Drought vulnerability in the Danube basin, the Czech Republic and the Republic of Moldova in 2022

Vulnérabilité à la sécheresse dans le bassin du Danube, la République tchèque et la République de Moldavie en 2022

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ABSTRACT: This study delves into assessing drought vulnerability using a comprehensive framework. By leveraging the Drought Vulnerability Index (DVI), the study explores the intricate dynamics within the basin. The exposure component scrutinizes the region's susceptibility to agricultural drought through the SPEI-3 index for the year 2022, coupled with a nuanced analysis of population density across 151 administrative units NUTS-3 from the Danube Basin, Czech Republic and the Republic of Moldova. Sensitivity analysis encompasses critical factors such as the share of crop area from ESRI Land Cover Explorer, the proportion of the aged population (aged 65+), and the prevalence of poverty rates (PPP 2018). Moreover, the evaluation of adaptive capacity incorporates the GDP per capita in $ for each administrative region, shedding light on the region's resilience to mitigate drought impacts. This research offers a holistic perspective on drought vulnerability, emphasizing the need for targeted interventions and adaptive strategies in the study area to enhance resilience and sustainability in the face of changing climatic conditions.

KEY WORDS: Drought, Drought Vulnerability Index, SPEI, GIS.

RÉSUMÉ: Cette étude se penche sur l'évaluation de la vulnérabilité à la sécheresse à l'aide d'un cadre global. En s'appuyant sur l'indice de vulnérabilité à la sécheresse (IVS), l'étude explore les dynamiques complexes au sein du bassin. La composante exposition examine la sensibilité de la région à la sécheresse agricole grâce à l'indice SPEI-3 pour l'année 2022, associé à une analyse nuancée de la densité de population à travers 151 unités administratives NUTS-3 du bassin du Danube, de la République tchèque et de la République de Moldavie. L'analyse de sensibilité englobe des facteurs critiques tels que la part des surfaces cultivées provenant de l'ESRI Land Cover Explorer, la proportion de la population âgée (65 ans et plus) et la prévalence des taux de pauvreté (PPA 2018). En outre, l'évaluation de la capacité d'adaptation intègre le PIB par habitant en $ pour chaque région administrative, mettant en lumière la résilience de la région à atténuer les impacts de la sécheresse. Cette recherche offre une perspective holistique sur la vulnérabilité à la sécheresse, soulignant la nécessité d'interventions ciblées et de stratégies d'adaptation dans zone d'étude, afin d'améliorer la résilience et la durabilité face à l'évolution des conditions climatiques.

MOTS CLÉS: Sécheresse, Indice de Vulnérabilité à la Sécheresse, SPEI, SIG.

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1. Introduction

1.1. Drought types

The IPCC (Intergovernmental Panel on Climate Change) Sixth Assessment Report defines drought simply as drier than normal conditions (Douville et al., 2021). This means that drought is a lack of moisture relative to the average water availability in each location and season.

Drought has the most serious effects on agriculture, both in terms of quantity and quality of production, and even complicates the sub-operations of technological processes (e.g. Semenov and Shewry, 2011; Rotter et al., 2012). Globally, drought causes huge annual losses to agriculture, $37 billion in 2021, according to FAO (2021). Increasing the frequency, duration and/or intensity of drought can fundamentally alter agricultural systems (Chloupek et al., 2004; Potopová et al., 2021, 2022a-b, 2023). Drought can be classified into four types (Potopová et al., 2021): meteorological drought, agricultural drought, hydrological drought and socio-economic drought.

- Meteorological drought – a period of months to years with below-normal rainfall. It is often accompanied by above-normal temperatures and precedes and causes other types of droughts.
- Agricultural drought – a period of dry soils resulting from below-normal rainfall, intense but less frequent rainfall, or above-normal evaporation, all of which lead to reduced crop production and plant growth.
- Hydrological drought – occurs when river flows and water storage in aquifers, lakes or reservoirs fall below long-term average levels.
- Socio-economic drought – considers the impact of drought conditions (meteorological, agricultural or hydrological drought) on the supply and demand of economic products. Socio-economic drought occurs when demand for a product exceeds supply due to a shortage of water supply due to weather conditions.

Vulnerability to drought is determined by three factors: exposure, sensitivity, and adaptive capacity. Exposure is the frequency of drought, the state's population, and the freshwater ecosystems likely to be affected. Sensitivity is the likelihood of a state being adversely affected by drought, considering industries such as agriculture, water resources, and hydropower. Resilience is a state's drought preparedness and recovery capacity, considering the state's drought plan, irrigation infrastructure, and economic strength (Engström et al., 2020).

1.2. Overview of Drought 2022

According to the Copernicus Climate Change Monitoring Service report for 2022, one of the hazards affecting Europe in 2022 was drought. Much of Europe had fewer than average snow days during the winter of 2021-2022, and in spring, precipitation was below average across much of the continent, with May recording the lowest precipitation on record for the month. The lack of snow in winter and high temperatures in summer led to a record loss of ice for Alpine glaciers, equivalent to more than 5 km^3 of ice. Below-average precipitation, which continued throughout the summer, together with exceptional heat waves, also caused an extended and prolonged drought that affected several sectors, such as agriculture, river transport, and energy. In the Republic of Moldova, precipitation for the period May-July amounted to 30-90 mm, which is about 15-45% of the norm, in Romania the total precipitation amount was 18% lower than the standard reference interval (1991 - 2020), constituting 65% of the norm. The annual average air temperature in the Republic of Moldova exceeded the multi-annual norm by +1.8-2.6 °C (State

Hydrometeorological Service), in Romania it was 1°C higher (National Meteorological Administration of Romania), and in the Czech Republic, the annual average temperature exceeded the norm by 0.9°C (Czech Hydrometeorological Institute).

The annual soil moisture anomaly was the second lowest in the last 50 years, with above-average soil moisture conditions only in isolated areas. In addition, river flows in Europe were the second lowest ever recorded, marking the sixth consecutive year with below-average flows. In terms of area affected, 2022 was the driest year on record, with 63% of Europe's rivers recording below-average flows (Copernicus Climate Change, 2022).

2. Materials and Methods

2.1. Standardized Precipitation and Evapotranspiration Index (SPEI)

Quantification of the SPEI is based on the following steps: (a) indirect determination of potential evapotranspiration (PET); (b) evaluation of the moisture balance of the landscape based on the calculated difference between the calculated potential evapotranspiration and the measured precipitation at different time intervals (P-PET); and (c) standardization of the moisture balance using a statistical probability distribution to obtain the SPEI drought index.

The first step to determine the SPEI value is to calculate the potential evapotranspiration (PET). A detailed analysis of methods for estimating and calculating evapotranspiration using different meteorological parameters is given by Potopová et al. (2015, 2020, 2021). The next step is to calculate the moisture balance as the difference of precipitation (Pi) and evapotranspiration (PETi) according to Eq:

$$Di = Pi - PETi \quad (1)$$

The calculated Di values are aggregated into different time intervals, following the same procedure as Vicente-Serrano et al. (2010). The deviation of *Dki,j* in a given month *j* and year *i* depends on the chosen time scale *k* (cumulative value over 1, 3, 6, 12 and 24 months). To express the SPEI, a three-parameter distribution should be used, since in a two-parameter distribution the random variable (x) has a negative value ($0 > x < \infty$), whereas in a three-parameter distribution, x can take values in the range ($\gamma > x < \infty$, where γ is a parameter of the original distribution), as a consequence x can take negative values that are commonly found in sets of values of D. Log-logistic distribution probability density functions are used to standardize Di values at different time intervals:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2} \quad (2)$$

where α, β, and γ are the parameters of the distribution, respectively, for the value of D in the interval ($\gamma > D < \infty$).

The log-logistic distribution used to standardize the set of D values at all time intervals is given by Eq:

$$F(x) = \left[\left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]\right]^{-1} \quad (3)$$

The value of F(x) is then converted to a normal variable:

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 + d_2 W^2 + d_3 W^3} \quad (4)$$

where Co, C1, C2, d1, d2, d3 are similar constants as for SPI and W is the probability-weighted moment. A detailed algorithm for calculating the SPEI is presented in (Potopová et al., 2016, 2017). The mean value of the SPEI is 0 and the standard deviation is 1. The SPEI is a standardized variable and can therefore be compared with other SPEI values in time and space. For each time series, each dry period (period where the SPEI value is always negative and SPEI ≤ -1) is defined by the duration (time from start to end) and the intensity of the drought (SPEI level for each month according to the classification).

2.2. Data storage and processing

The data for the SPEI indicators were collected for some countries that are located entirely or partially in the Danube Basin, Austria, Bulgaria, Hungary, Romania, Slovakia, and Slovenia, as well as the Czech Republic and the Republic of Moldova. The regions were selected based on publicly available datasets for the indicators used in the drought vulnerability study. A NUTS-3 map (Nomenclature of Territorial Units for Statistics) provided by Eurostat for the European Union was downloaded. Separately for the Republic of Moldova, the administrative map with level 2 regions (raioane) was downloaded to facilitate a more detailed analysis. For each NUTS-3 polygon monthly data on the SPEI has been calculated. Center points were determined using the Centroid function in Arc GIS. After all data were processed, they were exported in tabular form to calculate the area share of each class for the March-September 2022 period.

For the indices used to determine the drought, the data were downloaded for the year 2022 in tabular form from the official websites of the statistical offices of the following countries, Austria, Slovenia, Czech Republic, Slovakia, Hungary, Romania, Bulgaria and the Republic of Moldova.

2.3. Drought Vulnerability Index (DVI) and Vulnerability Classes (VC)

To calculate the vulnerability index in the Danube Basin, the Czech Republic, and the Republic of Moldova, a series of indicators were used (Table 1), which were classified according to the three sub-categories of the drought vulnerability index: exposure, sensitivity, and adaptive capacity.

Table 1 Indicators used to determine the Drought Vulnerability Index.

Subcategory	Component	Indicator	Indicator name	Correlation
Exposure	Agricultural drought	SPEI-3	Drought frequency (%)	Positive
	Social	Pop.density	Population density	Positive
Sensibility	Agricultural	Cropland	Share of cropland (%)	Positive
	Social	Pop.65+	Elder population (%)	Positive
	Economy	Poverty	Poverty rate (%) PPP	Positive
Adaptive capacity	Economy	GDP/cap	GDP per capita ($)	Negative

The following equations are used to calculate each indicator. Equation (5) is used for indicators with a positive correlation with overall vulnerability, such as population density, while equation (6) is used for indicators with a negative correlation with overall vulnerability, such as GDP/capita.

$$Z_i = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \quad (5)$$

For indicators with a positive correlation with overall vulnerability (Equation (5).

$$Z_i = 1 - \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \quad (6)$$

For indicators with a negative correlation with overall vulnerability (Equation (6), where *xi* is the value of a specific indicator for the tenth state, and x_{min} and x_{max} are the maximum and minimum values of the indicator in all states. The normalized values (Z) range from 0 to 1, where zero represents the least sensitive, least exposed and most adaptive. Setting a high adaptive capacity at zero is somewhat counter-intuitive, but is necessary for a proper comparison with the other sub-indices and for calculating overall vulnerability. First, a deterministic assessment is carried out. The Z-averages for each category are calculated for each NUTS to create sub-indices (Exposure, Vulnerability and Adaptive Capacity) and then all categories are averaged to create DVIs showing the relative vulnerability of all NUTS. The resulting Vulnerability Index is scaled according to equation (1) and divided into five Vulnerability Classes (VC) reflecting different levels of relative vulnerability. The first group (DVI < 0.2) represents states with very low vulnerability, the second group (DVI 0.2-0.4) states with low vulnerability, the third group (DVI 0.4-0.6) states with medium vulnerability, the fourth group (DVI 0.6-0.8) states with high vulnerability, and the fifth group (DVI 0.8-1) states with very high vulnerability.

3. Results and discussions

To determine vulnerability, the DVI was calculated for each indicator and then for each of the 3 sub-categories, exposure, sensitivity, and adaptive capacity, and finally the total vulnerability by calculating the average of the 3 sub-categories**.**

3.1. Exposure

Two indicators, SPEI-3 and population density, were used to determine drought-prone regions. The first indicator, SPEI-3, was used to identify the agricultural regions most exposed to drought in the year 2022. The second indicator, population density, was used to identify regions with dense populations. The larger and denser the population, the greater the exposure to drought-related complications and the greater the demand for water and, consequently, the more vulnerable the state. Population density was chosen rather than population numbers because population numbers in each region vary quite a lot and population density in this case is more representative.

The frequency of SPEI-3 within the basin varies from 0 to 7 months with drought, with the lowest frequency in the mountainous areas of the Carpathians and Alps and the highest in the Pannonian Plain, Romanian Plain, Lower Prut Plain, and Dobrogea.

To calculate the population density, data for the number of population in each administrative region provided by the statistical offices of each state for the year 2022, and the area of each region using the Geometry Calculator tool in ArcGIS were used. Thus the most densely populated regions were the capitals of the states, the regions of Austria, the Czech Republic, and Slovakia, and the least densely populated regions were the regions of the Republic of Moldova and Bulgaria (Figure 1).

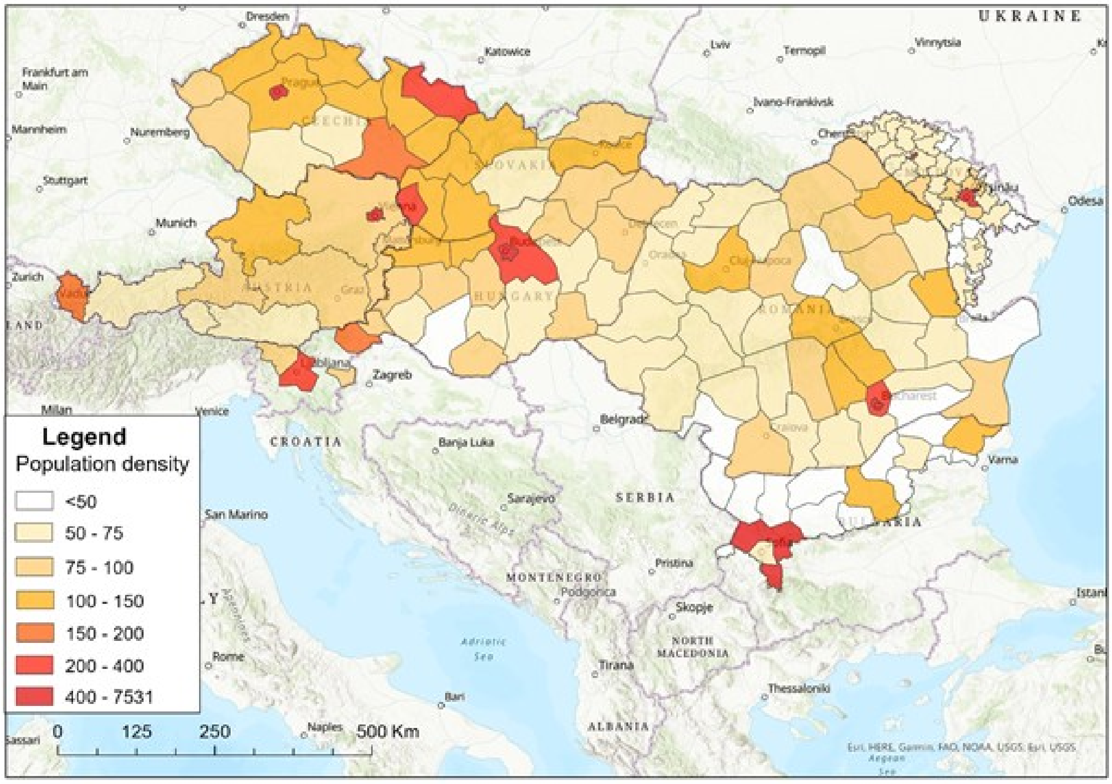

Figure 1 Population density in 2022 year.

Calculating the DVI for each indicator separately and then averaging the two together gave the DVI for the subcategory, exposure. Thus out of 151 administrative regions, 16 regions have vulnerability class very low, 71 regions low class, 44 regions medium class, 17 regions high class, and 3 regions very high class. The most exposed regions are the densely populated regions with a high frequency of drought in 2022.

3.2. Sensitivity

Sensitivity indicators are related to the geography, demography and economics of administrative regions, and represent characteristics that influence the likelihood that the region will experience negative impacts during drought. Three indicators, share of arable land, share of the elderly population (Fig.3), and poverty rate, were used to identify drought-sensitive regions. Share of arable land and and share of the elderly population are presented in Figure 2.

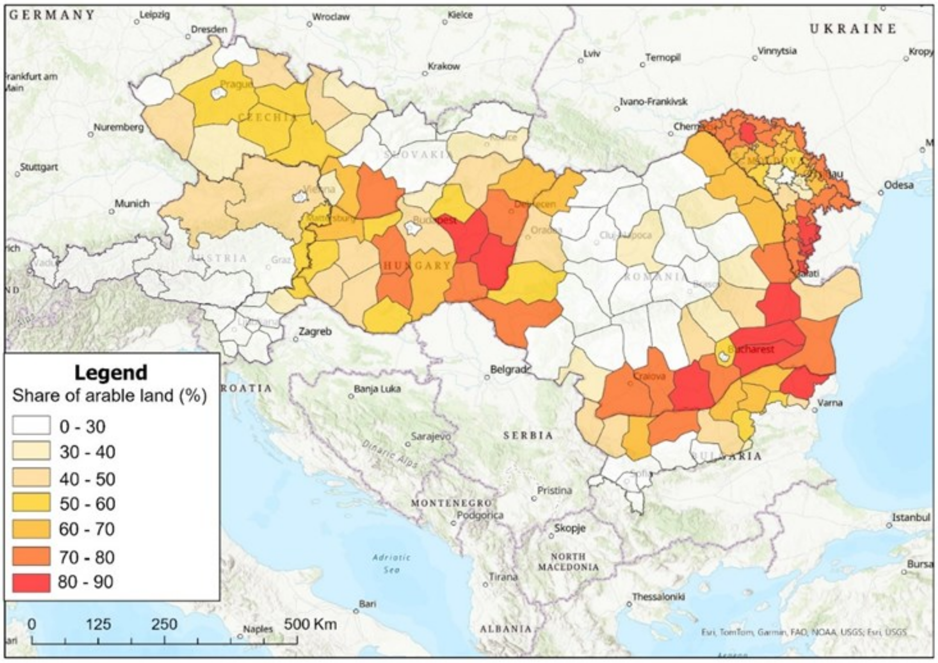

Figure 2 Share of arable land (%).

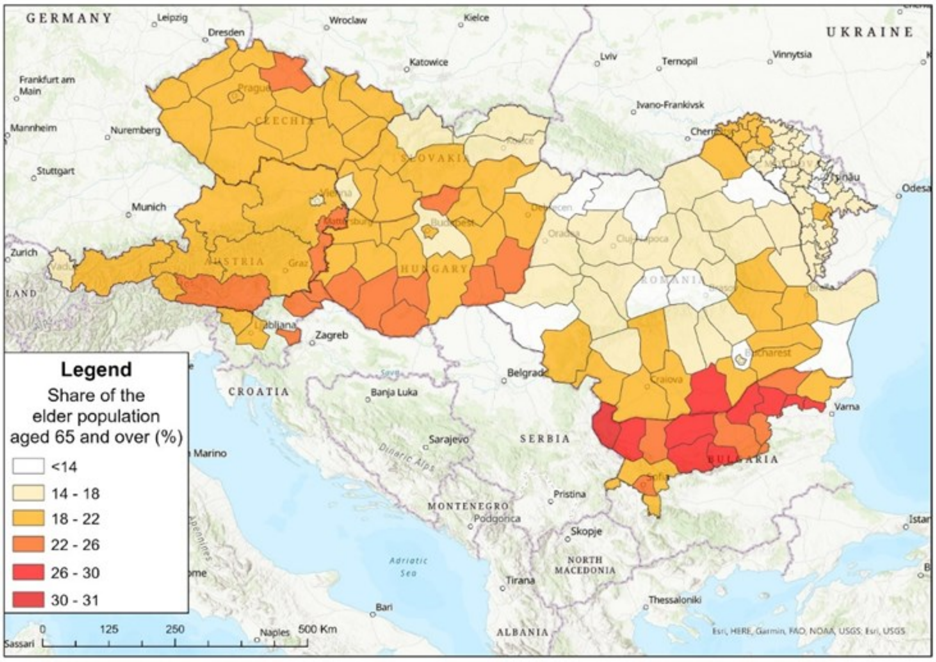

Figure 3 Share of elderly population aged 65 and over (%).

The regions with the highest share of arable land are the lowland regions and the regions with the lowest share are the mountain regions. The regions with the highest share of elderly population are Bulgaria, Austria, the Czech Republic, and Hungary. The regions with the highest share of poverty rates are the regions of the Republic of Moldova, especially those in the southern development region, the regions of eastern and south-western Romania, and some regions in

Bulgaria. Thus out of 151 administrative regions, 4 have very low vulnerability class, 43 have low class, 68 have medium class, and 36 have high class.

3.3 Adaptive capacity

Adaptive capacity reflects the ability of a state and its population to adapt to drought and to recover from drought when it occurs. Generally, indicators include both the economic strength of the state, or region, and state policies and private mitigation strategies. In this study, only one indicator reflecting the economic strength of regions was used, namely Gross Domestic Product (GDP) per capita (Figure 3), which gives an indication of the economic strength of the state and its population. A strong economy makes a region less vulnerable to drought because it is more likely to have the financial strength to mitigate and recover from the risk of drought than a state with more limited financial means.

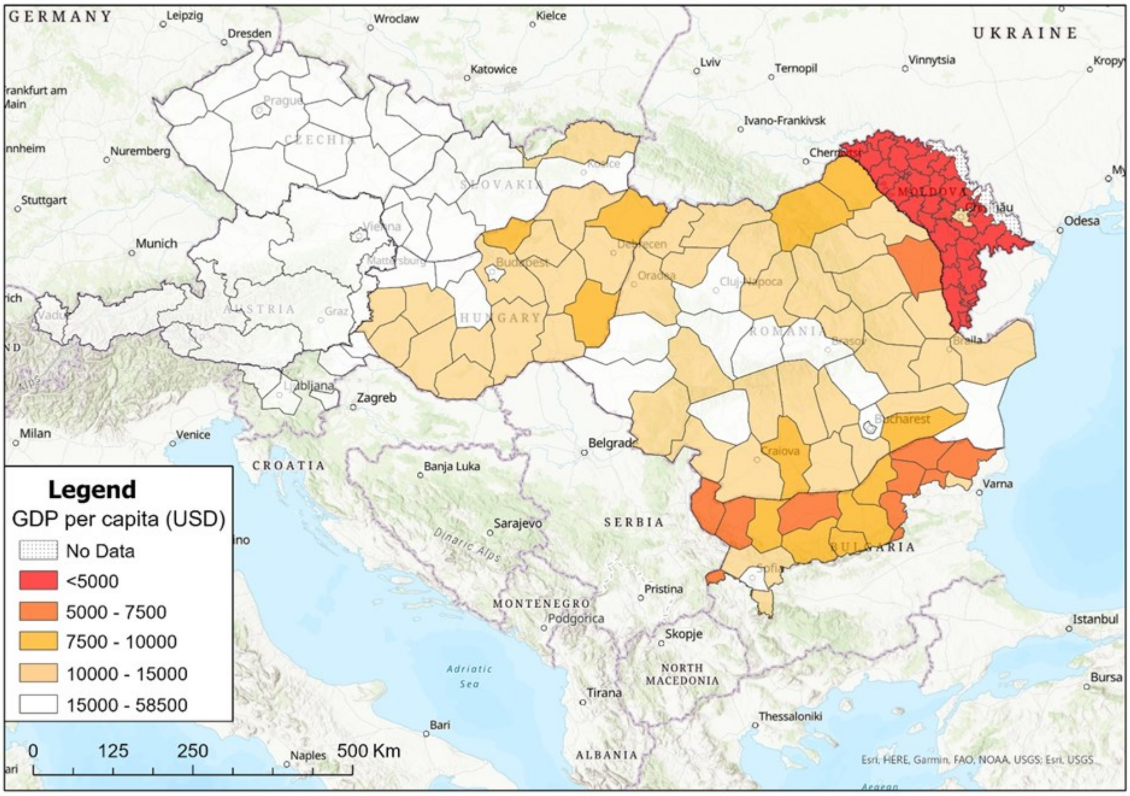

Figure 4 GDP per capita in USD.

Thus the regions with the highest GDP per capita are the capitals of the states, the regions of Austria and the Czech Republic, and the poorest regions, the regions of Moldova, the regions of Eastern Romania and the regions of Bulgaria. Thus out of 151 administrative regions, 8 have very low vulnerability class, 3 class, low, 18 class, medium, 65 class, high, and 57 class, very high.

3.4 Total vulnerability

Using the values for the sub-categories exposure, sensitivity and adaptive capacity, the total vulnerability to drought was calculated and the following results were obtained: of the 151 regions covered, 14 regions have a low vulnerability class, 90 regions have a medium vulnerability class, and 47 regions have a high vulnerability class (Figure 2).

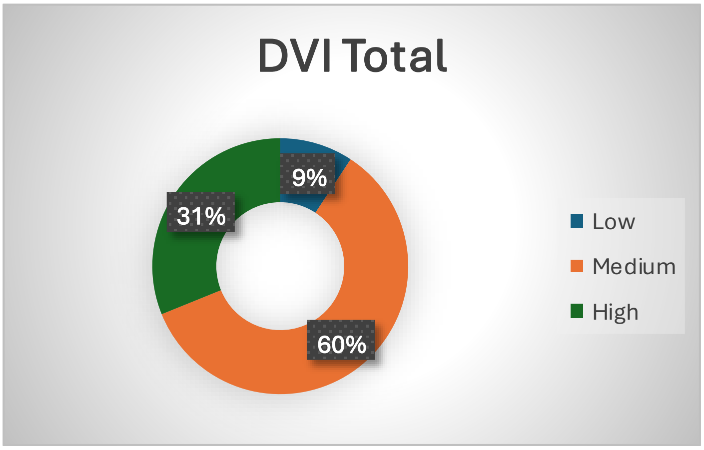

Figure 5 DVI total share (%) from the NUTS-3 regions.

The regions in the high vulnerability class are regions in the Republic of Moldova, Bulgaria, and Romania, with the highest score for the regions: Taraclia, Cahul, Basarabeasca, Gagauzia, Cimislia, and Balti in the Republic of Moldova, Dobrich, Ruse, Razgrad, Veliko Tarnovo, and Silistra in Bulgaria, and Galati, Braila, Vaslui, Botoșani, and Constanta in Romania.

Conclusions

This study takes a holistic view of drought vulnerability in the Danube basin of the Czech Republic and the Republic of Moldova. There is no universal method for assessing vulnerability to drought or other natural hazards; therefore, the choice of indicators is directly related to the resulting vulnerability score. In this study, the selection of indicators is limited to the publicly available ones and to those for which quantitative values are available on a regional scale for all NUTS-3 regions within the study area. This study is a case study that takes a holistic view of drought vulnerability using the drought of 2022, one of the most severe droughts on record in Europe, according to Copernicus Climate Change Monitoring Service, in terms of affected areas 2022 was the driest year on record, with 63% of Europe's rivers recording below-average flows, also 2022 was the second warmest year on record in Europe, at 0.9°C above average. Summer was the warmest on record, at 1.4°C above average, and 0.3–0.4°C above the previous warmest summer, in 2021. Areas for future research in this study will focus on the inclusion of more indicators for the study of vulnerability such as more adaptive capacity indicators, indicators related to water resources and water use, the presence of drought response plans, etc., as well as climate change projections.

The use of additional indicators, such as climate change and social perception of hazard, may improve the overall performance of the drought vulnerability analysis in the study area. Another useful point is to focus specifically on those regions with high and very high DVI. In these regions, current indicators and techniques can be improved and a more detailed analysis would be beneficial. Access to more indicators at a regional scale provides an opportunity to make a reliable forecast and develop effective strategies for potential droughts in the near future in these states.

The indicators included are chosen to represent a broad spectrum of vulnerability, from agricultural drought to demographic and economic factors, many of which are closely linked to societal well-being. Using indicators representing different aspects of drought exposure, sensitivity and adaptive capacity to drought, a drought vulnerability score is calculated and the level 3 administrative regions within the Danube basin of the Czech Republic and the Republic of Moldova are ranked according to their relative vulnerability. Taraclia, Cahul, Basarabeasca, Gagauzia, Cimislia, and Balti regions in the Republic of Moldova, Dobrich, Ruse, Razgrad, Veliko Tarnovo, and Silistra in Bulgaria, and Galati, Braila, Vaslui, Botoșani, and Constanta in Romania, are classified as the most vulnerable, while the regions of Styria, Vienna, Upper Austria, Carinthia, Burgenland, Bucharest, Prague, South Bohemia, Lower Austria, and Plzen are classified as the most resistant.

The geographical distribution of relative vulnerability across regions partly reflects the climate of different regions, with arid regions usually more vulnerable than those with a wetter climate, and also reflects the level of economic development, with countries with higher GDP per capita and lower poverty rates being less vulnerable. However, the results also indicate the importance of adapting (or not adapting) the local economy to the climate to reduce sensitivity, as well as developing adaptive capacity to limit the negative impacts of drought, and provide insights for local and regional planners on how to effectively allocate funds to reduce the drought vulnerability of regions now and in the future. The extreme drought conditions experienced in 2022, characterized by record low river flows, high temperatures, and below-average precipitation, serve as indicators of potential future trends and also provide a snapshot of the severe drought conditions in the study area, its relevance for understanding long-term conditions lies in its ability to offer insights about the potential implications of extreme events on the region’s climate resilience and adaptation strategies.

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