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Major drivers of land degradation risk in Western Serbia: Current trends and future scenarios

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ABSTRACT

Land degradation and desertification (LDD) is one of the greatest ecological challenges of today, with climate change resulting from anthropogenic factors a major cause of it. Recent projections of LDD in the Mediterranean region indicate a gradual widening of arid areas due to increased aridity and global warming by the end of the 21st century. Therefore, this study used the MEDALUS method to identify sensitivity to LDD in Western Serbia between 1986 and 2005 and to assess possible effects of climate change (RCP4.5 and RCP8.5 scenarios) on land degradation processes by the end of the 21st century. Likewise, analysis of possible major drivers of degradation was conducted using principal component analysis (PCA) and multiple linear regression analysis (MLRA). The study revealed that degradation processes in the study area were found to be most influenced by anthropogenic drivers (34.4%), less so by natural/anthropogenic ones (23.5%), and least by natural factors (20.1%). Results also showed that critical areas of LDD susceptibility account for nearly 37% of the study area, transitional areas cover 35%, while 27% constitutes potentially safe areas. Additionally, critical areas were projected to expand by 33.6% (RCP4.5) and 51.7% (RCP8.5) by 2100 as a result of predicted temperature increases and a reduction in precipitation in the study area. This study also revealed that the Standardised Precipitation-Evapotranspiration Index (SPEI) better explains the impact of climate change on LDD than other indices, bearing in mind the capacity of this index to detect temporal oscillations in drought in the context of climate change, and it is therefore a reliable climate parameter for this method.

1. Introduction

At present, land degradation and desertification (LDD) is one of the greatest environmental challenges caused by climate change resulting mainly from anthropogenic activities. LDD leads to a series of economic and social problems due to its negative impact on soil productivity and food availability, biodiversity and ecosystem functioning (Vieira et al., 2015; Prăvălie et al., 2017). Desertification is defined as the process of land degradation in arid, semi-arid and dry sub-humid areas occurring as a result of various factors, including climatic variations and human activities (UNCCD, 1994). The main processes in LDD include the chemical, physical and biological degradation of the environment. Besides the environment, LDD also affects society, e.g. the quality of social coexistence, political stability, social equality, etc. (Kadović et al., 2016).

Recent data shows that over 75% of the Earth's land surface is already degraded, and this could surpass 90% by 2050. Those regions with the highest sensitivity to LDD include states in the Sahara region and large areas stretching between East and South Africa. LDD also affects a large part of Eastern and Central Asia, parts of South America, and relatively large expanses of Western Australia and North America (Cherlet et al., 2018; Ferrara et al., 2020). Likewise, LDD is also considered a major environmental problem in Europe, particularly in the Mediterranean region because land aridity expansion is 70% higher than previously estimated. Within the region, Spain is most at risk, with land that is highly sensitive to degradation covering 49% of the

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country's total surface area, followed by Greece (34%), Portugal (28%), Bulgaria (29%), Romania (11%) and Italy (10% of the total area) (Prăvălie et al., 2017).

At the national level, in the Republic of Serbia, 86.4% of the total surface area is at risk from different types and intensities of land degradation; approximately 13% of the area is affected by degradation from hazardous and harmful materials (MEP, 2015). However, so far there has been no detailed assessment of areas threatened by LDD, apart from two local studies focussing on the northern part of the country (Kadović et al., 2016; Momirović et al., 2019).

Given the significance of LDD-related issues, it is absolutely essential to understand these processes on a spatial and temporal scale, as well as to detect major drivers of degradation. To that effect, an array of methodologies and parameters have been developed in many countries across the world in the past decades to provide a complex analysis of LDD (Prăvălie et al., 2017). The most commonly applied methodologies include the FAO/UNEP methodology (FAO-UNEP, 1984, 1997), the DSPIR framework (GIWA, 2001), MEDALUS (Kosmas et al., 1999), LADA (Liniger et al., 2008) and DRAST (Karavitis et al., 2020). The Mediterranean Desertification and Land Use (MEDALUS) method was designed specifically for this European region, with it being used, for example, for Italy (Salvati and Bajocco, 2011; Ladisa et al., 2012; Smiraglia et al., 2019), Spain (Lavado Contador et al., 2009), Romania (Prăvălie et al., 2020), and Turkey (Budak et al., 2018; Uzuner and Dengiz, 2020), but also for other parts of the world, like Egypt (Bakr et al., 2012), Algeria (Boudjemline and Semar 2018), Iran (Sepehr et al., 2007), and Morocco (Ait Lamqadem et al., 2018). It is based on the principles of Environmental Sensitive Areas (ESAs), through which LDD is analysed in a complex, multifactorial way (Prăvălie et al., 2017). This method involves analysing degraded areas using visual observations, measuring stations and fields, and the processing of environmental indicators through the application of statistical and mathematical models (Salvati and Bajocco, 2011; Salvati et al., 2016). In addition, in recent decades, LDD studies have included remote sensing and geographical information science (GIS) techniques, primarily through analysing satellite multispectral bands and various indices, along with the application of geostatistical techniques, DEM analysis, etc. As a result, the analysis process has been simplified and the dynamics of change in LDD processes can be followed more easily (Tavares et al., 2015; Gül and Erşahin, 2019; Salunkhe et al., 2018; Kolios et al., 2018). Specifically, the multiple ecological and socioeconomic relationships that characterise LDD call for the development and application of analytical frameworks and statistical methodologies that evaluate and quantify the spatial and temporal evolution of complex systems (Salvati et al., 2015).

Previous research has shown the close correlation between LDD sensitivity and soil characteristics, vegetation type, and climate features, and also socio-economic factors, land management options and the quality of policy responses (Smiraglia et al., 2019; Ferrara et al., 2020). Including these factors allows time series to be analysed, trends to be followed, the major drivers of degradation to be determined, and LDD sensitivity in various scenarios to be predicted, particularly in the light of future climate change (Ferrara et al., 2020; Zhang et al., 2020). In this regard, projections to date indicate that increased aridity and global warming, as well as rapid population growth, will heighten the risk of LDD in the near future (Huang et al., 2016) and may lead to the gradual widening of arid areas in many parts of the Mediterranean region (Giorgi, 2006).

Despite evidence of the permanent links between LDD and climate change, no previous study has integrated future projections of climate change with the situation regarding LDD in the Western Balkans and further afield. Bearing this in mind, this study analyses the spatial and temporal dynamics of LDD changes in Western Serbia and assesses the major drivers of degradation. Hence, the basic aims of this study are: (i) to assess LDD in Western Serbia using the MEDALUS method, taking into account the socio-economic specificities of the study area; (ii) to identify the major drivers of LDD using principal component analysis (PCA) and multiple linear regression analysis (MLRA); (iii) to estimate the possible effects of climate change on LDD processes (using two scenarios of the regional climate model: RCP4.5 and RCP8.5), and (iv) to identify critical areas of LDD susceptibility using differential local Moran's I analysis.

2. Material and methods

2.1. Study area

The Zlatibor District is located in south-west Serbia (Fig. 1). The centre of the region is the town of Užice, situated at latitude 43°51′21″ and longitude 19°50′28″. The district stretches across an area of 6140 km^2, which is 6.9% of the surface area of Serbia and, in terms of area, is the largest district in the country. It borders the Mačva and Kolubara Districts to the north, the Moravica District to the east, the Raška District to the southeast, the Republic of Montenegro to the south and southwest, and Bosnia and Herzegovina to the west. In terms of administration, the Zlatibor District comprises the town of Užice and the municipalities of Arilje, Bajina Bašta, Kosjerić, Nova Varoš, Požega, Priboj, Prijepolje, Sjenica and Čajetina.

The relief of the Zlatibor District rises gradually from north to south. The mountains in the study area have typical features of tectonic relief and have undergone major changes due to various exogenous processes. Plateaus dominate this part of Serbia, intersected by gorges and canyons. The mountains of Zlatibor, Tara and Zlatar, as well as the Pešter Plateau, are notable for their importance and beauty. The climate is mostly temperate-continental and is characterised by moderately cold to cold winters and mild summers.

Traditionally, land use has been associated with livestock farming, but tourism-related activities are becoming an ever-increasing feature (Dragović et al., 2008). All watercourses in this area belong to the Black Sea basin, but to the Western Morava and Drina hydrological regions. The Zlatibor District is characterised by a great diversity of geological substrates. Shales and sediments occupy a large area along the Drina River. It is estimated that about 20% of the territory of Western Serbia is covered by slates, phyllites, sandstones and conglomerates. Large areas of massive limestones and alevrolites with inclusions of sandstone, limestone, and ophiolite are found in the south of the region, while the western part is characterised by a serpentinite substrate (Pavlović et al., 2017). The land cover of Western Serbia is also very diverse. The most widespread soils are leptosols, dystric cambisols, calcocambisols and calcomelanosols, followed by stagnosols and vertisols (Mrvić et al., 2013; Pavlović et al., 2017).

2.2. The MEDALUS method and its components

The MEDALUS method identifies regions that are environmentally sensitive areas (ESAs). It provides a composite indicator that can be used to better understand factors causing LDD and comprises multiple parameters, such as relief, soil, geological substrate, vegetation, climate, and human activities. Such an approach can therefore be seen as a good 'early warning' indicator of the level of sensitivity of soil to LDD and its changes over time (Salvati and Bajocco, 2011). Each indicator is generated from several parameters, which combine to produce a quality indicator, and it should be emphasised that this method allows the number of parameters and indicators used for quality assessment to be changed (Kadović et al., 2016). In this study, the MEDALUS method includes indicators and parameters adapted to the methodology described by Kosmas et al. (1999).

According to the MEDALUS method, there are four types of ESAs based on the stage of LDD (Kosmas et al., 1999): Critical ESAs (C1, C2 and C3), Fragile ESAs (F1, F2 and F3), Potential ESAs (P) and Non-Threatened ESAs (N). In this study, analysis of ESAs was conducted on the basis of five quality indicators: Climate Quality Index (CQI), Soil Quality Index (SQI), Vegetation Quality Index (VQI), Management Quality Index (MQI) and Social Quality Index (SoQI) according to the

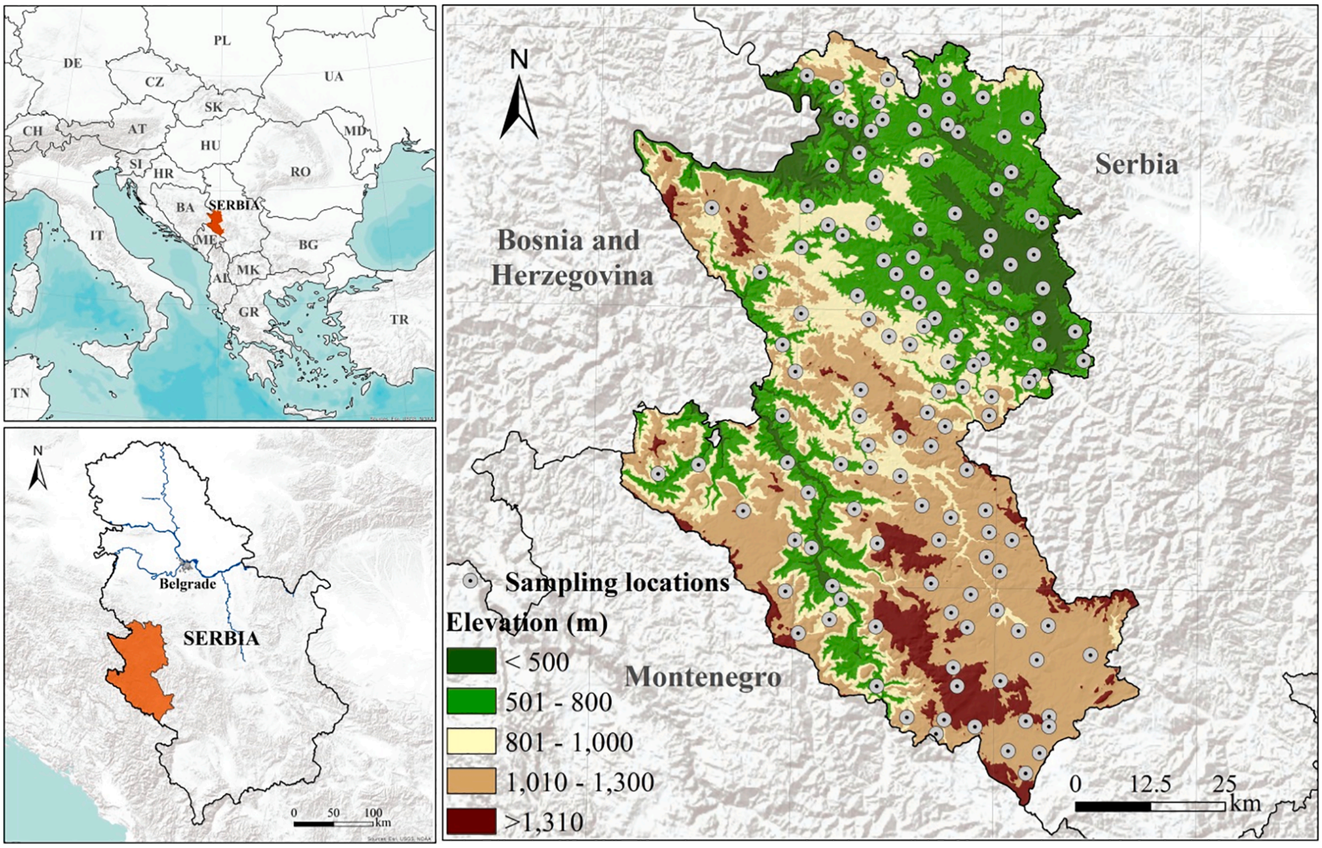

Fig. 1. The location of the study area.

formula (Kosmas et al., 1999):

$$ESAs = (CQI \times SQI \times VQI \times MQI \times SoQI)^{1/5} \quad (1)$$

2.2.1. Climate quality Index (CQI)

The Climate Quality Index (CQI) is related to the impact of climate variation on LDD, and in this study, it was estimated based on the following five parameters: Rainfall, Aridity Index (AI), Rainfall Erosivity, Standardised Precipitation-Evapotranspiration Index (SPEI), and Aspect (Table 1). The Aridity Index (AI) was calculated according to the following formula:

$$AI = P/PET \quad (2)$$

where P is precipitation and PET the potential evapotranspiration, obtained using the Penman-Monteith method. Rainfall Erosivity is a numerical value that quantifies the effects of a raindrop's impact, but also provides relevant information on the amount and rate of runoff that occurs after rain (Kadović, 1999). When calculating Rainfall Erosivity, the algorithm developed by Van der Knijff et al. (1999) and Grimm et al. (2003) was used. The SPEI has the capacity to detect temporal oscillations of drought in the context of climate change (Lu et al., 2019; Myoung-Jin et al., 2020). The SPEI time series encompassed a six-month period (March-August), while the index was calculated using the SPEI package in R environment (https://CRAN.R-project.org/package = SPEI). The package uses Gamma and log-logistic distributions to standardise SPEI values, while the monthly PET was obtained using the Penman-Monteith method, which can better characterise drought episodes. Aspect determines the distribution of solar radiation and temperatures, which have a significant impact on vegetation growth (Kostadinov, 2006). This parameter was calculated using ASTER Global Digital Elevation Model V003. CQI was calculated according to the formula by Kosmas et al. (1999):

$$CQI = (\text{rainfall} \times \text{aridity index} \times \text{rainfall erosivity} \times \text{Standardised Precipitation} - \text{Evapotranspiration index} \times \text{aspect})^{1/5} \quad (3)$$

Table 1
Description of parameters used to obtain the Climate Quality Index (CQI).

Indicator	Parameter	Description	Score	References
CQI	Rainfall (mm)	>1000	1	Tavares et al. (2015)
		650–1000	1.5	
		280–650	1.8	
		<280	2	
	Aridity Index (mm/mm)	Humid (>0.65)	1	Prăvălie et al. (2017)
		Dry sub-humid (0.5–0.65)	1.5	
		Semi-arid (<0.5)	2	
	SPEI*	SPEI < -2	2	Vicente-Serrano et al. (2010)
		−2 < SPEI < -1	1.8	
		−1 < SPEI < -0.50	1.5	
		−0.5 < SPEI < +0.5	1	
	Rainfall* erosivity (MJ mm/ha h yr)	<610	1	Prăvălie et al. (2017)
		610–730	1.5	
		>730	2	
	Aspect	N, NE, NW, W, flat areas	1	Kosmas et al. (1999)
		S, SE, SW, E	2	

* Modified MEDALUS parameters.

2.2.2. Soil quality Index (SQI)

Soil organic matter (SOM) as the primary indicator of soil quality affects the aggregation and stability of the soil structure, the infiltration rate and available water capacity, as well as resistance to erosion from water and wind (Salunkhe et al., 2018). Soil texture/granulometric composition, particularly the size and shape of the particles, affects the loss of soil by wind or water and also the rate of water infiltration, which again influences the amount of surface runoff. In this study, SOM content and granulometric composition were ascertained in 130 soil samples collected from the study area (Fig. 1). An SOM map was obtained using the ordinary kriging interpolation method as an effective linear unbiased estimator (Yao et al., 2019), while the spatial distribution of textural classes was obtained using the Soil texture plugin in QGIS software (QGIS Development Team, 2020). A 1:100,000 geological map was taken in vector form from the University of Belgrade's Faculty of Mining and Geology (Serbia), on the basis of which different types of geological substrates were grouped into several classes according to their petrological and mineralogical composition. Topography and slope data was obtained from ASTER Global Digital Elevation Model V003. SQI (Table 2) was calculated according to Kosmas et al. (1999) as:

$$SQI = (\text{texture} \times \text{parental material} \times \text{humus content} \times \text{slope})^{1/4} \quad (4)$$

2.2.3. Vegetation quality Index (VQI)

VQI was analysed on the basis of four standard parameters for the MEDALUS method: Fire Risk, Erosion Protection, Drought Resistance and Plant Cover. The geospatial data was obtained using the CORINE database (CLC, 2018) and the Normalised Difference Vegetation Index (NDVI), which are most commonly used for regional assessments of VQI (Prăvălie et al., 2017, 2020; Budak et al., 2018; Symeonakis et al., 2016), and each parameter was created from land cover/use classes according to the CORINE classification system and NDVI values based on certain theoretical aspects found in scientific literature (Prăvălie et al., 2017; Ferrara et al., 2020). Thus, Vegetation Cover (%) was obtained by classifying NDVI values into 11 categories, while Fire Risk, Erosion Protection and Drought Resistance were obtained using CORINE data by the grouping of land cover types (Table 3). VQI was calculated according to the formula by Kosmas et al. (1999):

$$VQI = (\text{fire risk} \times \text{erosion protection} \times \text{drought resistance} \times \text{plant cover})^{1/4} \quad (5)$$

2.2.4. Management quality Index (MQI)

The various anthropogenic environmental pressures contributing to LDD were quantified in relation to Agricultural Intensity and Policy Enforcement. Agricultural Intensity refers to LDD processes such as soil erosion and soil structures. An agricultural intensity map was generated from the CORINE database using three categories - low, medium and high intensity, while the agricultural policy implementation map, relating to the implementation of existing environmental regulations, was taken from the reference map of the protected natural resources of the Zlatibor District. This region has been declared a protected area in order to safeguard the geomorphological and hydrological phenomena of this highly dissected terrain with its striking canyons and gorges, preserved ecosystems of karst terrain and the rocks of the serpentinite gorges with their particularly diverse and specific vegetation, and coniferous forests, and rare and endangered animal species, as well as extremely important, well preserved historical monuments and ethnic heritage (MEP, 2012). MQI (Table 4) was calculated according to the formula by Kosmas et al. (1999):

$$MQI = (\text{intensity of land use} \times \text{protection policies})^{1/2} \quad (6)$$

2.2.5. Social quality Index (SoQI)

In more complex analyses of LDD potential, the index of socio-economic quality is relevant since certain anthropogenic aspects can directly affect the condition of the soil (Prăvălie et al., 2017). Social indicators are linked to LDD processes as a result of human activities, with Population Density (Pd) and the Old Age Index (Oa) the two basic parameters used to evaluate the SoQI. Pd is closely related to the

Table 2
Description of parameters used to obtain the Soil Quality Index (SQI).

Indicator	Parameter	Description	Score	References
SQI	Texture	L, SCL, SL, LS, CL	1	Kosmas et al. (1999)
		SC, SiL SiCL	1.2	
		Si, C, SiC	1.6	
		S	2	
	Parent material	Shale, schist, basic, ultra basic, Conglomerates, unconsolidated	1	Kosmas et al. (1999)
		Limestone, marble, granite, Rhyolite, Ignibrite, gneiss, siltstone, sandstone	1.7	
		Marl, Pyroclastics	2	
	Organic Matter, (Humus Content)			Kadović et al. (2016)
		>3.0	1	
		1.0–3.0	1.5	
		<1.0	2	
	Slope (%)	<6	1	Kosmas et al. (1999)
		6–18	1.2	
		18–35	1.5	
		>35	2	

Table 3
Description of parameters used to obtain the Vegetation Quality Index (VQI).

Indicator	Parameter	Description	Score	References
VQI	Fire risk*	212, 331	1	Prăvălie et al. (2017)
		211, 221, 231,241, 242, 311, 321	1.3	
		324, 243	1.6	
		222	2	
	Erosion protection*	311	1	Prăvălie et al. (2017)
		222, 231, 243, 321, 324	1.3	
		241, 242	1.6	
		211, 212, 221, 331	2	
	Drought resistance*	212, 311, 324	1	Prăvălie et al. (2017)
		321	1.2	
		221, 222, 243	1.4	
		231, 241, 242	1.7	
		211, 331	2	
	Plant cover	=> 0.80	1	Ferrara et al. (2020)
		0.72 < 0.80	1.1	
		0.62 < 0.72	1.2	
		0.50 < 0.62	1.3	
		0.38 < 0.50	1.4	
		0.26 < 0.38	1.5	
		0.18 < 0.26	1.6	
		0.13 < 0.18	1.7	
		0.11 < 0.13	1.8	
		0.1 < 0.11	1.9	
		< 0.1	2	

* Codes are nomenclature of the CORINE Land Cover database.

Table 4
Description of parameters used to obtain the Management Quality Index (MQI).

Indicator	Parameter	Description	Score	References
MQI	Agricultural intensity*	222, 243, 311, 321, 324, 331	1	Prăvălie et al. (2017)
		211, 231, 242	1.5	
		21, 221	2	
	Policy enforcement	Complete: >75% of area under protection	1	Kosmas et al. (1999)
		Partially: 25–75% of area under protection	1.5	
		Incomplete: <25% of area under protection	2	

* Codes are nomenclature of the CORINE Land Cover database.

intensity of human pressure on natural resources, while Oa emphasises the strong imbalance between a large number of elderly people in relation to the total population (Tavares et al., 2015). In this study, the parameter Pd (the number of people per square kilometre) was taken at 30 arc-second horizontal resolution in accordance with national censuses and population registers (CIESIN, 2018), while data for the parameter Oa was taken from the Statistical Office of the Republic of Serbia (www.stat.gov.rs). SoQI (Table 5) was determined as the geometric mean of these two factors using the following formula (Tavares et al., 2015):

$$SoQI = (\text{population density} \times \text{old age index})^{1/2} \tag{7}$$

2.3. Climate change scenarios

The climatological periods used in this study were based on the recommendations of the IPCC's Fifth Assessment Report (IPCC AR5), which takes the period between 1986 and 2005 as the base or reference period, 2016–2035 as the near future, 2046–2065 as mid-century and 2081–2100 as the end of the 21st century. EURO-CORDEX datasets for nine different models were used (Jacob et al., 2014), (Table 6), as well as two Representative Concentration Pathway (RCP) scenarios for GHG emissions: RCP4.5 - a stabilisation scenario with a GHG emission peak in 2040 and then declining, and RCP8.5 - a steady increase scenario. EURO-CORDEX scenario simulations use the new Representative Concentration Pathways (RCPs), (Moss et al., 2010). Unlike Special Report on Emissions Scenarios (SRES), RCP scenarios do not use socio-economic scenarios, but assume pathways to various target radiative forcing levels at the end of the 21st century (Jacob et al., 2014). A comparison between the climate effects of the SRES and RCP scenarios indicates that the A1B scenario leads to a global mean temperature increase of between 2.8 °C and 4.2 °C, which is close to RCP6 (between RCP4.5 and RCP8.5), (Rogelj et al., 2012). In this way, the applied methodology allows the comparison of results from other regions in the fight against the negative impacts of climate change (Vukovic et al., 2018).

2.4. Statistical analysis

Raster data on CQI, SQI, VQI, MQI and SoQI was converted to a vector format so the major drivers of LDD in Western Serbia could be analysed and estimated. Then, Principal Component Analysis (PCA) was applied to a matrix composed of these five indicators, thus enabling the grouping of factors with a similar influence, selected by the percentage of variance. The absolute principal scores from PCA were further analysed using MLRA as independent factors over the quality indicators of the MEDALUS method as dependent factors (Čakmak et al., 2018), on the basis of which a percentage distribution of possible types of degradation sources was obtained. Kaiser-Meyer-Olkin (KMO) testing was used to evaluate the quality of the PCA results obtained, thereby establishing the compactness and reliability of the factor model (Salvati et al., 2014). A complete statistical analysis was achieved using SPSS software (IBM SPSS Statistics, 2016).

Table 5
Description of parameters used to obtain the Social Quality Index (SoQI).

Indicator	Parameter	Range	Score	References
SoQI	Old age index (%)	>5	1	Tavares et al. (2015)
		5–10	1.4	
		10–20	1.5	
		>20	2	
	Population density (inhabitants/km^2)	<4	1	Ferrara et al. (2020)
		4 < 30	1.1	
		30 < 80	1.2	
		80 < 170	1.3	
		170 < 300	1.4	
		300 < 500	1.5	
		500 < 850	1.6	
		850 < 1400	1.7	
		1400 < 2000	1.8	
		2000 < 2700	1.9	
		≥ 2700	2	

Table 6
Multi-model ensemble members, consisting of results from listed regional climate models (RCM).

RCM	GCM	Ensemble member
CCLM4-8-17	CNRM-CERFACS-CNRM-CM5	1
CCLM4-8-17	ICHEC-EC-EARTH	1
CCLM4-8-17	MOHC-HadGEM2-ES	1
CCLM4-8-17	MPI-M-MPI-ESM-LR	1
HIRHAM5	ICHEC-EC-EARTH	1
RACMO22E	ICHEC-EC-EARTH	1
RACMO22E	MOHC-HadGEM2-ES	1
REMO2009	MPI-M-MPI-ESM-LR	1
REMO2009	MPI-M-MPI-ESM-LR	2

* GCM stands for Global Climate Model and RCM for Regional Climate Model.

In addition, differential local Moran's I (DLM) analysis was used in this study, implemented in GeoDa (version 1.14) software. DLM analysis is based on changes over time, i.e. on the difference between yt and yt^{-1}. Spatial and temporal dynamics of change in LDD patterns (ESA values) were analysed for 1986–2005 (the base or reference period) and 2080–2100 (the end of the 21st century). These time series allowed change patterns to be identified and the spatial dynamics of LDD to be better interpreted. DLM analysis was tested using 999 permutations with a level of significance of 0.05. It should be borne in mind that this is the actual difference, and not the absolute difference between the two time series of data; hence, positive changes will be seen as high and negative ones as low (Anselin, 2018). The formula for DLM is as follows:

$$ID, i = c\left(yi, t - yi, t^{-1}\right)\sum_{j} Wij\left(yj, t - yj, t^{-1}\right) \tag{8}$$

where yi, t and yi, t^{-1} are the normalised values of the changes in the two periods.

3. Results

3.1. LDD dynamics from the reference period (1986–2005)

Seventeen LDD parameters including five climate parameters (CQI), four soil quality parameters (SQI), four vegetation quality parameters (VQI), two management parameters (MQI) and two socio-economic parameters (SoQI) were calculated to determine the map of ESAs in Western Serbia using the geometric mean. The results showed that the majority of the study area can be classed as high quality in terms of CQI (an average value of 1.14; SD 0.34; Fig. 1S, 2S), VQI (an average of 1.25; SD 0.31; Fig. 1S, 2S), MQI (an average of 1.2; SD 0.22; Fig. 1S, 2S) and SoQI (an average of 1.13, SD 0.09; Fig. 1S, 2S). In the case of SQI, the study area was found to be of medium quality, with an average value of 1.38 (SD 0.25; Fig. 1S, 2S). ESAs were obtained by integrating all five quality indicators (Fig. 2). According to the results, those areas falling into the categories of C1, C2 and C3 are located in the low-lying, northern part of the region, as well as in the hilly and mountainous parts, mainly in the southeast and southwest of the study area. These areas, with index values over 1.375, account for 2304.42 km^2, representing 37.53% of the total study area (Table 7). Fragile areas (F1, F2 and F3), with index values of 1.225–1.375, cover 2152.34 km^2, or 35.05% of the total area, mainly in the central part of the region on the slopes of mountains and in foothills. Areas at relatively low threat from LDD (index values of 1.170–1.225) are also found in the central part of the region, covering 749.13 km^2 (12.2%), and are located in wetter zones where there are large expanses under natural forests (Table 7).

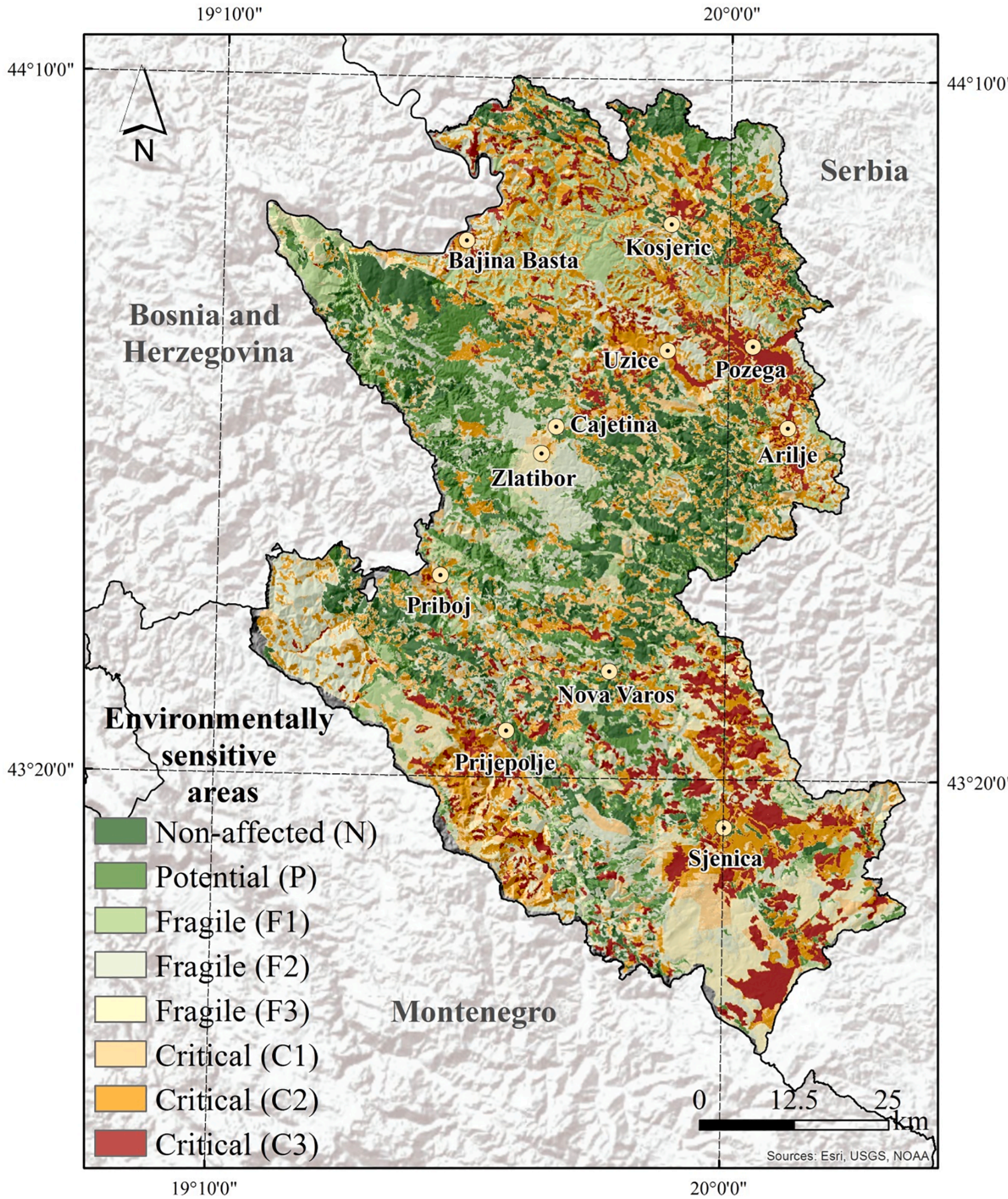

Fig. 2. The distribution of ESAs in Western Serbia.

Non-threatened areas (index values < 1.170) account for 15.21% of the total area or 934.11 km^2 (Table 7).

Using PCA and MLRA, three components were identified that accounted for 77.9% of the variance (Table 1S). The first component, accounting for 34.4% of the variance, comprises VQI and MQI (loading = 0.927; Fig. 3, Table 2S), which indicates an anthropogenic influence on LDD, i.e. it shows that the said component had the greatest impact on the current processes of LDD. Specifically, the VQI component was found to be 92.14% dependent on anthropogenic factors, while MQI dependence on this factor was 93.03% (Fig. 4). Accounting for 23.5% of the variance, the second component, consisting of SQI and SoQI (loading = 0.755 and 0.775; Table 2S), indicates a natural/anthropogenic influence on LDD. SQI was most influenced by natural/anthropogenic factors (77.49%) and partially by natural ones (21.07%). A similar trend was found for SoQI, where the impact of natural/anthropogenic factors is dominant with 62.64%, while the influence of natural factors is lower at 20.46% (Fig. 4). The third component (CQI) (loading = 0.992 and 0.775; Table 2S), accounting for 20.1% of the variance, indicates a natural influence (92.83%), meaning that only 19.8% of the impact on the current state of LDD can be attributed to climatic parameters (Figs. 3 and 4). The Kaiser-Meyer-Olkin (KMO) value for the above variables was 0.501 (Table 3S), which represents a value above the recommended cut-off of 0.5, indicating the existence of a compact correlation and showing that PCA provides clear and reliable factors (Field, 2009).

Table 7
Summarised results of ESAs (Ferrara, 2005).

Class	Sub-class	Score range	km^2	%
Non-affected	N	>=1.00<=1.170	934.11	15.21
Potential	P	>1.170<=1.225	749.13	12.2
Fragile (high)	F1	>1.225<=1.275	577.13	9.4
Fragile (medium)	F2	>1.275<=1.325	1002.27	16.32
Fragile (low)	F3	>1.325<=1.375	572.94	9.33
Critical (high)	C1	>1.375<=1.425	575.05	9.37
Critical (medium)	C2	>1.425<=1.530	1124.48	18.31
Critical (low)	C3	> 1.530	604.89	9.85
	Total		**6140**	**100**

Note: N – Areas which are not at threat or are at virtually no threat from degradation; P – Areas with low sensitivity to land degradation; F – Areas with medium sensitivity to land degradation; C – Areas with high sensitivity to land degradation

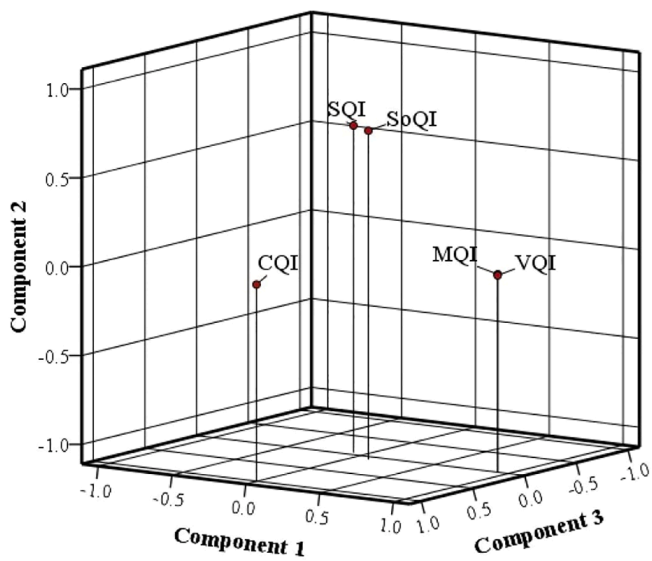

Fig. 3. PCA loading plot for MEDALUS quality indicators.

3.2. LDD dynamics in the future (2046–2065 and 2081–2100)

In this study, EURO-CORDEX datasets for nine different models and two representative concentration pathways (RCP4.5 and RCP8.5) were used. Climate change in the near future (2016–2035) did not have a significant impact on LDD processes when compared to the reference period (1986–2005), and hence this period was not taken into further consideration in this research. Fig. 5 shows the categorisation of soil sensitivity according to the RCP4.5 scenario for 2046–2065 and 2081–2100. It was simulated that climate change would result in a 25.6% expansion of critical areas (C1, C2 and C3) by 2065 and a 33.6% expansion by 2100 compared to the reference period (Table 8). Research based on the RCP8.5 scenario indicates a continuous increase in GHG emissions. With this in mind, a dramatic increase in critical areas (C1, C2 and C3) was simulated, amounting to an increase of 39.2% by 2065 and as high as 51.7% by 2100 compared to the reference period (Fig. 5 and Table 8).

3.2.1. Spatio-temporal cluster analysis

In this study, different types of LDD spatial patterns were identified for the period 1986–2005 (reference period) and 2080–2100 (the end of the 21st century) using DLM. Essentially, high positive values indicate a high level of change (above average), while high negative values point to a low level of change (below average). In this regard, Fig. 6 illustrates the spatial and temporal distribution of LDD patterns, with two types of spatio-temporal clusters predominant: High-High (HH) and Low-Low (LL). Analysis based on the RCP4.5 scenario shows that the majority of the HH spatio-temporal clusters are concentrated in the northern part of the study region (Fig. 6a), where agricultural areas with intensive production predominate and with a higher population concentration as well. On the other hand, results obtained on the basis of the RCP8.5 scenario point to an overall increase in the number of HH spatio-temporal clusters, particularly in the southern part of the study region (Fig. 6b), which leads us to the conclusion that these regions are susceptible to LDD processes in the reference period and that this trend will continue up until the end of the century. Generally speaking, the pattern of HH spatio-temporal clusters in Western Serbia is tied to those areas with insufficiently good quality indicators like CQI, MQI, SQI and VQI. Conversely, in the central and northern parts of the region, there are a significant number of locations with LL spatio-temporal clusters, i.e. locations with negative changes surrounded by locations with similar

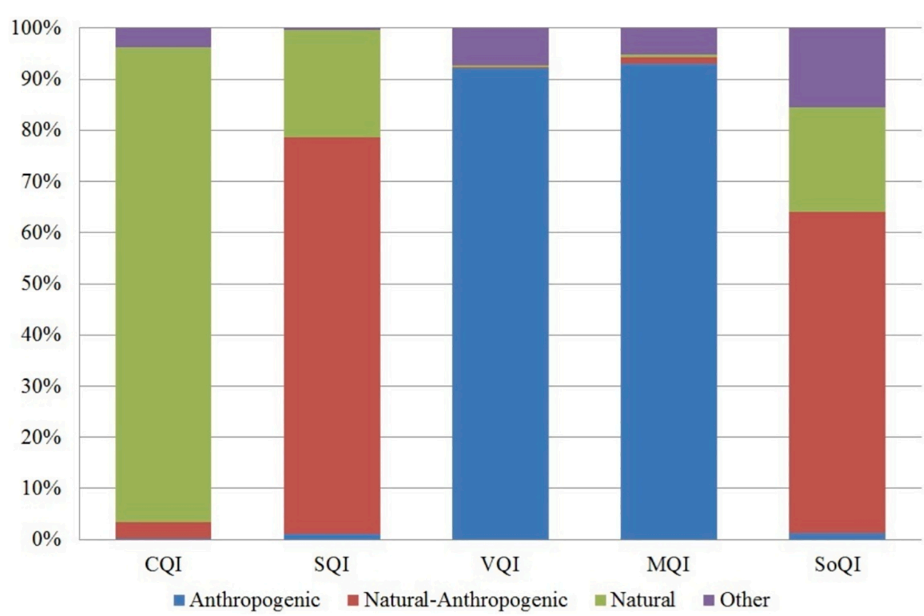

Fig. 4. Percentage distribution of possible types of degradation source.

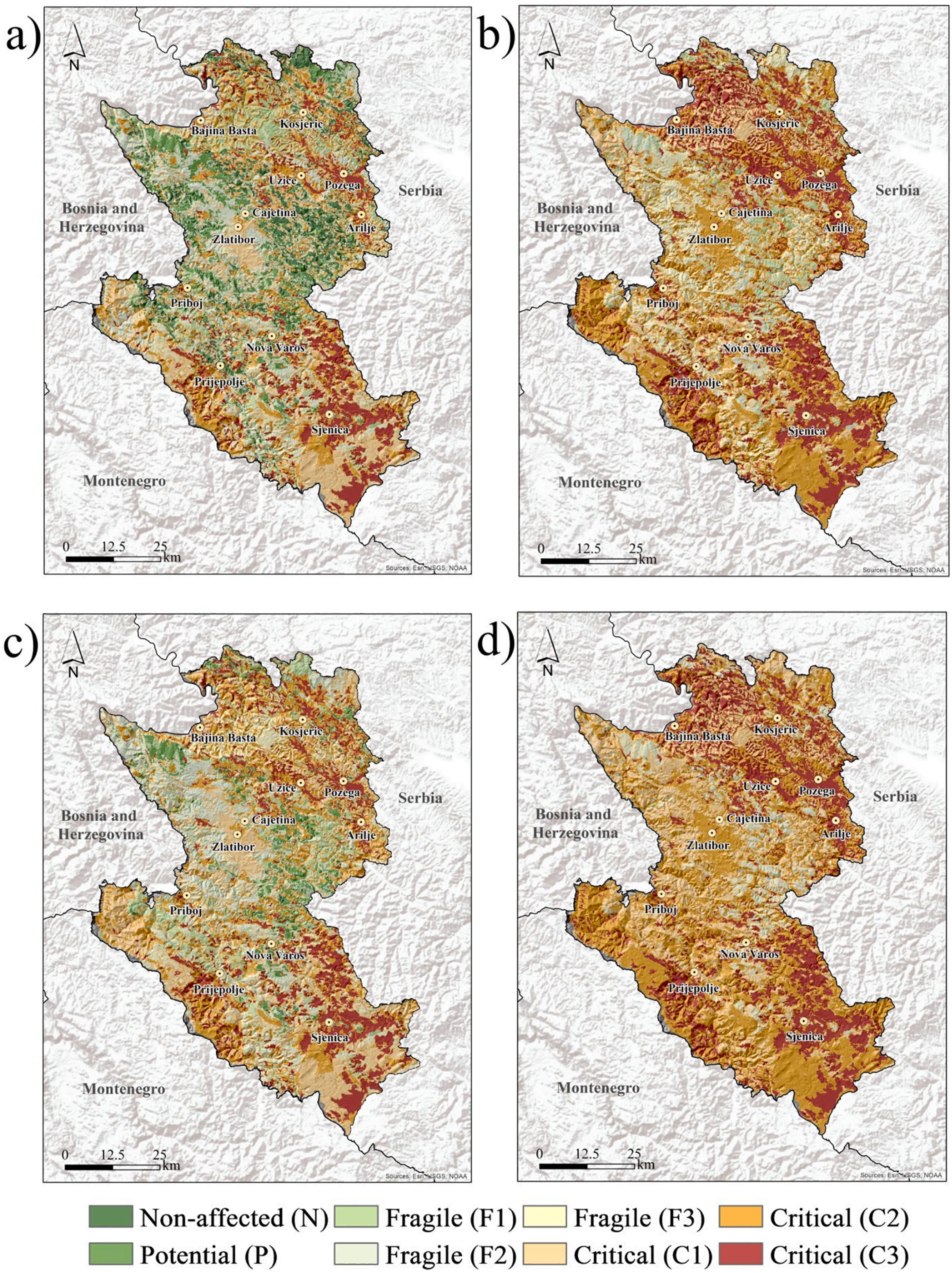

Fig. 5. The spatial distribution of areas sensitive to LDD under the RCP4.5 and RCP8.5 scenarios a) 2046–2065 (RCP4.5); b) 2046–2065 (RCP8.5); c) 2081–2100 (RCP4.5); d) 2081–2100 (RCP8.5).

Table 8
Summarised results of LDD sensitive areas under the RCP4.5 and RCP8.5 scenarios.

Sub-class	RCP4.5 2046–2065		RCP8.5 2046–2065		RCP4.5 2081–2100		RCP4.5 2081–2100	
	km^2	%	km^2	%	km^2	%	km^2	%
N	553.5	9.01	57.98	0.94	52.69	0.86	28.99	0.47
P	593.67	9.67	409.62	6.67	428.68	6.98	58.3	0.95
F1	515.9	8.4	494.52	8.05	934.22	15.22	265.29	4.32
F2	941.97	15.34	786.17	12.8	750.6	12.22	232.85	3.79
F3	436.29	7.11	601.77	9.8	504.68	8.22	783.55	12.76
C1	1068.74	17.41	1322.85	21.54	1156.91	18.84	955.57	15.56
C2	1303.23	21.23	1606.94	26.17	1402.07	22.84	2395.72	39.02
C3	726.7	11.84	860.16	14.01	910.13	14.82	1419.73	23.12
Total	6140	100	6140	100	6140	100	6140	100

Note: N – Areas which are not at threat or are at virtually no threat from degradation; P – Areas with low sensitivity to land degradation; F – Areas with medium sensitivity to land degradation; C – Areas with high sensitivity to land degradation.

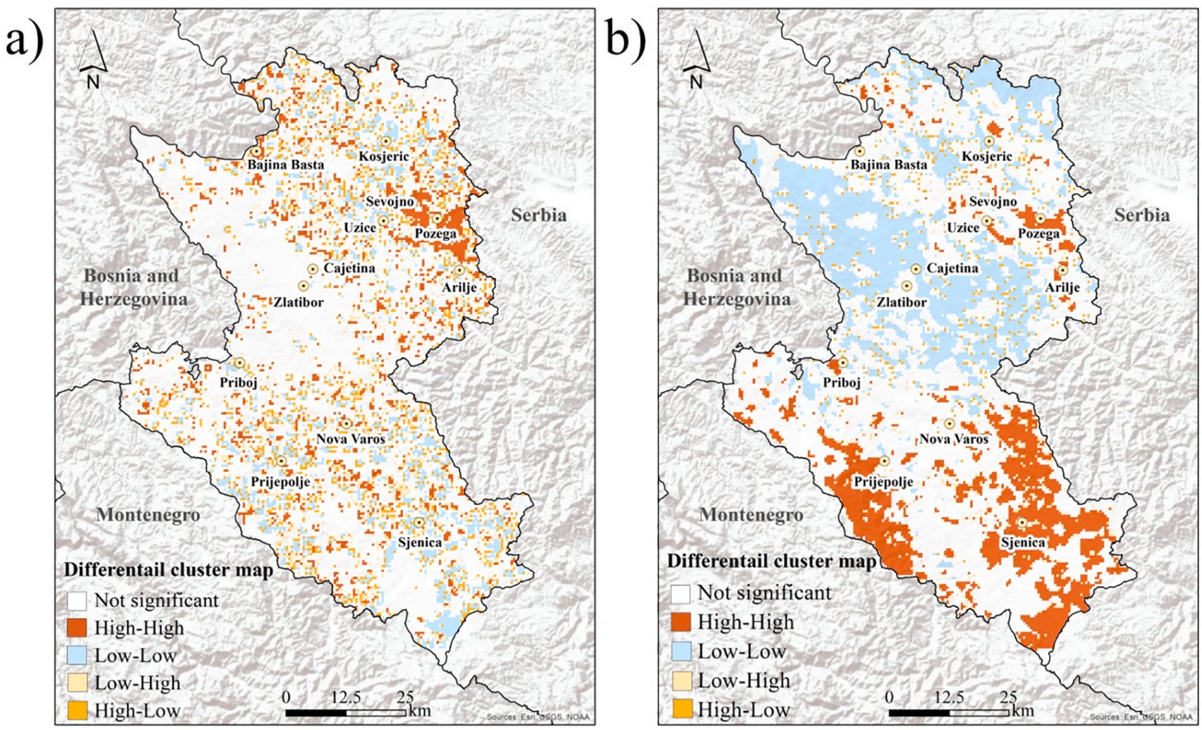

Fig. 6. LDD differential cluster map: a) for the reference period (1986–2005) and future period (2080–2100) according to the RCP4.5 scenario; b) for the reference period (1986–2005) and future period (2080–2100) according to the RCP8.5 scenario.

trends. These regions are characterised by significant areas of forest, as well as zones of protected natural resources.

4. Discussion

4.1. Major drivers of LDD processes from the reference period (1986–2005)

The MEDALUS method was designed primarily for the Mediterranean region and validated for the socio-economic conditions in Mediterranean countries and other parts of Europe; however, its conceptual approach can be applied globally (Mairota et al., 1998; Ladisa et al., 2012). As LDD is a dynamic spatial and temporal process that is multidimensional in nature and impacts a variety of socio-economic and biophysical factors (Vogt et al., 2011; Kosmas et al., 2016), researchers have devoted a lot of time over the last few decades to analysing LDD and its links to natural and anthropogenic factors on a global, regional, national and local scale (Prăvălie et al., 2017; Kadović et al., 2016; Momirović et al., 2019). With LDD representing a serious problem in Serbia as well, this study sought to assess and quantify the spatial and temporal evolution of LDD processes in Western Serbia.

Our study demonstrated that the major drivers of LDD in Western Serbia are primarily related to anthropogenic activities, with VQI and MQI having a 34.4% influence (PCA 1; see section 3.1.), which fully supports earlier findings for the Mediterranean region (Feoli et al., 2003), as well as for the entirety of Europe (Ferrara et al., 2020). In Western Serbia, the dominant anthropogenic factors are VQI and MQI (Figs. 3 and 4), which have been identified as the main drivers of LDD in many studies in other parts of Serbia (Kadović et al., 2016; Momirović et al., 2019), as well as the Balkan Peninsula (Gül and Erşahin, 2019). Their negative impact in Western Serbia is related to the improper use and management of forests, including deforestation, especially pronounced in the southern part of the region, and also to the conversion of pastures and semi-natural vegetation into arable land, intensive soil erosion, and an overall lack of integrated natural resource management. Although Western Serbia is rich in forests, its development is hindered by various constraints related to the degradation of parts of the forested area as a factor in diminished productivity and biological stability, insufficient area and age structure of forest vegetation, insufficient activity in accessing appropriate forest development funds and inefficient management of the total forest resource. A good example of well preserved natural forests are coniferous forests, mostly pine forests and to a lesser extent spruce forests, while other types of forests are devastated and degraded, having been reduced to smaller open formations (MEP, 2012). Mountainous areas with a slightly wetter climate are characterised by oak forests, which are mainly found on the steep slopes of valleys and ravines prone to erosion processes. Much of the pasture of Western Serbia is subject to the most diverse forms of erosion caused by water, ice and snow, while traces of aeolian erosion are also not uncommon (MAFWM, 2018). Surface runoff is a frequent occurrence in the sparse grassy areas, causing the shallow layer of soil to disappear from entire slopes. Also, a lot of the pasture in the south of the study area (Pešter Plateau, Nova Varoš, Prijepolje) has been used for livestock grazing for hundreds of years, and it is only natural that such overgrazing causes the land to be degraded (Papanastasis, 1998), the grassy surface becomes thinned out, and the floristic composition of the grass communities is modified. Given the mountainous character of this part of Serbia, the threat from potential natural disasters such as landslides, fires, and earthquakes is pronounced (Dragićević et al., 2011). Fires are particularly frequent in areas with pine forests (Aleksić et al., 2009), after which soil degradation is accelerated due to changes in the physical properties of the soil (Certini, 2005; Gül and Erşahin, 2019). Fires also change the vegetation cover and thus significantly reduce the protection of soil from the erosion power of rain and, consequently, from soil erosion (De Paola et al., 2013). Similar and somewhat more intense forms of LDD exist in the Mediterranean, but also in certain parts of Central and Eastern Europe (EEA, 2012; Çolak and Sunar, 2020).

The influence of the natural/anthropogenic component was noted in Western Serbia, consisting of SQI and SoQI, with its impact on LDD processes being 23.5% (PCA 2; see Section 3.1.). These are areas with pronounced topography, i.e. steep slopes, with poor SQI and SoQI indicators above all, indicating a strong correlation between land quality and demographic and socio-economic divisions (Salvati et al., 2017). The topography of this part of Serbia has a strong impact on land use and factors contributing to soil erosion (Kostadinov et al., 2006). The slope of the terrain affects the infiltration rate in particular and accelerates runoff, with the slope length increasing the transport of sediment (Kadović, 1999). The steepest slopes often create landslides and avalanches, damaging vegetation and increasing soil erosion (Pérez-Trejo, 1994; Ristić et al., 2011).

In addition, in areas where ESA index values fell into the C1, C2 and C3 categories, the SOM content was reduced. It is believed that the low SOM content, which is frequently ≤2%, is a consequence of high summer temperatures, which stimulates the faster mineralisation of fallen leaves, increases the occurrence of fires, and results in the domination of open shrubland (García-Ruiz et al., 2013). The replacement of forest vegetation with grassland in many areas of Western Serbia has caused changes in morphology, which above all has affected the accumulation of humus and the creation of a humus horizon. As a major indicator affecting the physical, chemical and biological properties of soil, the lack of SOM accelerates soil erosion and leads irreversibly to LDD (Salunkhe et al., 2018). Moreover, the deep ploughing of arable land is practised in many agricultural areas, leading to the rapid mineralisation of labile components of SOM. Erodible texture classes that are more prevalent in the southern part of the region affect the stability of soil structure, reducing the rate of infiltration and available water capacity, as well as resistance to water and wind erosion (Le Bissonnais and Arrouays, 1997). For this reason, soil texture is one of the key factors that affect the risk of LDD (Vieira et al., 2015). Similar to these findings, natural/anthropogenic factors are also among the major indicators of LDD across Europe (Imbrenda et al., 2013). In general, soils in the highest ESA class (C1, C2 and C3) are shallow and disappear due to erosion processes.

This is especially the case with soils formed on soft limestones (marly and soft limestone) and serpentinites, which predominate in this region (Pavlović et al., 2017). Although soils on limestone and serpentinite are not sandy, in most cases they have a silty texture, which makes them poorly bound and erodible. In addition, soils formed on serpentinite are very shallow and impermeable to water, which affects the formation of defiles, gullies, ravines and various other types of water erosion features (Alexander and DuShey, 2011). Earlier research showed that it is precisely those areas with a geological substrate predominantly composed of shales, flysch sandstones, serpentinites and limestones that are most vulnerable to erosion processes (Tanasijević et al., 1966) and the study area is one such area. Specifically, many areas on limestone formations in the Mediterranean region have already been ravaged and eroded, while vegetation cover has been completely devastated (Basso et al., 2012). The accumulation capacity of these soils is insignificant, which is why large swathes of pasture and meadow in these areas become dry habitats, unsuitable for the good development of grass and other types of vegetation. From the point of view of the spatial distribution and organisation of agricultural production, these areas have a negative character in agro-ecological and socio-economic terms, as well as an underdeveloped infrastructure and higher rates of rural poverty and unemployment. These factors, especially poverty, tend to affect LDD, primarily due to the dependence on biomass-focused production (Prakash et al., 2016). In addition, since Serbia, like many other countries in transition, is facing a demographic decline, especially in rural areas (Manojlović et al., 2018), the impact of socio-economic factors on the study area is negligible, primarily due to the low population density, particularly marked in the central and southern areas of the region. It should be noted that the study area is a significant area in terms of tourists, and tourism, although not a direct cause of LDD, can have a significant impact on the environment (Ladisa et al., 2012), especially in relation to land use patterns and the availability of water resources (Pérez-Trejo, 1994). For the reasons mentioned above, we can conclude that there has been a disturbance in the balance between anthropogenic and natural/anthropogenic factors in the study area, which has led to the intensification of LDD processes.

The current impact of climate parameters (CQI) on LDD in this part of Western Serbia is 20.1% (PCA 3; see Section 3.1.), as this region is exposed to air currents from the west, making precipitation slightly more abundant here than in the rest of Serbia. Since a higher altitude region separates Western Serbia from the influence of the Adriatic Sea, the climate of this part of Serbia is slightly cooler. However, due to the existence of valleys, these influences converge and weaken here. The central area and certain parts in the north and south of the region are in the low risk zone, primarily because of the lower intensity of agriculture and the larger areas under forests. Specifically, these areas mainly extend into zones of protected natural resources, such as the Tara National Park, 'Golija' Nature Park, 'Ovčar-Kablar Gorge' (classed as 'a landscape of exceptional features'), 'Uvac' Special Nature Reserve, and 'Zlatibor' Nature Park.

4.2. Major drivers of the LDD process in the future (2046–2065 and 2081–2100)

The spatial distribution of LDD in the future will depend on the interaction between various drivers, with climatic aspects having the greatest impact (Lu et al., 2019). Therefore, this study analysed future CQI projections (according to the RCP4.5 and RCP8.5 scenarios), as it is expected that Western Serbia will experience the negative effects that climate change can cause in the near future, and particularly in the forthcoming decades (Vukovic et al., 2018). Namely, it is estimated that global temperatures will increase by 1.4 °C according to RCP4.5 and by 1.8 °C according to the RCP8.5 scenario for 2046–2065 compared to 1986–2005, while for the period from 2081 to 2100, it is estimated that this increase will be 2.0 °C and 4.4 °C respectively (IPCC, 2013). In Serbia, analyses show that by the end of the century, global warming will cause an increase of over 2.5 °C in the mean temperature under the RCP4.5 stabilisation scenario and of over 5 °C under the constant RCP8.5 scenario with a decrease in summer precipitation (Vukovic et al., 2018). Beyond these findings, there is generally a broad scientific consensus that Southeast Europe, and especially the Mediterranean region, can be considered one of the most critical areas for climate change in the 21st century (Giorgi, 2006; Diffenbaugh et al., 2007; Spinoni et al., 2017, 2018). In this regard, according to projections for both climate scenarios, changing climate patterns caused by climate change will intensify the process of LDD in Western Serbia, especially in the C1, C2 and C3 categories, as is shown by the spatial grouping patterns of the HH spatio-temporal clusters following DLM analysis (Fig. 6; Table 8). Specifically, according to the RCP4.5 and RCP8.5 scenarios, temperatures are expected to increase and precipitation to decrease, especially in the summer months, while the AI and SPEI indicate an increase in aridity and drought. In addition, a reduction in the annual Rainfall Erosivity Factor is projected by the end of the century, primarily due to a decrease in precipitation. However, of all of the climate parameters mentioned previously, the SPEI is the most reliable index for assessing the impact of climate change on the occurrence of drought, i.e. LDD (Manzano et al., 2019; Spinoni et al., 2017; Lu et al., 2019), thus confirming the usefulness of including the SPEI in the climatic parameters of the MEDALUS method. This recommendation could improve the reliability assessment of the methodology, primarily when analysing climate parameters. In this regard, the SPEI in this study was calculated over a six-month period (March-August), which allows for the monitoring of the dynamics of change during the warmer part of the year, especially for those periods when, on the one hand, maximum rainfall is expected in Western Serbia (May-June-July) and when, on the other, the largest deficits are projected (Vukovic et al., 2018). Hence, if the SPEI is <0, it indicates processes related to a dry climate, while if it is >0, it indicates wet climate processes (Gao et al., 2017). When looking at the SPEI for 2081–2100 for both scenarios (Fig. 3S), it is clear that the RCP4.5 scenario indicates that much of Western Serbia will be affected by a dry climate (values < -0.50) and moderately severe droughts, while RCP8.5 shows an even more dramatic forecast, whereby nearly the entire area will be affected by severe droughts (values < -1), including zones of extreme drought (values < -2), especially in those areas that border Montenegro.

The spatial distribution of the SPEI in Western Serbia coincides with the majority of studies which have analysed this index in Europe and which predict episodes of increased risk of fire (Cardil et al., 2019), disturbance events in forest ecosystems (Tognetti et al., 2019), patterns of water deficit (Lu et al., 2019) and an overall increase in areas of drought (Carrão et al., 2017; Jacob et al., 2014; IPCC, 2013; Spinoni et al., 2017, 2018; Lu et al., 2019). Moreover, it is important to mention that the highest number of HH spatio-temporal clusters were mapped in the southwest and southeast of the region (Fig. 6), which coincides geographically with the lowest SPEI values (values < -1), thus pointing to a link between ESAs and climate change, but also the impact of other factors, such as vegetation, topography and soil.

In this regard, it is predicted that projected climate components, based on the MEDALUS method, may influence LDD in Western Serbia (particularly in the southern part of the region) and beyond through the occurrence of meteorological drought, caused by the long-term reduction in precipitation that is expected in the study area. Therefore, these processes will lead to a prolonged period of reduction in surface runoff and a lack of groundwater, causing hydrological drought. Furthermore, in this region, there will be the possibility of pedological drought, caused by the decrease in available water capacity, which is expected by the end of this century. Finally, agricultural or ecological drought, caused by low water availability at critical stages for crop growth, will certainly occur (Lal, 2012).

On the other hand, the central part of the region is covered by forests and other vegetation with high evapotranspiration rates, which resulted in the occurrence of not only a large number of LL spatio-temporal clusters, but also the greater spatial distribution of Not Significant areas, which indicates that the changes coincide over time.

Although the results obtained in this study are rather worrying, they are corroborated by several other studies which investigated the issue in similar conditions. Namely, under the milder RCP4.5 scenario, arid areas are expected to expand to about 50% of the global land area, whereas under the RCP 8.5 scenario, as much as 56% of the global land area will be affected by arid conditions (Huang et al., 2016). Research in Europe has indicated an increase in aridity, especially in the Mediterranean region (Feng and Fu, 2013), with an increase in drought sensitivity in the future, resulting in the extension of aridity zones towards central parts of Europe (Prăvălie et al., 2019). In this regard, European Commission projections indicate that there is a high risk of LDD by the end of the century, especially in Spain, southern Italy, and Portugal, as well as in Southeast Europe (Spinoni et al., 2018). As the Balkan region is climatically linked to Southern Europe (Giannakopoulos et al., 2009), it is clear that the changes in the Balkans will follow the same trend as in the Mediterranean region, primarily in terms of the expansion of arid areas (Spinoni et al., 2017; Carrão et al., 2017; Ciscar et al., 2018). At the same time, the spread of arid areas is likely to lead to humanitarian crises associated with increased food insecurity, the emergence of new diseases and famines, large population migration, and probably the outbreak of conflicts over the remaining natural resources (Prăvălie et al., 2019; Perović et al., 2019).

5. Conclusions

LDD is one of the most serious environmental problems globally, regionally, nationally and locally. Given the dynamic nature of this phenomenon, it is crucial to understand the underlying processes primarily on a spatial and temporal scale.

The results of this study showed the spatial distribution of varying degrees of LDD susceptibility in the study area obtained through the MEDALUS method. Primarily, the results obtained for the reference period (1986–2005) highlight the significant critical areas in the C1, C2 and C3 categories, covering 37.53% of the study area, while 27% constitutes potentially safe areas. In terms of the major drivers of LDD, three components were identified, using PCA and MLRA, which explain 77.9% of the variance. The first component, with a contribution rate of 34.4%, indicated that anthropogenic factors have the greatest influence on the occurrence of degradation processes in the study area. The second component, explaining 23.5% of the variance, indicated a natural/ anthropogenic influence, while the third component indicated that natural (climate) parameters have a 20.1% impact on the current state of LDD.

However, with increasing temperatures and spatial and temporal changes in the precipitation regime due to the climate changes expected in Western Serbia, and all the other related components, these two climate parameters will have a negative impact on LDD. Specifically, by the end of the 21st century, according to the RCP4.5 scenario, critical areas (C1, C2 and C3) will expand by 33.6%, while under the RCP8.5 scenario these areas will increase by 51.7% compared to the reference period, with the effects of climate change being particularly marked in the southern part of Western Serbia, as indicated by the identification of critical areas through DLM analysis. It can be concluded that even those areas that might receive more precipitation in the future may become drier due to increased evaporation and changes in the seasonal distribution and intensity of precipitation. This is the conclusion most strongly supported by analysis of the SPEI, which has the ability to identify the role of evapotranspiration and temperature variability in relation to drought assessment in the context of global climate change. This, in our view, justifies the inclusion of the SPEI in the climatic parameters of the MEDALUS method.

Therefore, one of the main results of this study is a new methodological approach in characterising and identifying major drivers, as well as in isolating those spatio-temporal areas susceptible to LDD. In addition, this study is one of the first in the wider Balkan region that has allowed possible scenarios related to LDD and projected climate change to be analysed. In this regard, future research should enable a more detailed analysis of the effects of climate change, above all from the aspect of assessing the other indicators of the MEDALUS method.

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CRediT authorship contribution statement

Veljko Perović: Conceptualization, Methodology, Data curation, Software, Validation, Writing - original draft. **Ratko Kadović:** Supervision, Investigation, Conceptualization, Writing - original draft. **Vladimir Đurđević:** Methodology, Software, Writing - original draft. **Dragana Pavlović:** Writing - review & editing, Visualization. **Marija Pavlović:** Writing - review & editing, Visualization. **Dragan Čakmak:** Investigation, Data curation, Software, Formal analysis. **Miroslava Mitrović:** Writing - review & editing, Visualization. **Pavle Pavlović:** Supervision, Conceptualization, Funding acquisition.

Declaration of Competing Interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.107377.

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