,i}^2 = |r_j - r_i|^2$ in one-dimensional and $d_{j,i}^2 = \|r_j - r_i\|^2$ in the two-dimensional case. Where r_j determines the position of the excited neuron, and r_i - the position of the winning neuron (in the case of a two-dimensional grid $r = (x, y)$, where x and y are the coordinates of the neuron in the grid). SOM is characterised by a decrease in the topological neighborhood in the learning process. This can be achieved by changing σ according to the formula:

$$\sigma(n) = \sigma_0 \exp\left(-\frac{n}{\tau_1}\right), n = 0,1,2, \ldots \tag{4}$$

where τ_1 is a constant, n is the learning step, σ_0 is the initial value of σ.

The function $h_{j,i}$ at the end of the ANN SOM training phase should cover only the nearest neighbors.

SOM Process III: Adaptation

The adaptation process involves changing the synaptic weights of ANN. The change in the vector of weights of neuron j in the lattice can be expressed as follows:

$$\Delta \mathrm{w}_j = \eta h_{j,i}(\mathrm{x} - \mathrm{w}_j) \tag{5}$$

where η - learning speed parameter.

As a result, we have the formula of the updated weights vector at the moment of time n:

$$\mathrm{w}_j(n+1) = \mathrm{w}_j(n) + \eta(n) h_{j,i}(n)(\mathrm{x} - \mathrm{w}_j(n)) \tag{6}$$

In the SOM learning algorithm, it is also recommended to change the learning speed parameter η depending on the step:

$$\eta(n) = \eta_0 \exp(-\frac{n}{\tau_2}) n = 0,1,2,\ldots \tag{7}$$

where $\tau 2$ – is another SOM constant. After updating the scales, we return to step 2 and our process repeats cyclically.