Risk of Drought Impacts for Agriculture (RDrI-Agri)

This Factsheet provides a detailed technical description of the Risk of Drought Impacts for Agriculture (RDrI-Agri) indicator, which is implemented in the Global Drought Observatory (GDO) of the Copernicus Emergency Management Service, and which is used for detecting and monitoring the likelihood of drought impacts globally. The three determinants or "dimensions" that make up the drought risk (i.e. Hazard, Exposure and Vulnerability), as well as the indicator's temporal and spatial scales and geographic coverage, are summarized below. Examples of the RDrI-Agri indicator are shown in Figures 1 and 3.

Variable	Temporal scale	Spatial scale	Coverage
Risk of Drought Impacts for Agriculture	10 days (= 1 dekad)	1 degree	Global

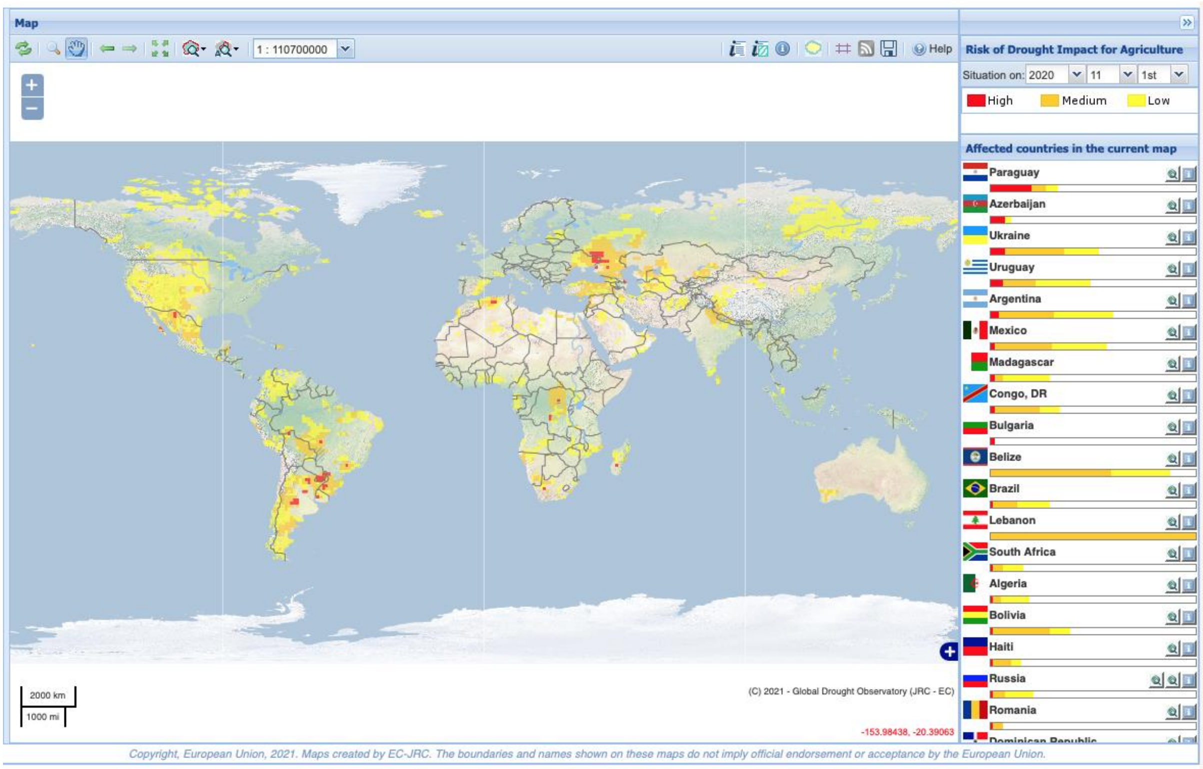

Figure 1*: Example of the continuously updated Risk of Drought Impacts for Agriculture (RDrI-Agri) indicator, implemented in GDO, highlighting the areas with higher likelihood of impacts in late 2020.*

1. Brief overview of the indicator

The Risk of Drought Impacts for Agriculture (RDrI-Agri) indicator that is implemented in the Global Drought Observatory (GDO) of the Copernicus Emergency Management Service, is used for determining the area more likely to be affected by droughts. The RDrI-Agri indicator is computed as the combination of the dynamic layers of drought hazard, exposure and vulnerability. Higher risk means that the areas affected will be the most likely to report impacts due to droughts.

2. What the indicator shows

In line with the terminology of the UN Office for Disaster Risk Reduction (UNDRR, 2019), drought risk may be defined as the probability of harmful consequences or likelihood of losses resulting from the interactions between three independent determinants: drought hazard (i.e. the possible future occurrence of drought events of a certain severity), drought exposure (i.e. the total population, its livelihoods and assets in drought-prone areas), and drought vulnerability (i.e. the propensity of exposed elements to suffer adverse effects when impacted by a drought event).

In this context, the "Risk of Drought Impacts for Agriculture" (RDrI-Agri) indicator which is implemented operationally within GDO, models global drought risk based on a conceptual product relationship, as follows:

RISK = HAZARD X EXPOSURE X VULNERABILITY

While drought has impacts in various socio-economic sectors (e.g. public water supply, agriculture, energy production, and waterborne transport) GDO provides an assessment of global drought risk with emphasis on impacts on the agriculture sector. Moreover, in order to provide decision-makers and stakeholders with an effective, standardized and systematic means for assessing drought impacts within political jurisdictions, as well as to foster better coordination and collaboration within and between different governance levels, global drought risk is computed in GDO at the sub-national administrative level.

3. How the indicator is calculated

The following sub-sections describe how the three determinants of drought risk (i.e. **hazard**, **exposure** and **vulnerability**), which are used to compute the RDrI-Agri indicator, are derived. Since the scores of regional drought risk range from 0 (i.e. lowest risk) to 1 (i.e. highest risk), the three determinants of drought risk must also be normalized to a range from 0 to 1, representing respectively the lowest and highest hazard, exposure and vulnerability conditions. The normalization method, which considers the maximum and minimum values of each determinant across all available sub-national administrative regions, is also described below.

i) Computation of drought hazard:

For the purposes of computing the RDrI-Agri indicator, global drought hazard is derived in the same way as for the Combined Drought Indicator (CDI) which is produced in EDO, by integrating the following three main drought indicators, which are implemented operationally within GDO:

- Standardized Precipitation Index (SPI): The SPI indicator measures precipitation anomalies at a given location, based on a comparison of observed total precipitation amounts for an accumulation period of interest (e.g. 1, 3, 12, 48 months), with the long-term historic rainfall record for that period (McKee et al., 1993; Edwards and McKee, 1997).
- Soil Moisture Anomaly (SMA): The SMA indicator is derived from anomalies of estimated daily soil moisture (or soil water) content - represented as soil suction, or "pF" - which is produced by the JRC's in-house LISFLOOD hydrological model (de Roo et al. 2000), and which has been shown to be effective for drought detection purposes (Laguardia and Niemeyer, 2008).
- FAPAR Anomaly: The FAPAR Anomaly indicator is computed as deviations of the biophysical variable Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), composited for 10-day intervals, from long-term mean values. Satellite-measured FAPAR represents the fraction of incident solar radiation absorbed by land vegetation for photosynthesis, and is effective for detecting and assessing drought impacts on vegetation canopies (Gobron et al., 2005).

ii) Computation of drought exposure:

The four indicators that are used to derive global drought exposure, which is used in the computation of GDO's Risk of Drought Impacts for Agriculture (RDrI-Agri) indicator, are listed in Table 1. These data represent a comprehensive approach to drought exposure, with emphasis on characterizing agricultural activities, which takes into account the spatial distribution of different types of physical assets (or proxy indicators) that are on the ground.

Table 1: The four indicators used to derive drought exposure, and corresponding data sources.

INDICATORS	*DATA SOURCE*
Population	Landscan
Global agricultural lands	SEDAC
Gridded livestock of the world	FAO
Baseline water stress	Aqueduct Water Risk Atlas

In order to construct a composite indicator that quantifies the relative exposure of a region to drought, based on a multi-dimensional set of indicators, the linear optimization method known as Data Envelopment Analysis (DEA) is used. An important property of the DEA model is that it is "non-compensatory", in the sense that a superiority of one indicator's values cannot be offset by an inferiority in another indicator's values. Thus, a region is considered highly exposed to drought if at least one type of asset is abundant there. For example, an agricultural region that is completely covered by rain-fed crops is considered fully exposed to drought, independently of the presence of other elements at risk.

The DEA method, as described in OECD and JRC (2008), involves construction of a so-called "performance frontier" within the multi-dimensional framework made up of the base indicators, which is then used as a benchmark to measure the relative performance of regions. For any given region, a "performance indicator" is computed based on its distance from the benchmark.

The concept is illustrated in Figure 2, for the simple case of four regions (a, b, c, d) and two base indicators (i.e. the two axes). In Figure 2, the regions a, b, c, and d are ranked according to their indicator scores. The line connecting regions a, b and c constitutes the performance frontier, which serves as the benchmark for region d which lies beyond the frontier. The regions making up the frontier are classified as the "best performing" (in our case, the most exposed to drought), while region d is the “worst performing” (in our case, the least exposed to drought). The performance indicator for region d is computed as the ratio of the distance between the origin and the region (i.e. between 0 and d) and the distance between the origin and the projected region in the frontier (i.e. between 0 and d’). Regions most exposed to drought will have a performance score of 1, and regions least exposed to drought will have a performance score of less than 1. Precise details on how the DEA model is applied to derive global drought exposure, which is used to compute GDO’s RDrI-Agri indicator, are provided by Carrão et al. (2016).

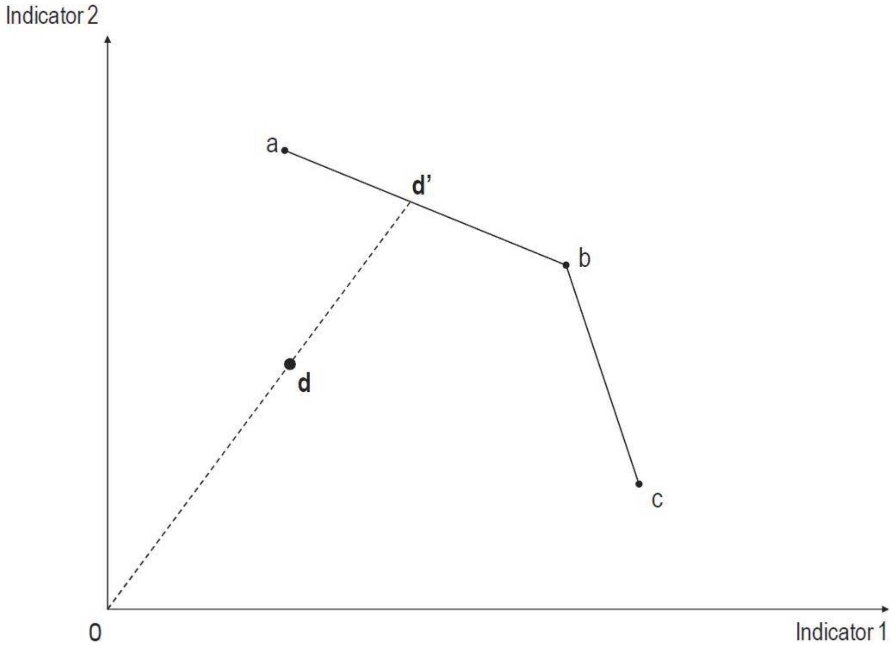

Figure 2: Computation of the benchmark or “performance frontier”, used in Data Envelopment Analysis (DEA), illustrated for the simple case of four regions (a, b, c, d) and two base indicators (the two axes). From: OECD and JRC (2008). Source: Rearranged from Mahlberg and Obersteiner (2001).

iii) Computation of drought vulnerability:

The indicators that are used to represent the social, economic, and infrastructural factors of global drought vulnerability, for the purposes of computing GDO’s Risk of Drought Impacts for Agriculture (RDrI-Agri), are listed in Table 2. Drought vulnerability is computed in two steps. Firstly, for each region, the indicators for each of the three vulnerability factors (social, economic, infrastructural), are combined separately using a Data Envelopment Analysis (DEA) model, as described earlier for drought exposure. Secondly, the social, economic and infrastructural vulnerability indicators resulting from the independent DEA analyses, are arithmetically combined (by averaging) into a composite indicator of drought vulnerability.

iv) Normalization of values of drought hazard, exposure and vulnerability:

Following the removal (masking) from the drought risk analysis of sub-national administrative regions according to specific criteria - i.e. regions not covered by geographic layers of exposure and vulnerability, regions entirely covered by water bodies, and arid and cold regions (where the concept of drought is meaningless) - the raw values of the drought exposure and vulnerability indicators have been normalized, by taking into account the maximum and minimum value of each indicator across all regions, in order to guarantee that input model values have an identical range between 0 and 1 (OECD and JRC, 2008).

Table 2: List of indicators used to derive global drought vulnerability, and corresponding vulnerability factors and data sources. (Adapted from Carrão et al., 2016).

FACTORS	*INDICATORS*	*DATA SOURCES*
Social	Rural population (% of population)	World Bank
	Refugee population (% of population)	World Bank
	Improved water source (% of rural population with access)	World Bank
	Life expectancy at birth (years)	World Bank
	Population ages 15–64 (% of population)	World Bank
	Literacy rate (% of people ages 15 and above)	World Bank
	Government Effectiveness	WGI
	Disaster Prevention &Preparedness (US$/Year/capita)	OECD
Economic	Agriculture (% of GDP)	World Bank
	Poverty headcount ratio at $1.25 a day, purchasing power parity (% of population)	World Bank
	GDP per capita (current US$)	World Bank
	Energy Consumption per Capita (Million Btu per Person)	U.S. EIA
Infrastructural	Agricultural irrigated land (% of agricultural land)	FAO
	% of retained renewable water	Aqueduct Water Risk Atlas
	Road density (km of road per 100 sq km of land area)	gROADSv1

4. How to use the indicator

The GDO MapViewer enables the visualization of the latest available map of the RDrI-Agri indicator, as well as the past archive (see Figure 3). These maps provide information on the spatial distribution of the risk of drought impacts globally, and their evolution over time.

The maps of the RDrI-Agri indicator can be used as a proxy for the presence of potential impacts due to ongoing droughts. Due to the complexity of drought propagation through the hydrological cycle and different socio-economic sectors, as well as cascading effects, these impacts may well be observed much later.

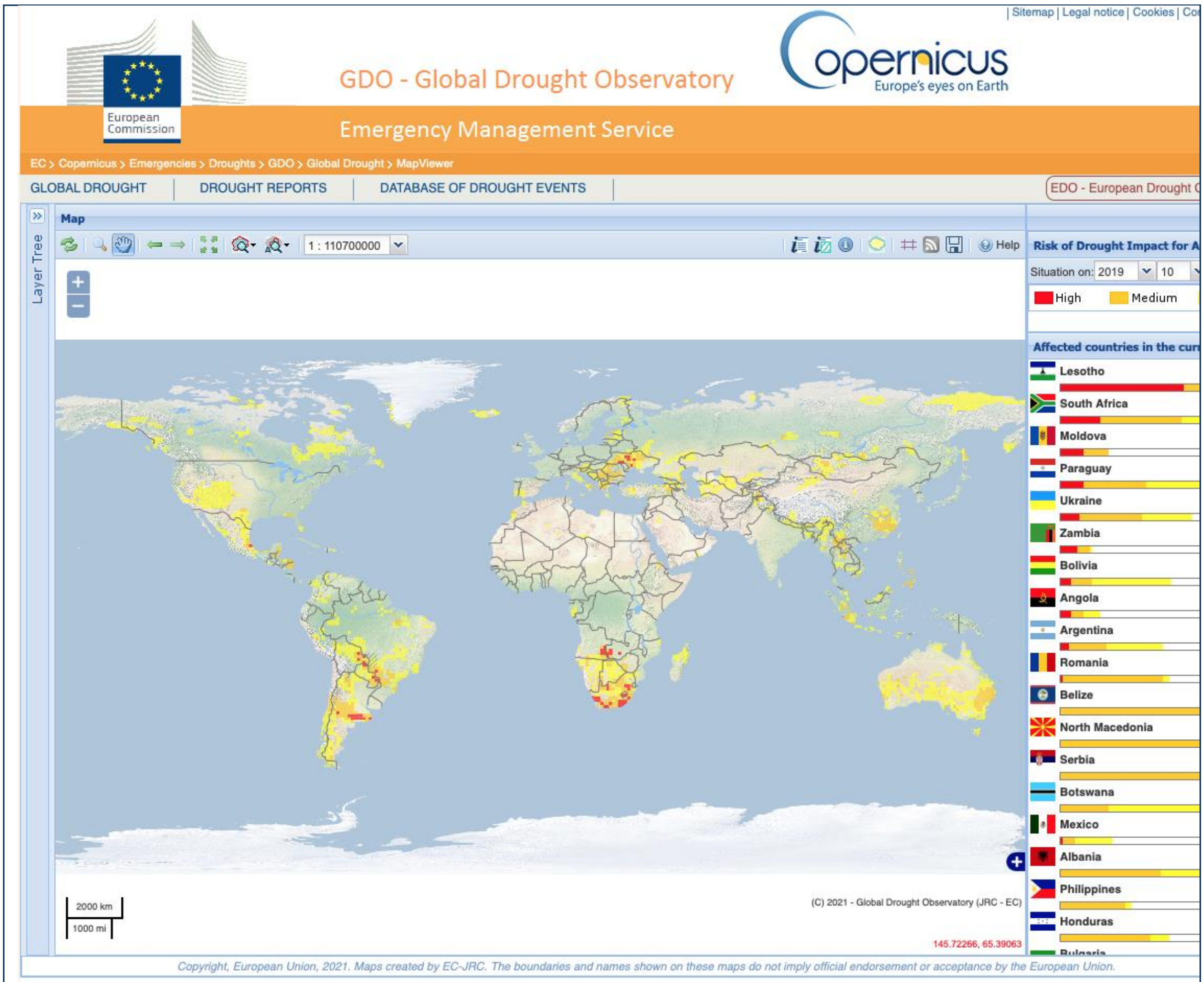

Figure 3: *Results of the Risk of Drought Impacts for Agriculture (RDri-Agri) for September 2019, produced by the processing chain in the Global Drought Observatory (GDO) of the Copernicus Emergency Management Service. The percentage of the countries' total exposed population can be seen in the bar-graphs in the right-hand panel.*

5. Strengths and weaknesses of the indicator

Strengths:

- As the RDrI-Agri indicator is a relative measure of risk, it allows for a dynamic comparison of risk hotspots in different regions of the world.
- The methodology for computing the RDrI-Agri indicator builds a bridge between physical and social sciences tailored to policy-makers where all dimensions of drought risk are considered.
- Monitoring risk across regions can identify those areas where actions may be needed to reduce potential impacts, as well as the leverage points for reducing the impacts from drought.

Weaknesses:

- The proposed model of drought risk is relative to the sample of input geographic regions, and depends on the joint statistical distribution of the respective indicators of hazard, exposure and vulnerability. Therefore, the proposed scale of risk is not a measure of absolute losses or actual damage to human health or the environment, but is more suitable for ranking and comparison of the input geographic regions.
- The proposed approach is fully data-driven, and final results can be biased by uncertainties of the input indicators and propagation errors from their combination and aggregation.
- Most of the vulnerability indicators are only at the country level, and variations within the country may not be identified.

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