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INTRODUCING A DATA-DRIVEN APPROACH TOWARDS THE IDENTIFICATION OF GRID CELL SIZE THRESHOLD (CST) FOR SPATIAL DATA VISUALIZATION: AN APPLICATION ON MARINE SPATIAL PLANNING (MSP)

Vassilios Krassanakis[1,2*] and Vassiliki Vassilopoulou[1]

[1]*Institute of Marine Biological Resources and Inland Waters, Hellenic Centre for Marine Research, Greece*

[2]*School of Rural and Surveying Engineering, National Technical University of Athens, Greece*

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Abstract: Spatial data visualization techniques may have a great influence in several disciplines related to spatial management and hence decision-making process. Among them, marine spatial planning (MSP) constitutes an integrated procedure aiming at the optimal allocation of human activities in marine space. In MSP, mapping process referred either in human activities, marine ecosystems or indicative indices is based on the implementation of a grid approach. The present paper discusses some critical issues related to visualization procedure while a new data-driven approach is introduced towards the identification of grid cell size threshold. The proposed method gives a critical suggestion that may be easily extended in each field that considers this type of visualization for spatial data handling.

Keywords: Spatial analysis; spatial data; grid visualization; marine spatial planning

[*] Correspondence to: Vassilios Krassanakis Tel.: +30 210 9856717; Fax: +30 210 9811713.
E-mail: krasvas@hcmr.gr, krasvas@mail.ntua.gr

INTRODUCTION

Spatial data visualization is considered one of the most important procedures in several scientific disciplines (e.g. environmental, education, historical research etc.) considering that it may reveal critical patterns. Especially, the interpretation of cartographic products, referred either to classical maps or spatial data infrastructures (SDIs), has a critical role in research fields where the research objectives are directly connected with decision making process either in scientific or political level. Hence, methodological approaches that provide critical indications about visualization tools and techniques are essential in order to support decision-making process (see e.g. Blasco *et al.*, 2008).

Among the several disciplines, Marine Spatial Planning (MSP) constitutes a process which results influence directly decision-makers and users (Gilliland and Laffoley, 2008). MSP is an integrated approach towards the achievement of ecological, social, and economic targets at the same time (Douvere, 2008). Basically, MSP is a practical tool which is used for the implementation of an effective management process of the entire ecosystem including the human dimension (Ehler & Douvere, 2009). The collection and mapping of geospatial data constitute a necessary step towards the practical implementation of MSP (Shucksmith & Kelly, 2014). More specifically, geospatial data are used in order to describe the spatial distribution of ecosystem components and human activities as well as to reveal possible patterns referred to discrete time periods (e.g. the spatial distribution of fishing effort, see Campell *et al.*, 2014). The representation of spatial data distribution can be based on methods that include the harmonization of the available data (Tammi & Kalliola, 2014) as well as their categorization in representative classes.

Data visualization has major importance in the practical implementation of MSP process as it highlights areas of special concerns (Longley and Lipsky, 2013). Additionally, mapping is not limited only to the visualization of data spatial distribution (considering also the variable of time) but it is also used to represent indicative indices that have significant role in the decision-making process. These indices are mainly related to the analysis and the visualization of spatial interactions (i.e. conflicts, synergies, neutral) among human uses (i.e. analysis of overlapping uses) (see e.g., Gramolini *et al.*, 2013; Krassanakis *et al.*, 2015a) as well as to the quantification of cumulative impacts produced by human uses on marine ecosystems (see e.g., Halpern *et al.*, 2008; Halpern *et al.*, 2009; Korpinen *et al.*, 2012; Micheli *et al.* 2013; Kelly *et al.*, 2014) or cumulative noise produced by specific human activities (e.g. shipping) (see e.g., Erbe *et al.*, 2012).

Spatial data management is supported by several GIS-based tools (Snickars & Pitkänen, 2009; Stelzenmüller *et al.*, 2013). In a wide range of these tools (e.g. Marxan (Ball *et al.*, 2009), EcoGIS (Nelson *et al.*, 2009), GRID (Gramolini *et al.*, 2013) etc.) the representation of spatial data is based on the implementation of a grid which is used in order to visualize either the presence/absence of an ecosystem or activity, or the level of their intensity. Despite the fact that several studies in MSP and general marine management follow grid approach for data visualization (e.g. Busch *et al.*, 2013; Arkema *et al.*, 2014; Álvarez-Berastegui *et al.*, 2014; Turner *et al.*, 2015; Krassanakis *et al.*, 2015b etc.) a conceptual framework that fully supports the adaptation in marine spatial data has not yet be described clearly, to the best of our knowledge.

One of the major issues in marine spatial data visualization is related to data collection and mapping accuracy (Shucksmith & Kelly, 2014); spatial accuracy is not the same for all data involved in the analysis while there are also cases that its value is unknown (Shucksmith *et al.*, 2014). It also should be mentioned that several studies point out the need of high resolution data for the implementation of MSP procedures (e.g. Rengstorf *et al.*, 2013). Therefore, it becomes obvious that any process of data visualization must be conformed to the existing uncertainties of the used data (Vassilopoulou & Krassanakis, 2016). Furthermore, the spatiotemporal nature of marine spatial data requires the use of effective cartographic tools for the implementation of mapping procedure.

The aim of the present paper is twofold. Firstly, inspired of issues raised from practical implementation of MSP process, the paper aims to discuss some critical issues related to the visualization techniques in order to serve as a solid framework towards the effective execution of the procedure. Secondly, a novel method is introduced towards the establishment of optimal approaches of grid implementation for the visualization of spatial data and relevant indices used in spatial analysis studies. The proposed method is data-driven and considers the spatial accuracy of all available data that are involved in the analysis and aims to deliver an integrated methodological framework for the cartographic production of effective visualizations. An example using spatial data in marine space is presented in order to indicate the practical implementation of the proposed method.

METHODOLOGY

Nature of spatial data and their visualization

Sea constitutes a real complex system which involves a huge variety of ecosystem components while several human activities and uses take place within it.

The study of functions related to marine environmental processes (e.g. the analysis of ecosystem's vulnerability) is directly connected with the use of spatial data. The construction of SDIs constitutes an effective way to model and visualize elements of real world. The basis of 2D geospatial modeling requires the classification of geographic phenomena into three categories; points, lines, and areas. Additionally, the representation of geographic information can be based on 3D (i.e. planar and vertical dimension), 4D (i.e. planar, vertical, and temporal dimension) modeling. Generally, the development of SDIs allows the storage of spatiotemporal elements including several supplementary attributes that characterize them (e.g. indices). More specifically, the process of spatial data storing contributes to the organization of the databases into locational (geometric features), attribute (non-geometric features), and temporal data (Kraak & Ormeling, 2011). Both development and distribution of SDIs are considered very critical in order to produce a solid environment that allows the cooperation and interaction among the involved users (Rajabifard & Williamson, 2001).

The management of spatial data is mainly based on the use of GIS environments as they support the operation of geospatial databases as well as the performance of several visualization techniques. The visualization of the marine environment (including also human activities) is implemented in the 2D space in the majority of related studies which means that data are represented as points, lines, and areas. Additionally, third dimension can also be presented in 2D visualizations (i.e. contours). Visual variables (Bertin, 1967/1983) constitute the design elements for the development of several visualizations in 2D space. The original list of the design elements includes the variables of position, size, color value, texture (spacing), color hue, orientation and shape. These variables are used for the visualization of point, line, and area data in order to depict nominal, ordered, and/or interval/ratio differences. The function of the fundamental elements of cartographic visualization is presented in **Fig. 1** through indicative examples using point, line, and area data.

The representation of geographic information also needs the implementation of several classification methods (e.g. mean standard deviation, quantiles, natural breaks etc.) in order to produce visualizations that are based on the categorization of specific classes (e.g. classes that categorize the level of impact of a human activity on a marine ecosystem in low, medium and high values). Classification methods, which are well summarized in several studies (e.g. Slocum *et al.*, 2009; Krassanakis *et al.*, 2013), must be considered and adjusted according to the nature of the visualized geographic phenomena.

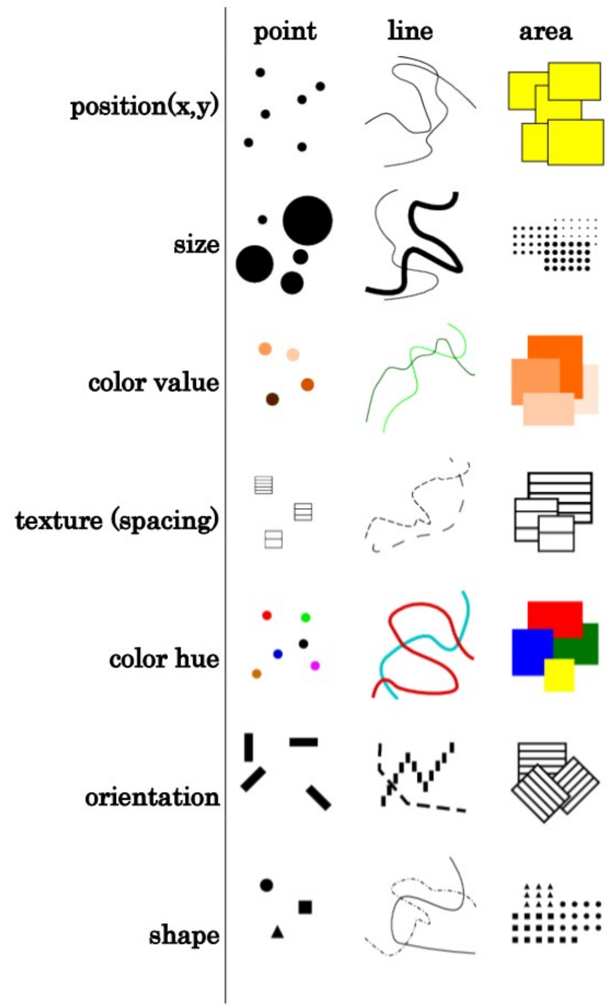

Fig. 1 The visual variables (Bertin, 1967/1983) used for cartographic visualization (image source: Krassanakis *et al.*, 2013).

Implementing a *"grid approach"* for data visualization

In several disciplines where the spatial analysis for management purposes is one of the overarching goals, the visualization of spatial data is based on the implementation of a *"grid approach"*. This approach is referred to a specific type of data visualization where spatial data are described as Boolean (presence/absence) or intensity values using a grid. The constructive grid elements mainly consist of rectangles, while hexagons or randomized grid coordinates are also used in order to avoid artifacts that may be produced (White & Engelen, 2000).

The use of grid technique for spatial data visualization meets several advantages as well as some limitations. Grid approach constitutes a simple way to manage and hence to visualize data of different nature serving as a solid framework for spatial data harmonization. More specifically, the method enables the comparisons of different layers and the evaluation of the *"load"* (expressed either as the intensity of a layer or as cumulative intensity of several layers) in each cell of the grid. Additionally, the use of grids for data visualization supports the development of robust data management platforms as it is compatible with both raster (expression as cell values) and vector (expression as attributes of point data) data. Therefore, the outcomes of grid implementation can be imported in GIS environments, either as standalone or WEB-GIS systems. Especially, in the case of raster data the outcomes can be easily supported from a huge variety of existing tools even of not specific ones (image viewers, web browsers etc.) while the compatibility is clearly enhanced in terms of computation efficiency (White & Engelen, 2000).

Hence, the grid approach using rectangle cells has become a well accepted methodology and it is implemented in a wide range of spatial analysis studies referring either to marine or land management. The primary limitation of this method is that in its standard form it only allows 2.5D visualization (i.e. 2D visualization plus an attribute, e.g. spatial distribution of cumulative impacts). The use of the third dimension (i.e. using different cell heights) can also be used in order to extend the visualization capacity of this method (in this case the outcomes are visualized using 3D space environments). For the purposes of the present paper grid approach is referred to the implementation of a continuous 2D grid consisting of rectangle cells.

As mentioned above, the most advantageous element of grid implementation is related to the harmonization of spatial data with different nature. Hence, this method can be performed for point, line, and area data. More precisely, as referred above the implementation of a grid with predefined cell size supports either the Boolean visualization of spatial data or their intensity (**Fig. 2**). In the case of predefined cell size, several issues related to the used values arise as indicated in **Fig. 2**. For example, in the case of point data the computation of intensity values can be based on the number of points inside a grid cell but the implementation of a 2D grid meets limitations if each point is related to other attributes (e.g. point data that indicate pollution spots can be connected with indices that express the level of pollution). In that case, the computation of cell values must be based on a combination of the number of points and the related attributes. The same issue is illustrated in the case that two different lines correspond to the area covered from only one cell. Additionally, the expression of intensity value is much more complicated for line data as it requires the definition of the area covered from the two lines within the cell which is not happened in the case of points. Furthermore, as pointed out in **Fig. 2** using an example of area data the value of a cell is directly related to the presence of the specific layer within the specific cell which means that the expression of cell values is not corresponded to the area percentage that is covered within the cell.

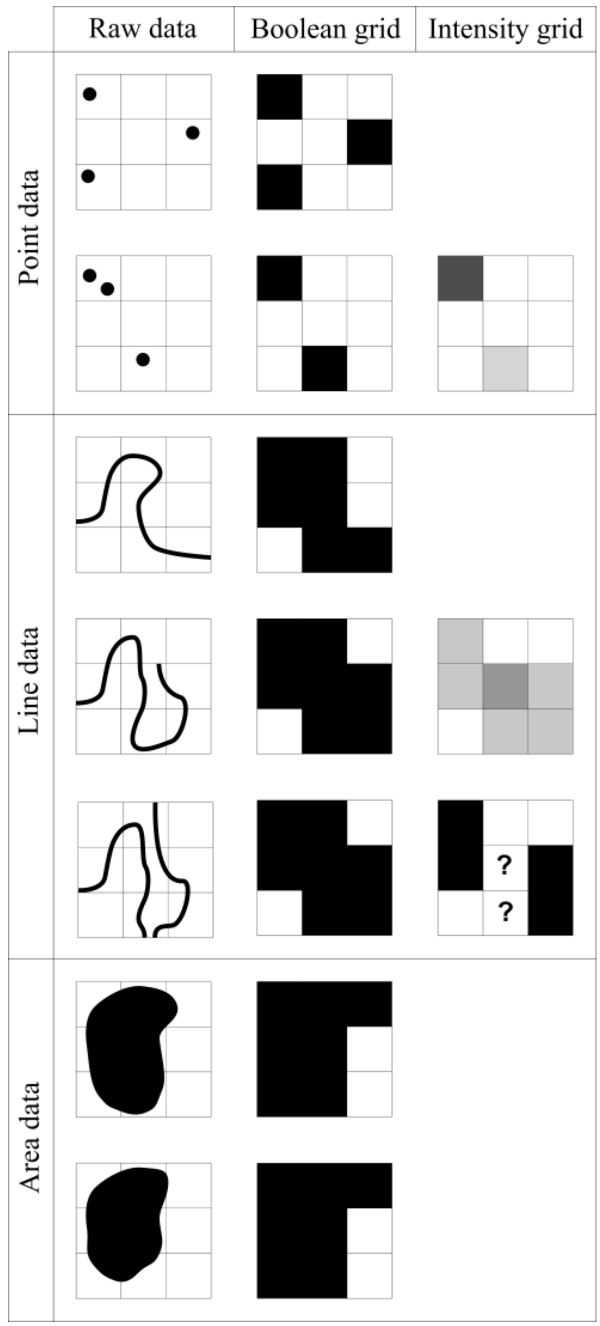

Fig. 2 Implementing grids with predefined cell size for the visualization of point, line, and are data expressed either as Boolean or intensity values.

The aforementioned examples are presented in order to highlight critical issues that may be raised during the implementation of a grid with predefined cell size especially in the case that distribution of spatial has not be taken into consideration.

A data-driven approach

The description for grid construction given in the previous section indicates that grid cell size seems to be the most crucial value related to the performance of the aforementioned methodology. In several studies, this value is defined according to specific standards or considering previous ones (see e.g. Dalton *et al.*, 2010). Additionally, a critical issue related to marine spatial data refers to the existing spatial accuracy, either for ecosystem components or human activities, which in most of the cases is unknown. This is a type of uncertainty that must be taken into account in order to perform analyses that considers the existing accuracy of the available data.

Many studies point out the emerging need of high resolution data for marine modeling purposes (e.g. Rengstorf *et al.*, 2013). The original resolution of spatial data influences directly the selection of cell size during the implementation of the grid approach. Specifically, in the case of remote sensed environmental data, cell size can be defined according to the spatial resolution of used images (see e.g. Oppel *et al.*, 2012). However, in many studies where raw data correspond to vectors with unreported spatial accuracy, the process of cell size selection is not clearly described. In the framework of the present paper, a new methodology is proposed towards the illustration of suitable techniques for data grid construction. The proposed method is based on a data-driven approach, which contributes to the identification of the minimum cell size that can be used in order to achieve data harmonization using grid visualization techniques. In other words, the introduced approach aims to deliver an objective method that indicates cell size threshold (CST) considering the spatial distribution of the used data.

The conceptual framework

In MSP process there is a clear need to use the best available data for the implementation of further analysis. As described above, despite the fact that the uncertainty produced by the several collection or production methods of spatial data is unknown in most cases, the density of the spatial distribution of vector datasets (points, lines, and/or areas) is specific. Hence, the computation of cell size can be based on the minimum value that describes the spatial distribution of the used dataset. In the case of point geospatial layers, this threshold can be defined considering the minimum distance which is reported after the computation of the distances for all points' combinations. A safe selection of CST can be based on values smaller than the half value of the minimum reported distance. In this way, the maximum number of points within each grid cell corresponds to value one. Note, that this is quite important as the values that are used for grid visualization can be based on any other attribute value related to this point. An interesting point of this approach is related to its extension in line and area types of datasets. Specifically, according to the fundamental nature of vector data, line vectors can be described as an amount of successive vertices. Therefore, a line dataset consists of an amount of points. Additionally, area data are characterized by their outline. Hence, both area and line vectors can be translated into layers of point data where the definition of cell size can be based on the computation of all combined distances as described above (**Fig. 3**).

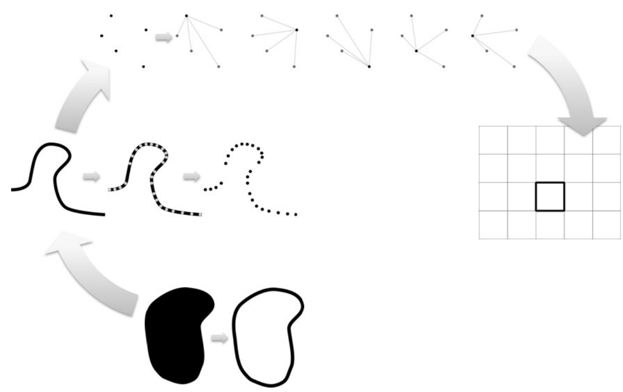

Fig. 3 Line and area vector data can be translated into points allowing the definition of grid cell size considering the minimum value of distance for all point combinations.

In order to achieve an integrated approach that takes into account all available datasets that are used for further analysis the computation of CST can be based on the consideration of the minimum distance produced for each dataset. Specifically, the computation of CST can be based on the formula (**Eq. 1**) below:

$$CST = \frac{1}{k} \times \min(\min(D_1), \min(D_2), ..., \min(D_n)) \quad (1)$$

$k \geq 2$, n: number of datasets

$$D = (D_{1,2}^{(i)}, D_{1,3}^{(i)}, ..., D_{1,m}^{(i)}, D_{2,1}^{(i)}, D_{2,3}^{(i)}, ..., D_{2,m}^{(i)}, ... D_{m,1}^{(i)}, D_{m,2}^{(i)}, ..., D_{m,m-1}^{(i)})$$

m: number of points in dataset i

In this way, the value of the final CST for grid construction is a result of all available datasets. Obviously, for cases where very dense datasets are used, the aforementioned process results to a grid with small

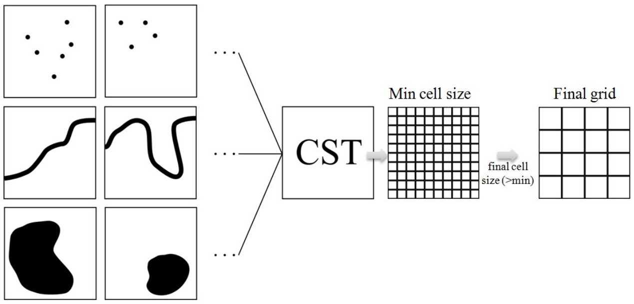

Fig. 4 An abstract representation of the proposed method for the generation of the final grid. The computation of CST indicates the minimum cell size considering spatial data with different nature.

grid size. Therefore, considering that in some cases the cell size is predefined in larger values (e.g. 1x1 km) (i.e. when the implementation of specific standards is required), the final value that corresponds to each cell of a predefined grid can be computed on the basis of the constructed grid (based on the computation of CST). Specifically, the implementation can be executed using similar interpolation methods applied in image resampling (*"downsampling"* techniques are considered to be appropriate for the specific case as the size of final cell is mainly bigger than the value of CST , see also Sachs, 2001) as the final output of the described method is compatible with raster data (see previous section). The proposed procedure is presented as an abstract diagram (**Fig. 4**).

CASE STUDY

A case study is presented for the application of the introduced methodology aiming to the identification of CST for the visualization of specific human activities that take place within the examined area. The human activities that are used for the analysis are characterized by different nature of data (points, lines, and areas), spatial and temporal distribution. Hence, the implementation of the present analysis illustrates how different types of data may be combined in order to by analyzed using an integrated approach.

Marine region & activities description

The case study is implemented in a marine region of the Northern Ionian Sea. Specifically, the examined area includes the marine space around the Diapontia complex of Islands (Othonoi, Erikoussa, & Mathraki) and the northwestern part of Corfu Island covering an area of approximately 671 km2 (**Fig. 5**). Three different human activities are used for the analysis including areas of fishing activity (Kavadas & Maina, 2012), shipping lanes (Vassilopoulou *et al.*, 2015) and suggested places for offshore wind farms (OWF) placement (Regulatory Authority of Energy):

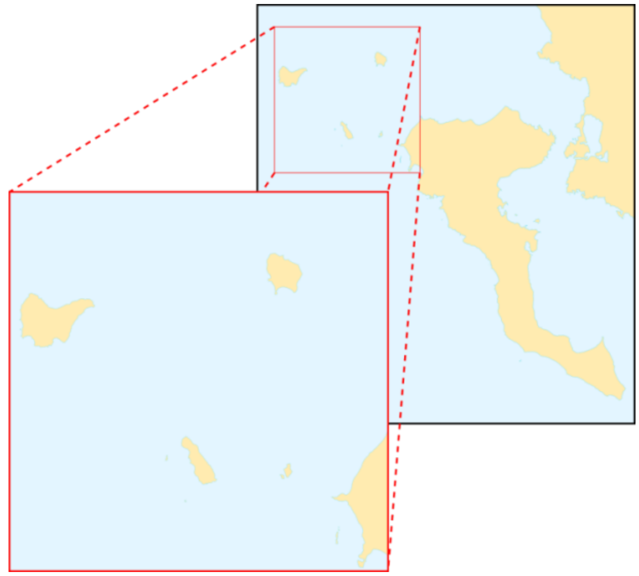

Fig. 5 The examined case study includes the marine region around Diapontia complex of Islands and the northwestern part of Corfu Island.

(a) Fishing activity is presented as 5x5km rectangles (area type of data) and refers to the fishing season 2010 - 2011 (October 2010 - May 2011).
(b) Shipping lanes are presented as line type of data. Yearly and seasonally (referred to the months October and May) shipping lanes are used for the present analysis.
(c) OWF are presented as point type of data (examined as permanent points for the performance of the analysis).

Method implementation

The implementation of the analysis refers to the fishing season 2010-2011 including also the suggested OWF places (OWF dataset is used in order to include also a point type dataset in the analysis). The introduced method towards the identification of a CST value is executed in successive and discrete steps;
(a) Spatial datasets are imported into a Geographic Information System (GIS) environment (ESRI ArcGIS®).
(b) Vertices of line and area (polygon) types of datasets are exported using standard GIS functions.
(c) Spatial coordinates of all points which connected each human activity are exported in order to compute CST value.

The transformation of spatial data during the execution of the methodological steps is also presented through a flow diagram referring to a specific time snapshot (**Fig. 6**). The spatial distribution (during all steps) of all datasets within the examined period is also visualized per minimum time unit (**Appendix 1**). Minimum time unit refers to a period of a month; this value is defined according to the minimum period for which spatial information is available.

The computation of CST is based on all exported point datasets referred to the whole examined time period for each human activity. For the practical implementation of the procedure, a computer script is developed using the scripting language of MATLAB from MathWorks® in order to support the automation of the procedure and the calculation of related statistics (see also the last section). The developed script for the calculation of CST and related statistics is presented in **Appendix 2**.

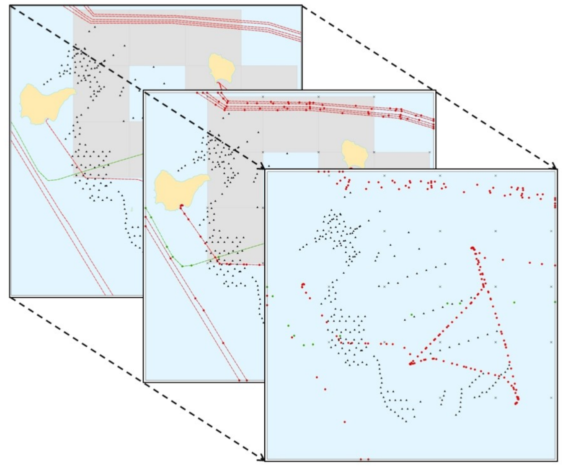

Fig. 6 Spatial transformations of all datasets for a specific time snapshot towards the identification of CST value. All spatial datasets are transformed in points.

Case study results

The calculation of CST value is based on the point datasets exported from GIS environment. Specifically, for the execution of the related computations the spatial coordinates (point data) of OWF and shipping lanes spatial layers are used. Point data produced by fishing activity are not taken into consideration as mapping resolution is specific (5x5km for the data referred in the case study) and hence it does not affect the process of minimum value computation. Despite this fact, fishing activity data define the minimum time threshold (here referred to the period of a month) that further analysis may be subdivided. Obviously, the final CST value that is calculated from the other activities must be compared with the cell size that fishing activity data are presented in order to select the minimum value of cell size. Therefore, fishing activity data are used in the present case study in order to include an example of area type of data and to reveal that the approach must be simplified in some cases, especially when spatial data are available using grid approach. Additionally, fishing activity data are considered very critical during the implementation of MSP process as they constitute one of the main human activities that may affect the ecosystem and produce conflicting interactions with other ones. For this reason, this type of data which also are mainly presented using this type of visualization, must always be considered in MSP studies.

For the performance of the analysis, the minimum value of k parameter is used (k=2) while zero distances are not considered. CST value corresponds to the minimum reported distance reported for all point datasets. Additionally, standard statistics (number of points and non zero calculated distances; minimum, maximum and average of non zero distances as well as its standard deviation) values are also calculated for OWF and shipping lanes point spatial layers and presented in Table 1. These statistical values are computed in order to demonstrate the numerical characteristics that characterize the used datasets as well as to give an impression of the computational load needed for the execution of the required analysis.

Table 1. Statistics produced after the performance of required computations using the point dataset of OWF and Shipping Lanes towards the identification of CST value.

	Case study statistics	
	OWF	Shipping Lanes
Number of points	220	230
Number of calculated distances (non zero)(m)	48180	52670
Minimum distance (m)	93.74	8.65
Maximum distance (m)	22156.25	29311.34
Average distance (non zero) (m)	9173.77	11697.86
Standard deviation of average (m)	5261.4	6114.05
Number of points	220	230

CST value corresponds to the half (k=2) of the minimum distance (i.e. approximately equal to 4.33m) which is reported in the point dataset of shipping lanes, which value is obviously much more greater than the cell size of fishing activity. This result indicates the minimum cell size value that can be used in order to visualize the specific spatial data.

DISCUSSION AND CONCLUSION

The process of spatial data visualization is considered very important for the implementation of the MSP procedures considering that its interpretation has a direct influence in the decision making process. In the framework of the present paper, specific cartographic rules and alternative approaches for spatial data visualization are presented in order to serve as guide for MSP studies. Among the several techniques, grid-based visualizations have a dominant role in MSP for the presentation of spatial data and/or related indices with spatial characteristics. For the purposes of the present work, a simple method is introduced aiming to provide a data-driven approach towards the identification of a threshold value for cell size selection in grid-based visualizations considering the *"spatial status"* (in terms of constructive elements) of each used spatial dataset and allowing the process of spatial data harmonization through an integrated approach that considers all type of spatial data. Therefore, the principal aim of the discussed method is to provide a critical suggestion for planners and map makers towards the construction of eligible cartographic products related to MSP.

Additionally, the calculated value illustrates the accuracy that can be achieved based on a specific dataset which is independent of the scale of analysis. In other words, the provided suggestion is not connected with the selected scale of the marine spatial plan but it indicates the finer scale that visualizations and hence further analysis (computation of overlapping scores, environmental impacts etc.) may be performed.

A case study is also presented in order to demonstrate the performance of the approach. The implementation concludes to the minimum value of cell size that can be used for grid construction. At this point, it is important to mention that the final selection of the grid cell size directly influences the final results in terms of eligibility as well as the size of the produced dataset. In any case, the produced method may be imported in any GIS software or in specific ecological/conservation software (e.g. conservation planning software). Additionally, the source code for the execution of the implemented method is freely distributed providing a prototype tool for further development and/or adaptation in other case studies.

The practical implementation of the introduced method requires the computation of all distance combinations among points characterize each used dataset. This fact means that, in the case of very large datasets, the execution process may be quite heavy in terms of processing capacity. For example for the computational execution of all distance combinations for the present case study the required time corresponds to approximately 14 seconds using a regular computer (Intel Core i5, 3.40GHz 3.40GHz, 4.00GB RAM, 64bit Windows 8.1) and executing the script in MATLAB 2013a edition. Obviously, this time may increase in larger, in terms of number of points or number of spatial layers, datasets. However, the proposed method can be easily extended considering more efficient ways of its implementation (e.g. using different programming environment/language and/or identifying methods that decrease the number of needed computation for the calculation of CST value).

The performed analysis indicates the limit value that is able to produce a visualization result that supports the finer scale of a spatial plan. Obviously, using greater values of cell sizes in the procedure directly affects the level of the final visualized information. Hence, the present paper is giving critical indication in decision-making process during the practical implementation MSP where management approaches may be refer from specific spatially-managed areas (e.g. Marine Parks) to marine regions with wider administrative boundaries.

The present paper is a first attempt to describe issues raised during the visualization process as a part of the practical implementation of MSP procedures. The proposed method serves as a critical indication which may be easily extended in other disciplines related to spatial analysis where grid based visualization is considered appropriate for further analysis. The present approach contributes to the typical 2D type representation of the available spatiotemporal information. In a next step, except from the several methods that have been developed for the 2D representation of time in conjunction with spatial information (e.g. multiple static maps, cartograms, space-time cube etc.) (see also Kraak, 2014), cartographic animations may be also involved in visualization process to support visualization in MSP procedures.

In MSP, and generally in studies related to marine research, the visualization of spatiotemporal data that describe either human activities (e.g. Le Guyader *et al.*, 2013) or ecosystem components (e.g. Zheng, 2013) is considered very important as it may indicate spatial patterns occurring over time. Spatiotemporal information may be presented as a sequence of static maps each of them visualize the footprint of a specific time period (e.g. fishing activity). Extending this approach, cartographic animations (animated maps or animations) can be produced by using as indicative frames the static maps that referred to specific temporal scales. Cartographic animations constitutes a modern approach as it is fully compatible with the use of digital monitors (e.g. in personal computers, mobile phones etc.) for data visualization and the new trends of web cartography (Neumann, 2012; Köbben *et al.*, 2012). Cartographic animations are characterized by the existence of motion which is used in order to visualize spatial differences over time (Slocum *et al.*, 2009). In the case of animated maps the original list of design variables for static maps (i.e. visual variables) is extended (DiBiase *et al.*, 1992; MacEachrean, 1995).

Specifically, the additional design tools in animated mapping include the variables of duration, rate of change, order, display date, frequency and synchronization while more information about the function of design variables in animated mapping is cited in previous studies (MacEachrean, 1995; Kraak & Ormeling, 2011; Slocum *et al.*, 2009; Kraak, 2014).
Concluding, it is very important to mention that for MSP must always be very critical to take the advantages from the outcomes produced in cartography and spatial science towards the generation of effective visualizations that really contribute to the correct interpretation of planners and decision-makers.

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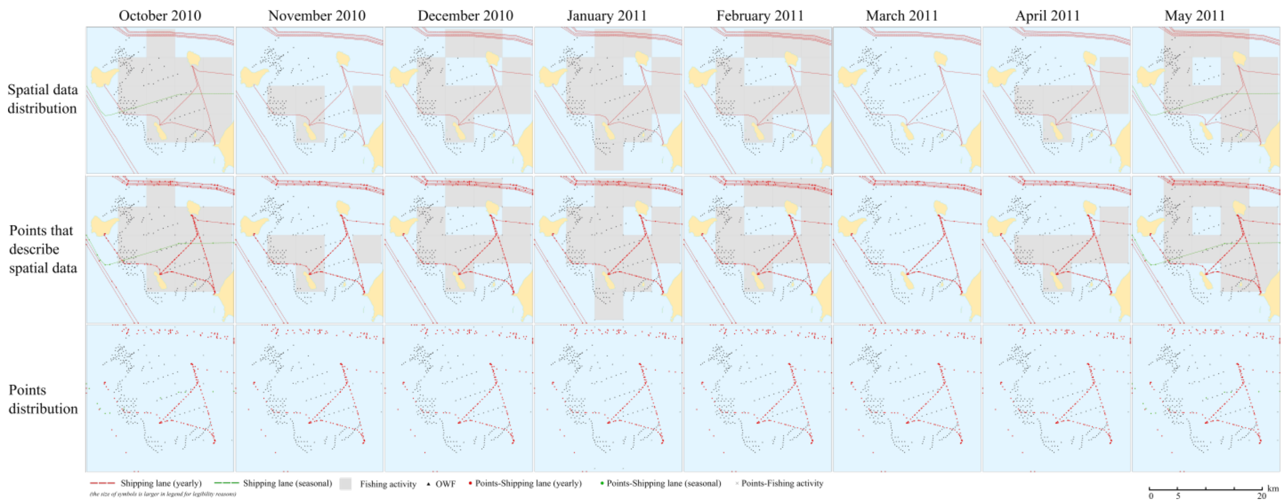
APPENDIX 1



APPENDIX 2

Main MATLAB script for the computation of CST and related statistics (The modification of the imported files allows the adjustment in other case studies):

```
%import data as points
fprintf('Loading OWF...\n');
OWF=load('OWF.txt');
fprintf('Loading Shipping Lanes (yearly)...\n');
ShipLanes_yearly=load('ShipLanes_yearly.txt');
fprintf('Loading Shipping Lanes (seasonal)...\n');
ShipLanes_seasonal=load('ShipLanes_seasonal.txt');
%integrate data of seasonal and yearly shipping lanes
ShipLanes=[ShipLanes_yearly;ShipLanes_seasonal];
fprintf('-Computing OWF distances...\n');
OWF_distances=all_distances(OWF);
OWF_distances=OWF_distances(:,3);
fprintf('-Computing Shipping Lanes distances...\n');
ShipLanes_distances=all_distances(ShipLanes);
ShipLanes_distances=ShipLanes_distances(:,3);
fprintf('-Defining grid size...\n');
OWF_min=min(OWF_distances(~~OWF_distances));
ShipLanes_min=min(ShipLanes_distances(~~ShipLanes_distances));
min_values=[OWF_min,ShipLanes_min];
%compute grid size(Grid_Size)
k=2;
Grid_Size=(1/k)*min(min_values);
fprintf('\n');
fprintf('Grid size(k=2): %.2f m',Grid_Size)
fprintf('\n\n');
fprintf('End of computations\n');
fprintf('-------------------------------------------\n')
fprintf('Calculate Data Statistics\n\n')
%OWF
%number of points
OWF_n_points=size(OWF);
OWF_n_points=OWF_n_points(1,1);
fprintf('OWF number of point data: %.f\n',OWF_n_points)
%number of distances (non zero)
OWF_n_dist=length(OWF_distances);
fprintf('OWF number of calculated distances (non zero): %.f\n',OWF_n_dist)
%min distance
fprintf('OWF min distance: %.2f m\n',OWF_min)
%max distance
OWF_max=max(OWF_distances);
fprintf('OWF max distance: %.2f m\n',OWF_max)
%average distance (non zero)
OWF_average=mean(OWF_distances);
```

```
fprintf('OWF average distance (non zero): %.2f m\n',OWF_average)
%standard deviation in distances
OWF_std=std(OWF_distances);
fprintf('OWF standard deviation of average (non zero): %.2f m\n',OWF_std)
fprintf('\n')
%ShipLanes
%number of points
ShipLanes_n_points=size(ShipLanes);
ShipLanes_n_points=ShipLanes_n_points(1,1);
fprintf('ShipLanes number of point data: %.f\n',ShipLanes_n_points)
%number of distances (non zero)
ShipLanes_n_dist=length(ShipLanes_distances);
fprintf('ShipLanes number of calculated distances (non zero): %.f\n',ShipLanes_n_dist)
%min distance
fprintf('ShipLanes min distance: %.2f m\n',ShipLanes_min)
%max distance
ShipLanes_max=max(ShipLanes_distances);
fprintf('ShipLanes max distance: %.2f m\n',ShipLanes_max)
%average distance (non zero)
ShipLanes_average=mean(ShipLanes_distances);
fprintf('ShipLanes average distance (non zero): %.2f m\n',ShipLanes_average)
%standard deviation in distances
ShipLanes_std=std(ShipLanes_distances);
fprintf('ShipLanes standard deviation of average (non zero): %.2f m\n',ShipLanes_std)
fprintf('\n')
fprintf('End of report\n')
```

The variable of Grid_Size corresponds to the value of CST.
Supplementary MATLAB functions for the execution of the main script:
Function to calculate the Euclidean distance between two points

```
function d=euclidean_distance(x1,y1,x2,y2)
d=sqrt(((x2-x1)^2)+((y2-y1)^2));
end
```

Function to calculate all possible distances among the existing points of the dataset

```
function distances=all_distances(data)
n=size(data);
n=n(1,1);
distances=[];
for i=1:n
    for j=1:n
        if j~=i
distances=[distances;[i,j,euclidean_distance(data(i,1),data(i,2),data(j,1),data(j,2))]];
        end
    end
end
end
```