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ABSTRACT

Mining activities depend significantly on water resources availability as it consists a major tool of the extraction, processing and the post closure mining operations. Especially, groundwater is the major water source in most mining areas. However, overexploitation, competition from the communities and climate change effects have caused significant stress on the groundwater resources in many areas of the Mediterranean basin. The sustainability of mining operations is threatened as well as the uninterrupted supply of raw materials to the industry. In this work spatial estimation and analysis of groundwater stress at hydrological basin-scale in the European part of the Mediterranean region is applied using local and global datasets. Aquifer productivity index and groundwater use information at monitoring sites are extracted from the River Basin Management Plans of the European Environment Agency, while groundwater recharge is considered from the World-wide Hydrogeological Mapping and Assessment Program (WHYMAP) after validation. The processing of these data using the Self Organized Maps technique and their integration within a novel function, provide the groundwater stress index. The output of this work can be used

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for governance and management decisions that will improve groundwater resources availability in vulnerable areas ensuring the sustainable use from the communities and the industry.

1. Introduction

Climate change is expected to have severe consequences for human and ecosystems (Huppmann et al., 2018; Ogunbode et al., 2020). The projections suggest a progressive decrease of the streamflow and significant changes of the surface water availability as well as for groundwater reservoirs (de Graaf et al., 2019). Groundwater is a basic indicator of the 2030 Agenda for Sustainable Development (UN, 2015) of the United Nations Sustainable Development Goals and for achieving Europe's goal of a green, digital economy and climate neutrality by 2050 (EU, 2019). Consequently, in terms of sustainable development under climate change projections, the groundwater resources stress needs to be studied and identified.

The Mediterranean region is among the "hot spots" to be affected by climate variability and change, associated with increases in the frequency and intensity of droughts and hot weather conditions (Lelieveld et al., 2012; Polade et al., 2017). Therefore, recent studies have designated that groundwater recharge and quantity in the Mediterranean region are expected to decline significantly (European Environment Agency, 2020; Reinecke et al., 2021). With regard to the expected impacts of climate change on water resources, a deficit ranging from 10% to 70% has been projected for all the combinations of emission, demand and infrastructure scenarios. Assuming that all climate scenarios are equally probable, average water availability is expected to drop from around 90%, to 70% during 2000–2050, which is already insufficient to cover the current demand (Garrote et al., 2015; Mas-Pla and Menció, 2019; Wada et al., 2010). For water management purposes, it is important to have information about groundwater quantity and quality status and especially about the dynamic relationship between quantity and hydro meteorological variables that affect the recharge of water table level, especially under climate change impact (ECMWF, 2020; Richey et al., 2015). Recent studies have acknowledged that groundwater use in the Mediterranean region will increase as a result of the declining availability of surface water and increased water demand from various sectors (Boretti and Rosa, 2019; Field and Barros, 2014; Pool et al., 2021).

A characteristic example is the raw materials sector. Overall, water resources demand is forecast to rise by the increasing demand of raw materials. Mining is one of the most water-intensive industries and often faces operational risks with regard to water supply that is expected to be affected by the variability of climactic conditions. The latter may increase water scarcity in some locations constraining water-dependent operations and site rehabilitation, while increasing the conflict with communities for water resources. The mining sector is primarily depended to groundwater. It is a very important source that affects the viability of the investment and the mining operation. Therefore, the spatial analysis of groundwater stress in vulnerable regions is a risk index that affects the sustainability of mining processes in such areas (Odell et al., 2018; Rüttinger et al., 2020).

The accurate mapping of groundwater stress in aquifers of the Mediterranean region, which hosts a significant number of mining operations and consists a hot-spot of climate change, is important for effective management and monitoring decisions. Information on the spatial locations of Mineral Resources occurrence and processing (Schweitzer, 2019) in the Mediterranean region is considered in this work along with the spatial distribution of groundwater stress index. In addition, the results will be discussed considering drought adaptiveness in the Mediterranean hydrological basins (Buddingh et al., 2019; Mattern et al., 2018; Schweitzer, 2019). This will designate areas where mining operations may be affected due to water scarcity.

Spatial statistics have been successfully applied in groundwater-related studies since the early stages of its development to provide reliable predictions, decision-oriented mapping and uncertainties estimation e.g. Christakos et al. (2000, 1993), Delhomme (1978, 1979), Desbarats et al. (2002), Hoeksema and Kitanidis (1984), Kitanidis (1997), Knotters et al. (1995), Manzione and Castrignanò (2019), Philip and Kitanidis (1989) and Varouchakis and Hristopulos (2013, 2019). However, spatial statistics have specific limitations when the aquifer system is inhomogeneous (discontinuities) since they cannot consider changes in flowline patterns and aquifer boundary conditions (de Marsily et al., 2005; Houlding, 2000; Kitanidis, 1997; Lallahem et al., 2005). The latter is more significant in large-scale hydrogeological applications. Therefore, spatial statistics' contribution in the field influenced the development and application of machine learning techniques that were based on spatial statistics principles (neighborhood of influence) to address such restrictions and perform estimation of groundwater related variables' spatial distribution e.g. Artificial neural networks (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000; Lallahem et al., 2005), Neural Kriging (Demyanov et al., 1998; Rizzo and Dougherty, 1994), Fuzzy Kriging (Kholghi and Hosseini, 2009) and recently Self Organized Maps in complex hydrogeological systems (Chen et al., 2018). The machine learning techniques estimate a function without a mathematical model (e.g., covariance) of how output depend on input.

In this research we introduce an approach to predict the spatial distribution of groundwater stress in the European countries of the Mediterranean region, as an example of what can be achieved when combining standalone information from different sources on groundwater pumping, recharge and aquifer productivity, by employing innovative tools like Self Organized maps (SOM). The latter is applied to approximate the presence of complex hydrogeological systems that introduce restrictions in the application of a convectional spatial statistics model, whose potential application would deliver unrealistic predictions and uncertainties. Although a machine learning technique, SOM is based on spatial statistics principles such as the Euclidean distance to support classification of observations to form a neighborhood. The latter corresponds to the correlation neighborhood principle in spatial statistics. SOM has been successfully applied in large-scale applications in different disciplines of hydrology e.g. to represent hydroclimatic patterns in Europe (Markonis and Strnad, 2020), for streamflow regionalization the Western United States (Agarwal et al., 2016) to characterize hydrogeology of transboundary aquifers in Latin America (Iwashita et al., 2017) and for rainfall regionalization at country level (India) (Mannan et al., 2018).

The objectives of this work are: (i) the estimation of the groundwater stress index at hydrological basin scale in the European countries of the Mediterranean region considering the application of a machine learning technique for the spatial processing of the available data and (ii) the indication of areas where mining activities sustainability is likely to be affected. The motivation of performing this research follows the concern of the mining sector related to the climate change and variability impact, expected to cause more frequent droughts and floods, altering water supply and disrupting operations. Even in areas with low water stress, certain water-intensive mining processes can be jeopardized. (Ayuk et al., 2020; Cosbey et al., 2016; Koch et al., 2005; Northey et al., 2017; Odell et al., 2018; Rüttinger et al., 2020).

2. Methodology

The SOM technique belongs to machine learning techniques and is a type of an unsupervised Artificial Neural Network approach. It is applied for data dimension reduction, to cluster complex data sets and to detect local data similarity (Hsu and Li, 2010; Kohonen, 2013; Richardson et al., 2003). SOM is an operative tool that can convert complex statistically based relationships of high-dimensional data to simple spatial or temporal relationships of lower display, i.e. mapping of high dimensional data sets to a grid of regular dimensions. It reduces dimensions by producing a map grouping similar data together. The SOM retains the data space and topology during the learning process. An N-dimensional input vector is applied to the network to calculate the distance between the weight neurons (nodes) of SOM and the inputs. Initially, the SOM weights are randomly assigned and are iteratively trained (Kohonen, 2013), while the Euclidean distance criterion is usually applied (Bowden et al., 2005).

The algorithm below presents the basic steps of training the SOM network consisting of X nodes. A data set of N points $\{s_1, s_2 \ldots s_N\}$ in n-dimensional space is considered:

1. Initialize weights, from N inputs to the nodes, to small random values. Set the initial radius of the neighborhood.

2. Present new input
$Z(s_1), \ldots, Z(s_n)$ where $Z(s_i)$ is the input to node i.
3. Compute distances to all nodes
Compute distances d_j between the input and each output node j using,

$$d_j = \sum_{i}^{N-1} \left(Z(s_i) - w\left(s_{i,j}\right)\right)^2 \tag{1}$$

where $Z(s_i)$ is the input to node i and $w\left(s_{i,j}\right)$ is the weight from input to output node j.
4. Select output node with minimum distance
Select output node j^* as the output node with minimum d_j.
5. Update weights to node j^* and neighbors
Weights updated for node j^* and all nodes in the neighborhood defined by N_{j^*}. New weights are:

$$w\left(s_{i,j}\right)(t+1) = w\left(s_{i,j}\right)(t) + \eta(t)\left(Z(s_i) - w\left(s_{i,j}\right)\right) \tag{2}$$

for j in N_{j^*}, $1 \leq i \leq N$. The term $\eta(t)$ is a gain term $0 \leq \eta \leq 1$. Both η and $N_{j^*}(t)$ decrease with time; t is the current iteration.

Repeat by going to step 2. The stopping criterion is that the SOM weights do not change in any further training cycles (Kohonen, 2014).

The quality and accuracy of the SOM results can be determined by two uncertainty indices, the quantization error and the topographic error. Quantization error is the average distance between the data vector and the best matching unit (BMU); the closest node. The quantization error shows how accurate is the representation of the given input patterns by a BMU. The smaller this index is, the better the representation. Topographic error is related to the quality of the map topology: it is assumed quality is high (so the error is low) if the nodes adjacent to each other on the grid correspond to similar input patterns (Beale and Jackson, 1990). It is calculated as the ratio of all of the vectors, for which the first and second best BMUs are not adjacent on the grid.

In this work, the SOM function ''selfOrgMap'' of Matlab® with appropriate coding to set training and parameters properties was implemented along with the SOM toolbox for Matlab® (Potocnik, 2012; Vesanto et al., 2000). The code details can be found in the aforementioned references for reproduction of the work.

The SOM methodology in this work was exploited to support the handling of large datasets (over 10 000 groundwater monitoring points) to determine the locally similar input data by identifying the associate neuron (node) defining a local neighborhood. Every neuron has as a neighborhood the measurements that are associated to that neuron. Another reason of applying SOM is the type of the case study. In this work the spatial variability is examined in large scale complex hydrogeological systems of porous and karst type aquifers. In a large-scale application with the presence of sequence of different aquifer types SOM methodology clusters the data based on local similarity.

The proposed approach to calculate the spatial variability of groundwater stress at basin scale is defined as:

$$GS = [P/(R * A)] * AW \tag{3}$$

where P is the average annual pumping rate (m^3/yr) in the basin, R denotes the average annual recharge (m/yr), A is the basin area (m^2) and AW the *aquifer type weight* in terms of the aquifer productivity.

Eq. (3) in a simpler form (Richey et al., 2015) *use/availability, where use* is the average annual pumping and *availability* denotes the average annual recharge provides a simplified approach to calculate groundwater stress. Previous researches have defined *use* as withdrawals based on national overall withdrawal statistics (Vörösmarty et al., 2000) and availability as mean annual recharge (Richey et al., 2015). On the other hand, more recent stress studies apply groundwater withdrawal considering as well nonrenewable groundwater use from compiled withdrawal statistics (Wada et al., 2011). Besides, the definition of availability has been based on the renewable rates of the

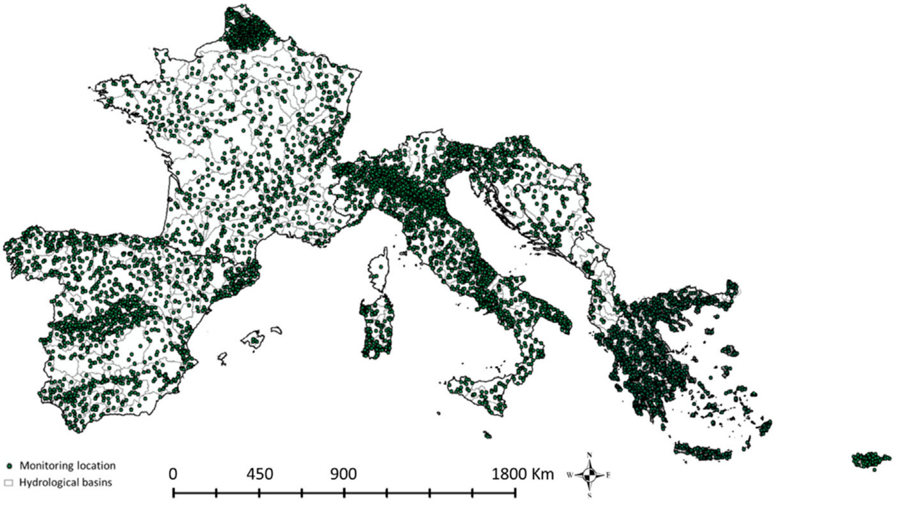

Fig. 1. Groundwater monitoring locations and hydrological basins in the European countries of the Mediterranean region.

water cycle including groundwater contribution to streamflow and groundwater recharge (Ahner, 2017; Gleeson and Wada, 2013; Gleeson et al., 2012).

These recent advances have improved the estimation of groundwater stress analysis. In this work a new variable is included in the stress calculation equation, the aquifer productivity. Depending on the productivity capability of the aquifer type (porous, karstic, fractured), the aquifers were divided by means of low (weight = 1), medium (weight = 2), and high (weight = 3), capability (European Environment Agency, 2020). Aquifer productivity is an index that can help to correct the bias from the average pumping rates.

Aquifer productivity index and pumping rates from groundwater monitoring locations (Fig. 1) were extracted and processed using information from the Water Framework Directive - 2nd River Basin Management Plans. For the European countries, the European Environment Agency EIONET spatial data was consolidated with the spatial data reported under the Water Framework Directive reporting obligations. For these countries, the reference spatial data set is the "WISE WFD Reference Spatial Datasets reported under Water Framework Directive" (European Environment Agency, 2020).

The river basin reports of the countries considered in this study have been explored in terms of groundwater pumping in each river basin district to allocate to each monitoring point its average annual monitored value. Then, using SOM method as previously described, a weight (node) in each hydrological basin was calculated that corresponds to a characteristic value obtained from source data (pumping rates) classification. In cases where more than one node corresponds in each basin due to high number of monitoring points and significant variability of pumping, the weights average is considered (Misra et al., 2020).

On the other hand, groundwater potential recharge (considering spring flows) was determined using information from the World-wide Hydrogeological Mapping and Assessment Programme (WHYMAP); map of water resources (Richts et al., 2011), that has been successfully used before for a similar topic (Richey et al., 2015). Sampling of groundwater average recharge rates has been performed in the corresponding nodes' locations to assign a characteristic recharge rate for each basin. Then, the resulted weighted groundwater stress index according to Eq. (3) was assigned to each hydrological basin.

More specifically, the employed technique in terms of SOM has been applied in Matlab® software as it was aforementioned providing the SOM network that clusters the available average annual pumping data. Then, the outcome was implemented in ArcGis 10.5® to consider the basins'

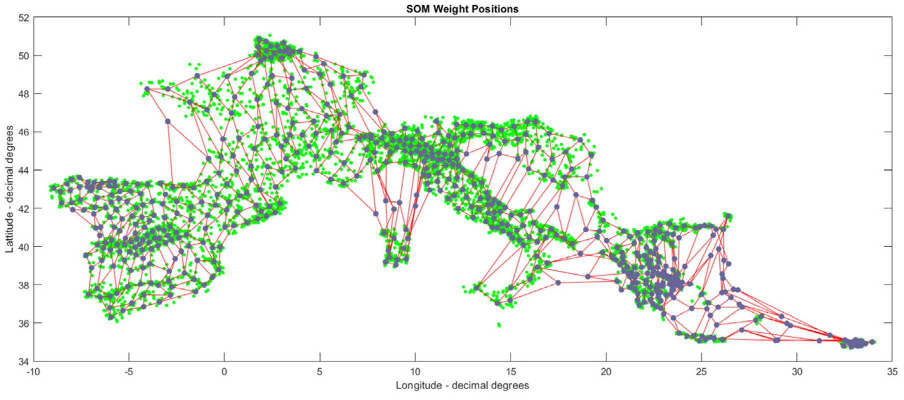

Fig. 2. Self-organized maps nodes network (blue nodes) clustering average annual pumping data from monitoring locations (green spots).

area A and aquifer type weight AW according to Eq. (3). Thus, to perform the stress index calculation and mapping in terms of high, medium and low risk. For each hydrological basin downloaded from the European Environment Agency (EEA) (2020) the fraction of *pumping* over *recharge* multiplied by a *weight of the underline aquifer productivity* has been calculated. These calculations are made at the hydrological basin scale for a more practical interpretation that could be useful for further analysis with hydrological data to study climate change effects.

3. Results and discussion

The sampling reliability of groundwater potential recharge was tested by correlating measurement data from two recent global groundwater recharge datasets using the values in the Mediterranean area (Moeck et al., 2020; Mohan et al., 2018) and sampling from WHYMAP in the corresponding locations. The correlation was significant, equal to 72%, and therefore the sampling of recharge from WHYMAP for the estimated nodes' locations was reliable.

The SOM network in terms of groundwater pumping rates at the monitoring locations is presented in Fig. 2, while the training animation for the final outcome is presented in S1.

The SOM quality was measured with two criteria: herein the final quantization error is 0.17 and the final topographic error is 0.019. Both very close to zero denoting optimal training. A cross validation analysis was implemented to validate the fraction, pumping over recharge, in 70 hydrological basins using available estimations, based on observations, from the 2nd River Basin Management Plans of the European Environment Agency (2019). The calculated fractions were validated with an error of 6.5% denoting a very good agreement with the observed data. As it can be observed from Fig. 3a the higher values of fraction mainly deviate. This means that in basins with high difference between pumping and recharge either the available data are slightly uncertain or the SOM method provides slightly inferior weights (characteristic values of P). However, the overall error is low and the basins at risk are reliably determined. In addition, any bias error is corrected from the application of the aquifer productivity index according to Eq. (3).

Furthermore, to investigate SOM applicability a similar clustering method such as k-means was applied (Hall and Blöschl, 2018; Naranjo-Fernández et al., 2020). The method provided a cross validation error of 8.1% (Fig. 3b) providing a similar but inferior to SOM method outcome. Thus, the clustering methods reliably classify the available data. The estimated errors are similar and comparable to those calculated in large scale hydrological applications using SOM and k-means (Hall and Blöschl, 2018; Markonis and Strnad, 2020; Naranjo-Fernández et al., 2020).

The resulted groundwater stress map (Fig. 4) was compared with similar maps of groundwater quantitative status developed from the EEA (European Environment Agency, 2020) and of recharge

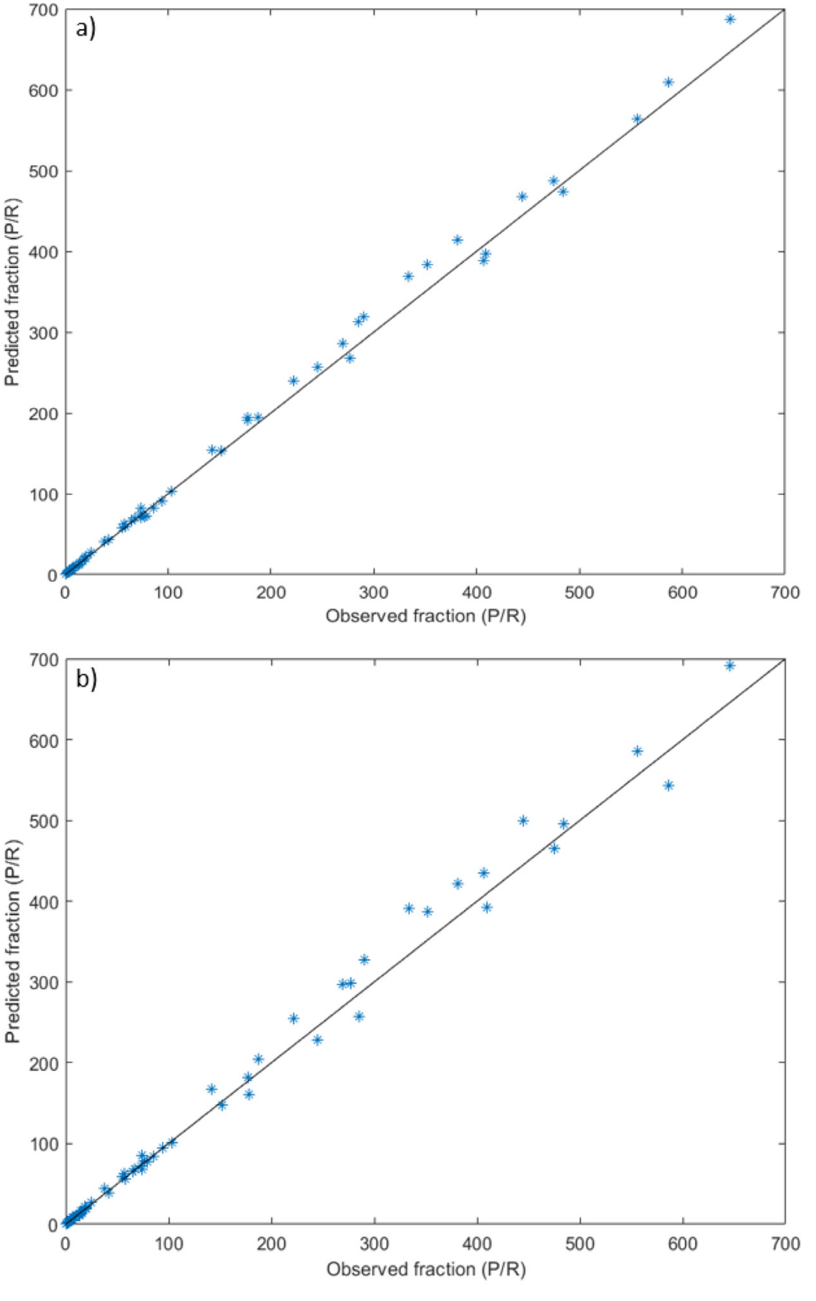

Fig. 3. Cross validation results between observed and predicted fraction of pumping (P) over recharge (R) at hydrological basin scale using (a) the Self-organized maps method and (b) for the k-means method.

rate variations based on climate change estimations and groundwater footprint (de Graaf et al., 2019; Gleeson et al., 2012; Reinecke et al., 2021; Wu et al., 2020). This work is significant and differentiates from similar approaches because it exploits observed, rather than simulated only, hydrological and hydrogeological data of every basin to provide the groundwater stress.

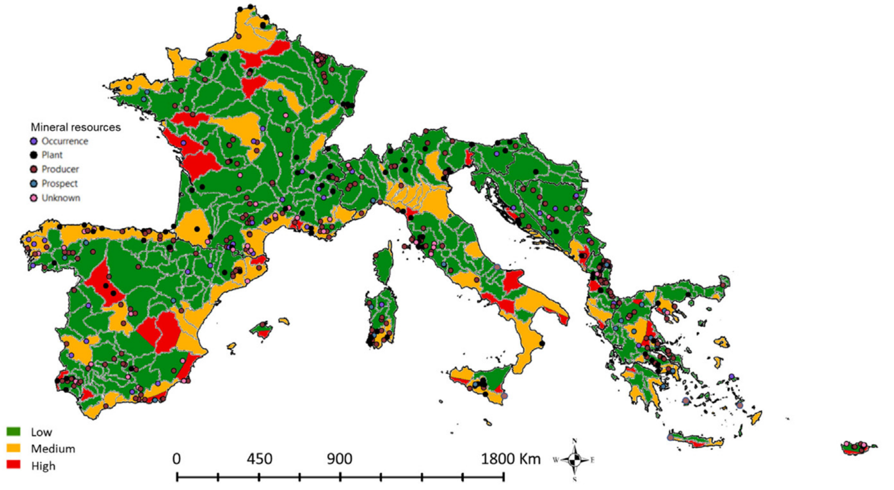

Fig. 4. Groundwater stress index at hydrological basin-scale in the European countries of the Mediterranean region.

The results are in very good agreement with these previous works regarding regions of significant groundwater stress but also provide new information highlighting new areas that are under high stress and in addition areas that are in potential risk (medium stress). As it can be observed from the developed map (Fig. 4) the groundwater stressed areas are located mainly at the south coastal part of the Mediterranean countries or in areas where the groundwater exploitation network is significantly dense (Figs. 1 & 4).

In addition, the mineral resources occurrence and processing locations are provided in Fig. 4, designating the areas where mining operations may face potential malfunctions due to groundwater stress (Schweitzer, 2019). On the other hand, the continuous intensive use will have additional environmental impact on groundwater resources. An integrated assessment of water resources scarcity in such areas should consider information from drought analysis researches. Thus, a drought adaptiveness map (Fig. 5) that presents the overall adaptiveness to drought considering data of recent decades is presented as a supportive tool to identify the vulnerable areas (Buddingh et al., 2019; Mattern et al., 2018). These areas correspond to groundwater and surface water stressed areas and have the highest risk of water resources scarcity that will affect both water resources availability for human consumption and agricultural use as well as industrial operations. Comparing the two produced maps there is a clear overlap on coastal areas, in mainland parts of Spain and at the south of France, Italy and Greece regarding areas that undergo significant groundwater stress and drought effects.

The mining companies at the Mediterranean region need to adapt to these physical changes and to design engineering practices to protect supply and sustainability of water resources in order not to affect the value chain of raw materials availability. Investments in integrated watershed management programs should occur as well as enhancement of local water supplies, and protection of existing water sources to secure the availability of sufficient clean water in light of increasing scarcity and competition. The exploitation of the developed risk map (Fig. 4) can engage mining companies and host communities as partners in water resources management, monitoring, and enhancement.

This management map (Fig. 4) is an example of what can be achieved with innovative applications when digital data sources are exploited and combined. This is only one step forward for European and national policymakers that may help to develop updated governance and management aimed at the sustainable long-term provision of groundwater resources in the Mediterranean region.

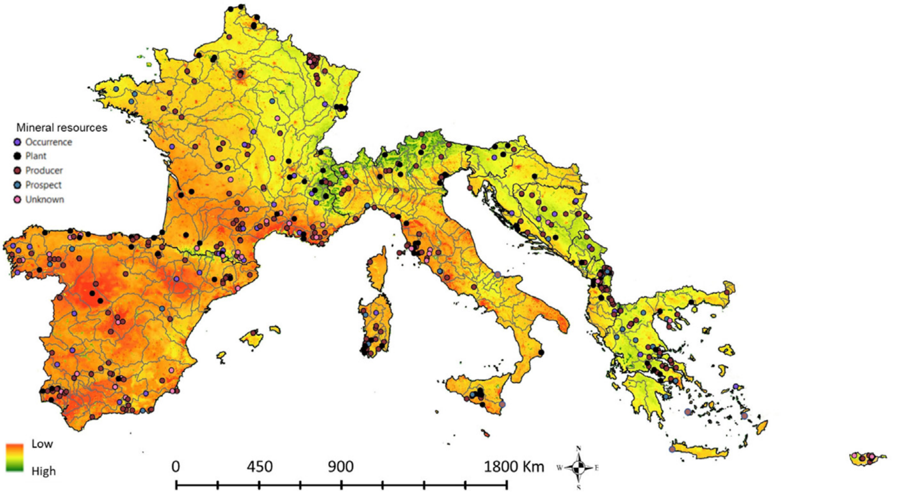

Fig. 5. Drought adaptiveness map at hydrological basin-scale in the European countries of the Mediterranean region after Buddingh et al. (2019) and Mattern et al. (2018).

4. Conclusions

The SOM method that accounts for principles of spatial statistics applied in this work to cluster the available data. It worked efficiently and provided reliable results validating its use in large scale applications. In addition, it proved a useful tool in a topic such as groundwater that requires dense clustering to accommodate local similarities. Generally, the clustering techniques as assessed herein can help to process large datasets. The resulted groundwater stress index mapping combining previous knowledge and the involvement of a new parameter such as the *aquifer type weight* in terms of the aquifer productivity, provided accurate and useful information on the groundwater stress status at hydrological basins scale in the Mediterranean region. A significant number of them are at risk and according to the expected climate change effects in the Mediterranean region the risk is expected to be extended in more hydrological basins vulnerable to high water resources demand and/or low recharge.

CRediT authorship contribution statement

Emmanouil A. Varouchakis: Originated the idea, Applied research design, Execution and led the write-up of the paper, Discussed and interpreted the results. **Gerald A. Corzo Perez:** Research design, Write-up, Discussed and interpreted the results. **Manuel Andres Diaz Loaiza:** Research design, Write-up, Discussed and interpreted the results. **Katerina Spanoudaki:** Research design, Write-up, Discussed and interpreted the results.

Data availability

The data that support the findings of this study are open access and the sources are referenced throughout the manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.spasta.2022.100625.

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