Tools4LDN Technical Report on Monitoring Progress Towards UNCCD Strategic Objective 3

A Review of Publicly Available Geospatial Datasets and Indicators in Support of Drought Monitoring

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Reviewers: Mariano Gonzalez-Roglich (Conservation International), Antje Hecheltjen (Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)), Hanspeter Liniger (World Overview of Conservation Approaches and Technologies), Graham Maltitz (Council for Scientific Industrial Research – Pretoria), Sara Minelli (United Nations Convention to Combat Desertification Secretariat), Monica Noon (Conservation International), Waltraud Ederer (GIZ), Neil Sims (Commonwealth Scientific and Industrial Research Organisation),Vivek Vyas (formerly Land Degradation Neutrality Target Setting Program for UNCCD, India for UNCCD) and Alex Zvoleff (Conservation International)

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Acronymns

ANPP	Annual Net Primary Productivity
AET	Actual evapotranspiration
ANPP	above-ground net primary productivity
AOD	Aerosol Optical Depth
AVHRR	Advanced Very High-Resolution Radiometer
AVHRR HRPT	AVHRR High Resolution Picture Transmission System
BETP	Berkeley Earth Temperature Product
BWS	Baseline Water Stress
CCD	Cold cloud duration
CCI-SM	Climate Change Initiative Soil Moisture product
CDD	Consecutive dry days
CDI	Combined Drought Indicator
CEC	Cation exchange capacity
CHANS	Coupled human and natural systems
CHIRPS	Climate Hazards group Infrared Precipitation with Stations
CHIRTS	Climate Hazards Center Infrared Temperature with Stations
CHRS	Center for Hydrometeorology and Remote Sensing
CIAT	Centro Internacional de Agricultural Tropical
CIESIN	Center for International Earth Science Information Network
CMAP	Climate Prediction Center Merged Analysis of Precipitation
CMORPH	CPC MORPHing technique
COP	Conference of the Parties
CPC	Climate Prediction Center
CRU	Climate Research Unit
CRUTEM	Climate Research Unit Temperature data
DEA	Data Envelopment Analysis
DHS	Demographic and Health Surveys
DIMAQ	Data Integration Model for Air Quality
DLDD	Drought, land degradation, and desertification
DVI	Drought Vulnerability Index
ECMWF	European Centre for Medium-Range Weather Forecasts
ECV	Essential Climate Variable
EDO	European Drought Observatory
EnKF	Ensemble Kalman Filter
ENSO	El Niño-Southern Oscillation
ERSST	Extended Reconstructed Sea Surface Temperature
ERA5	European Centre for Medium-Range Weather Forecasts Reanalysis version 5
ERA-Interim	European Centre for Medium-Range Weather Forecasts Reanalysis-Interim
ESA CCI	European Space Agency Climate Change Initiative
ESA CCI-LC	ESA CCI-Land Cover
ESA CCI-SM	ESA CCI-soil moisture
Esri	Environmental Systems Research Institute
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	FAO Global Food and Agriculture Statistics
FEWS NETS	Famine and Early Warning System Network
FIES	Food Insecurity Experience Survey
FR	Full Resolution
GDI	Global Drought Index
GDO	Global Drought Observatory
GDP	Gross Domestic Product
G-Econ	Global Gridded Geographically Based Economic Data
GEF	Global Environment Facility
GHCN	Global Historical Climatology Network
GHCN-M	Global Historical Climatology Network Monthly
GHS-BUILT	Global Human Settlement Layer – Built Up
GHSL	Global Human Settlement Layer
GHS-POP	Global Human Settlement Layer – Population
GHS-SMOD	Global Human Settlement Layer – Settlement Model
GIDMaPS	Global Integrated Drought Monitoring and Prediction System
GIMMS	Global Inventory Monitoring and Modeling System

Acronymns

GISS	Goddard Institute for Space Studies
GISTEMP	Goddard Institute for Space Studies Surface Temperature Analysis
GLW	Gridded Livestock of the World
GMAO	Global Modeling and Assimilation Office
GMAS	Global Multi-Hazard Alert System
GOES	Goddard Earth Observing System
GPCC	Global Precipitation Climatology Center
GPCP	Global Precipitation Climatology Project
GPM	Global Precipitation Measurement
GPWv4	Gridded Population of the World Version 4
GRACE	Gravity Recovery and Climate Experiment
GRUMP	Global Rural-Urban Mapping Project
GSMaP	Japanese Aerospace Exploration Agency Global Rainfall Watch
GWR	Geographically Weighted Regression
HDI	Human Development Index
HDR	Human Development Report
HII	Human Influence Index
IFL	Intact Forested Landscapes
IFPRI	International Food Policy Research Institute
IMERG	Integrated Multi-satellitE Retrievals for GPM
IMHE	Institute for Health Metrics and Evaluation
IPC	Integrated Food Security Phase Classification
IPCC	Intergovernmental Panel on Climate Change
IR	Infrared
ISRIC	International Soil Reference and Information Centre
IUCN	International Union for Conservation of Nature
JMP	WHO/UNICEF Joint Monitoring Program
JRC	Joint Research Centre of the European Commission
LCCS	Land Cover Classification System
LDN	Land Degradation Neutrality
LMIC	Low- and Middle-Income Countries
LSM	Land surface models
MER	Market Exchange Rate
MERIS	Medium Resolution Imaging Spectrometer
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications, version 2
MISR	Multi-angle Imaging SpectroRadiometer
MLOST	Merged Land–Ocean Surface Temperature Analysis
MODIS	Moderate Resolution Imaging Spectroradiometer
MPI	Multi-dimensional Poverty Index
MRLC	Multi-Resolution Land Characteristics
MSAVI	Modified Soil-Adjusted Vegetation Index
MSDI	Multivariate Standardized Drought Index
NASA	National Aeronautics and Space Administration
NCEP	National Centers for Environmental Prediction
NDVI	Normalized Difference Vegetation Index
NMHS	National Meteorological and Hydrological Services
NOAA	National Oceanic and Atmospheric Administration
nSPI	Nonstationary SPI
OPHI	Oxford Poverty and Human Development Initiative
ORNL	Oak Ridge National Laboratory
PCA	Principal Components Analysis
PDSI	Palmer Drought Severity Index
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
PERSIANN-CDR	PERSIANN Climate Data Record
PET	Potential evapotranspiration
PMW	Passive microwave
PPI	Poverty Probability Index
PPP	Purchasing Power Parity
PROBA-V	Project for On-Board Autonomy-Vegetation
RADI	Reservoir Area Drought Index
RR	Reduced resolution
RZSM	Root Zone Soil Moisture

Acronymns

scPDSI	Self-calibrating Palmer Drought Severity Index
SDG	Sustainable Development Goal
SDVI	Standardized Drought Vulnerability Index
SeaWiFS	Sea-Viewing Wide Field-of-View Sensor
SEDAC	Socioeconomic Data and Applications Center
SES	Social-ecological system
SLM	Sustainable land management
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture Ocean Salinity
SO	Strategic Objective
SPEI	Standardized Precipitation and Evapotranspiration Index
SPI	Standardized Precipitation Index
SPI-GEV	SPI Generalized Extreme Value
SPOT	Satellite Pour l'Observation de la Terre
SSFI	Standardized Streamflow Index
SSI	Standardized Soil Moisture Index
SST	Sea surface temperature
TIR	Thermal infrared
TRMM	Tropical Rainfall Measuring Mission
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
UNEP	United Nations Environment Programme
UNEP-WCMC	UNEP World Conservation Monitoring Centre
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNFCCC	UN Framework Convention on Climate Change
UNICEF	United Nations Children's Fund
UNISDR	United Nations International Strategy for Disaster Reduction
UNPD	United Nations Population Division
US	United States
USAID	United States Agency for International Development
USAPI	United States Affiliated Pacific Islands
USDA	United States Department of Agriculture
VI	Vegetation Index
WASH	Water, Sanitation, and Hygiene
WCMC	World Conservation Monitoring Centre
WDI	World Development Indicators
WDPA	World Database on Protected Areas
WGI	World Governance Indicators
WFP-VAM	World Food Programme Vulnerability Analysis and Mapping
WHO	World Health Organization
WMO	World Meteorological Organization
WOCAT	World Overview of Conservation Approaches and Technologies
WRI	World Resources Institute
WUE	Water Use Efficiency
WWAP	World Water Assessment Programme

Executive Summary

The open geospatial platform Trends.Earth was created in 2018 by Conservation International as part of the project entitled "Enabling the use of global data sources to assess and monitor land degradation at multiple scales", funded by the Global Environment Facility (GEF).

The goal of creating Trends.Earth was to simplify, streamline, and enhance the ability of member nations to the United Nations Convention to Combat Desertification (UNCCD) to report on their status and progress in achieving land degradation neutrality (LDN). Upon favorable receipt of the Trends.Earth platform by UNCCD country Parties, there was an expressed need to expand its functionalities to support understanding of the socio-environmental interactions between drought, land degradation, and poverty through the Tools for Land Degradation Neutrality (Tools4LDN) project to support monitoring and reporting of strategic objectives (SOs) before the 2021-2022 UNCCD reporting cycle in support of the UNCDD 2018-2030 Strategic Framework.[2]

This report is specifically focused on supporting monitoring and reporting for SO3 as adopted by the UNCCD Conference of the Parties (COP) at its 14th session[3]:

Strategic Objective 3: To mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems

Expected impact 3.1 Ecosystems' vulnerability to drought is reduced, including through sustainable land and water management practices.

Expected impact 3.2 Communities' resilience to drought is increased.

Towards this goal, we: 1) provide an introduction and develop conceptual frameworks for evaluating approaches for assessing ecological and socio-economic vulnerability to drought and its interplay with land degradation; 2) present a summary of databases and indices for monitoring SO3; and 3) recommend best practices for integrated data analysis towards a holistic SO3 monitoring approach with a focus on enhancing the Trends.Earth monitoring tool.

Cognizant of the monitoring framework for SO3, our overall summary recommendation is that Trends.Earth support a comprehensive framework for drought and land degradation monitoring that builds on exposure of ecosystems and populations to drought hazard and captures factors from social, infrastructural, economic, and ecosystem components that are vulnerable (i.e., have the potential to be adversely affected by climatic drought, land degradation, or mutual feedbacks between the two). To the extent that it is possible, and data are available, we recommend that the datasets used be contemporary, spatially gridded (or sub-national), and gender-disaggregable and that the chosen indicators be generic and valid for any region.

Efforts to standardize and enhance the assessment of progress on land degradation neutrality reporting for the UNCCD Strategic Framework in relation to drought vulnerability are currently hampered by the lack of a unified integrative framework on vulnerability within SO3 and agreement on the most appropriate indices and datasets to be included. This report reviews available datasets that can support more detailed reporting on the interactions between land degradation, drought, and socioeconomic factors as they contribute to the development of vulnerable communities and ecosystems and, conversely, determines how sustainable land and water management can be monitored to enhance community and ecosystem resilience.

Providing consistent global geospatial data to UNCCD country Parties has significantly lowered the reporting

2 See decision 7/COP.13: https://www.unccd.int/sites/default/files/sessions/documents/2019-08/7COP13_0.pdf

3 See decision 11/COP.14: https://www.unccd.int/sites/default/files/sessions/documents/2019-11/11-cop14.pdf

barrier and burden regarding efforts being made towards LDN [1]. Publicly available datasets offer the most cost-effective approach to monitor and evaluate large scale Earth surface change. Several spatially explicit datasets at relatively fine spatial resolution have become available in recent decades at no cost to end users.

The following sections of this report provide a brief introduction (Part I) and background for the need of the report (Part II), then subsequently develop conceptual frameworks (Part III), present recommended indices and datasets and their details (Part IV and V) for integration into Trends.Earth and offer a strategy for integrating biophysical and socioeconomic data (Part VI) for understanding the human and ecosystem dimensions of drought and land degradation.

Part III focuses on an integrative approach for the three levels of the indicator and monitoring framework for SO3 adopted by the UNCCD: Level I (Hazard), Level II (Exposure) and Level III (Vulnerability). The Hazard section reviews drought hazard indices and global climate and weather datasets that can be used to better understand the interplay between drought and land degradation (and vice versa), including indicators which use rainfall, soil moisture, and temperature changes, and includes recommendations for priority SO3 Hazard monitoring datasets and indices.

The Exposure section of Part III of the report develops a two-factor approach to assessing drought exposure of ecosystems and populations. First, we present a synthesis on global population datasets (such as those from WorldPop and the Center for International Earth Science Information Network or CIESIN) and discuss the potential for diasaggregation by gender or urban/rural populations. We also report on datasets and frameworks for monitoring drought Level II Exposure that go beyond population estimates alone, such as those datasets that consider agriculture, livestock density, and water demand, as well as health risks associated with fine airborne particulate matter exacerbated by drought, land degradation, and dust storms. Finally, we present a new ecosystem exposure indicator based on the land cover classes used by country Parties in Strategic Objective 1 reporting, which allows for the use of global or national land use/land cover datasets and is calculated in a manner that is harmonious with the current Level 2 human exposure indicator.

The Vulnerability section of Part III moves towards a comprehensive drought-vulnerability monitoring framework, with recommendations on available gender-disaggregated global socioeconomic and environmental datasets and provides recommendations for priority databases and indices for monitoring ecosystem and human drought vulnerability within the context of SO3.

Part IV presents a detailed description of relevant drought hazard indices and a review of scientific literature and methodologies for determining human and ecosystem drought vulnerability.

Part V discusses inclusion and exclusion criteria for freely accessible, spatially explicit datasets relevant to SO3, and provides details, metadata, spatial resolution, strengths, and weaknesses of each recommended (and some additional relevant) dataset. Datasets are reviewed and included that meet the overarching inclusion criteria of Fidelity to SO3, Comparability, Data Validity and Reliability, Readiness/Adaptability, Global Coverage, Spatial Resolution, Adequate Temporal Range, Adequate Temporal Resolution, Appropriate Data Types, Feasibility of Trends.Earth Integration (or User-friendliness), and Adequate Update Frequency. We summarize freely available data products and indices regarding biophysical monitoring of drought hazard (e.g. temperature, soil moisture, and precipitation), exposure (e.g. population, livestock, water demand, urban vs. rural settlements, health risks associated with airborne particulate matter) and vulnerability (e.g. demographic and health surveys, poverty, and existing drought vulnerability indices that have previously been used at the country or regional scale but that could be adapted to a more spatially explicit, gridded and global use case, so long as they could be validated in the future).

The last section of the report (Part VI) recommends approaches for the integration of diverse databases and indices on Hazard, Exposure and Vulnerability to monitor the subobjectives SO3.1 “Ecosystem’s vulnerability to drought is reduced” and SO3.2 “Communities’ resilience to drought is increased.” Part VI also discusses limitations to SO3 monitoring and considers future possibilities for improved integrated monitoring at national and international scales, including the potential for innovative data and the use of spatial statistics to enhance currently available data.

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I. Report Overview

Land degradation as defined by the UNCCD refers to any reduction or loss in the biological or economic productive capacity of the land resource base. It is generally caused by human activities, exacerbated by natural processes, and often magnified by and closely intertwined with climate change and biodiversity loss.

I.1. Introduction

I.1.1. Drought and land degradation

Land degradation as defined by the UNCCD refers to any reduction or loss in the biological or economic productive capacity of the land resource base. It is generally caused by human activities, exacerbated by natural processes, and often magnified by and closely intertwined with climate change and biodiversity loss. It is a global challenge – over 20% of the Earth's vegetated surface is estimated to be degraded, affecting over 1.3 billion people [2], with an economic impact of up to US$10.6 trillion [3]. Land degradation reduces agricultural productivity and increases the vulnerability of those areas already at risk of impacts from climate variability and change, especially in regions of the world where poverty rates remain high despite efforts to reduce poverty, inequality, and enhance the socio-economic well-being of all people worldwide. The United Nations Sustainable Development Goals (SDGs; **Figure 1, Box 1**) are an attempt to address, among other global pressing issues, land degradation around the globe.

Drought is a complex, slow-onset phenomenon that happens over different time scales. It is characterized by a reduction in water availability, leading to cascading effects on people's livelihoods and economic sectors. Drought is sometimes simplistically defined as a period of dry weather long enough to cause a hydrological imbalance, although a globally agreed upon definition for drought does not exist[4]. Moreover, drought hardly occurs as a single risk event but rather interlinked with other hazards such as heatwaves, wildfires, sand/dust storms, or floods.

4 The International Panel on Climate Change (IPCC) defines drought as *"a period of abnormally dry weather long enough to cause a serious hydrological imbalance. Drought is a relative term, therefore any discussion in terms of precipitation deficit must refer to the particular precipitation-related activity that is under discussion. For example, shortage of precipitation during the growing season impinges on crop production or ecosystem function in general (due to soil moisture drought, also termed agricultural drought), and during the runoff and percolation season primarily affects water supplies (hydrological drought). Storage changes in soil moisture and groundwater are also affected by increases in actual evapotranspiration in addition to reductions in precipitation. A period with an abnormal precipitation deficit is defined as a meteorological drought. See also Soil moisture"* (IPCC Assessment Report 5, 2014). The United Nations Disasters Risk Reduction (UNDRR) defines drought as *"a slow-onset hazard, often referred to as a creeping phenomenon. The absence of a precise, universally accepted definition of drought adds to the confusion. Definitions must be region specific because each climate regime has distinctive climatic characteristics"* (UNDRR GAR Chapter 6). The lack of agreed upon definition complicates monitoring efforts, as the definition and monitoring approach are typically context specific.

Drought increasingly impacts larger numbers of people, livelihoods, ecosystems, and economies worldwide[4]. When it occurs concomitantly with land degradation, it can expose already vulnerable populations to deleterious livelihood, environmental, socio-economic, and health risks and decrease population and community resilience.

Figure 1. United Nations Sustainable Development Goals (SDGs).

Vicious or Virtuous Cycles?

Feedbacks Between Human Vulnerability and Desertification, Land Degradation, and Drought

Community and ecosystem vulnerability and resilience to desertification, land degradation, and drought (DLDD) are interconnected and, depending on individual, household, and community dynamics and responses, feed back into DLDD. Community and ecosystem vulnerability to DLDD is decreased and resilience is enhanced to the extent that land and water management (as well as other demographic and socio-economic behaviors) responses to DLDD are positive adaptative behaviors for human livelihoods and ecological integrity. While adaptations can be positive for humans and not for the environment and vice versa, a virtuous feedback loop from human activity to DLDD can occur when human responses are not only positively adaptive for human livelihoods and wellbeing but also mitigate DLDD. As an example, imagine a Yucateco farm cooperative from Mexico which, in response to desertification and increased frequency and magnitude of droughts, switches from water intensive corn to more water-tolerant chili peppers. As chili peppers tend to be more labor demanding, the farmers may be inclined to intensify production, leaving prior cropped land to regenerate, thereby neutralizing and potentially reversing land degradation. In such a plausible hypothetical, the farmers' behavior would be contributing to both community and ecological resilience.

In **Figure 2**, the extent to which resilience is positively reinforced by human activity is shown in positive feedback loops with land and water management (as well as other demographic and socio-economic responses). These potential synergies (the same circular flows in **Figure 2**), however, can also become negative feedback loops or vicious cycles. Imagine if the Yucateco farmers, instead of switching from corn to chili peppers, do the opposite, ploughing over chili peppers and remaining forest and fallow land to sow a water-intensive corn monocrop, say in response to a spike in demand for corn. The farmers may earn more cash in the short term while exacerbating medium- and long-term community and ecological vulnerability and land degradation (not to mention increasing the risk of corn-hungry pests). Making sustainable land and water management choices can therefore catalyze virtuous cycles that increase community and ecosystem vulnerability to drought (and desertification and land degradation).

To the extent that water and land management lead to enhanced ecological and community resilience, various SDGs (**Figure 1**) may be advanced simultaneously. Sustainable land and water management synergize with community and ecological resilience through SDGs 1-15 (if not through more). Some of these synergies are direct while others are more distant or contingent. Returning to our Yucateco farmers, if the switch from land and water intensive corn to the potentially more land intensive and lucrative chili pepper results in a return of cropland to wildland, enhanced community and ecological resilience could provide manifold SDG returns. Cash revenue could be increased by shifting to the more lucrative market crop, reducing poverty (SDG 1), more cash could allow for greater household budget allocated to sufficient and diverse foods (and some corn and other subsistence crops could be retained as insurance), reducing hunger, and improving nutrition (SDG 2), and augmenting health and wellbeing (SDG 3). Increased income could also facilitate school-aged children attending school, increasing quality education (SDG 4), especially for girls, who are often the first to stay home from school to help with household income generation, thus enhancing gender equity (SDG 5). Indirectly, increased quality education might promote an appreciation for and the adoption of clean water and sanitation (SDG 6), e.g., through water filtering and hand washing; increased education may similarly facilitate the adoption of affordable and clean energy (SDG 7), e.g., through clean-burning, efficient stoves potentially run. The eco-friendly stoves could be run off the innovative infrastructure of a shared solar grid (SDG 9). Increased income from strategic land and water management is a form of economic growth (SDG 8) with the potential to reduce inequality (SDG 10). Scaled up to the village level, such activities could help promote sustainable communities (SDG 11), enabled by more responsible consumption and production (SDG 12), with climate action featured in several carbon-mitigation activities (SDG 13), promoting life on land (SDG 15), through increased wildlands. Such activities could also promote life below water (SDG 14) to the extent that toxic chemicals are replaced by natural soil enhancements and erosion is reduced through improved land management, thereby reducing polluted runoff and siltation entering local waterways.

We do not mean to belie that these connections are all complex and dependent on multiple socio-economic and ecological contingencies at multiple scales. The point is that SO3 expected outcomes of enhanced community and ecological resilience (and decreased vulnerability), particularly through sustainable land and water management, can catalyze multiple SDG positive feedback loops on communities and their surrounding ecologies. And to the extent that the Yucateco farmer cooperative example is plausible, while the conditions and relative contributions of each SDG may differ from place to place, multiple SO3-promoting virtuous cycles are possible. These possibilities are made more likely with enhanced monitoring capabilities based on freely available global geospatial datasets.

I.1.2. Trends.Earth

Trends.Earth was created through a partnership of Conservation International, Lund University, and the National Aeronautics and Space Administration (NASA) with funding from the Global Environment Facility (GEF). The platform aims to provide methods and datasets for the monitoring of land change (including degradation and improvement) using earth observations in an innovative desktop and cloud-based system. Primarily, the platform allows users to assess land degradation and monitor achievement towards Land Degradation Neutrality (LDN). Currently, the platform supports the monitoring of three sub-indicators of LDN (Sustainable Development Goal (SDG) Target 15.3): productivity, land cover, and soil organic carbon. The tool also supports member nations by giving them a means to analyze data to prepare their required reports for the UNCCD. Users can plot time series of these key sub-indicators of land change to produce maps and graphics that support monitoring and reporting, as well as allow tracking of the impacts of sustainable land management or related efforts. The data is processed such that, where possible, local data with global and national-scale information layers sourced through surveys and remotely sensed imagery are interleaved. With the favorable receipt of Trends.Earth by UNCCD member nations, there is an expressed desire to expand the current capabilities to support monitoring and reporting of additional UNCCD Strategic Objectives and the understanding of the socio-environmental interactions between drought, land degradation, and poverty, to better support of the UNCDD 2018-2030 Strategic Framework.

I.1.3. The UNCCD Strategic Framework

To support Parties in addressing the challenge of SDG15.3, the 13th Conference of the Parties (COP.13) of the United Nations Convention to Combat Desertification (UNCCD) adopted the Strategic Framework for 2018-2030 (Decision 7/COP.13). The Strategic Framework acknowledges the global challenges of desertification/land degradation and drought (DLDD), and their contribution to "economic, social, and environmental problems" that "pose serious challenges to sustainable development" and notes that addressing DLDD will involve long-term integrated strategies that simultaneously focus on the improved productivity of land and the rehabilitation, conservation and sustainable management of land and water resources. The vision of the Framework is:

A future that avoids, minimizes, and reverses desertification/land degradation and mitigates the effects of drought in affected areas at all levels and strives to achieve a land degradation-neutral world consistent with the 2030 Agenda for Sustainable Development, within the scope of the Convention.

The Strategic Framework encompasses three Strategic Objectives (SOs):

- **Strategic Objective 1:** To improve the condition of affected ecosystems, combat desertification/land degradation, promote sustainable land management and contribute to land degradation neutrality
- **Strategic Objective 2:** To improve the living conditions of affected populations
- **Strategic Objective 3:** To mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems
- **Strategic Objective 4:** To generate global environmental benefits through effective implementation of the UNCCD
- **Strategic Objective 5:** To mobilize substantial and additional financial and non-financial resources to support the implementation of the Convention by building effective partnerships at global and national level

SO1, a Strategic Objective consonant with SDG target 15.3 –LDN, sets out to "by 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and achieve a land degradation-neutral world." A best practice guidance for SDG 15.3.1 was developed by Sims et al [5]. SO2, in turn, aims "to improve the living conditions of affected populations" and advance the expected impacts of improving food security and adequate access to water, improving livelihoods for people in affected areas, empowering locals, especially women and children in decision-making processes in combating DLDD, and reducing migration forced by desertification and land degradation. SO3, the specific focus of this report, seeks *"to mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems"* (**Figure 2**). The two expected impacts of SO3 are increase in ecosystem resilience to drought via sustainable land and water management practices, and an increase in community resilience to drought (**Figure 2**). SO1, SO2, and SO3 further support and inform SO4 and SO5.

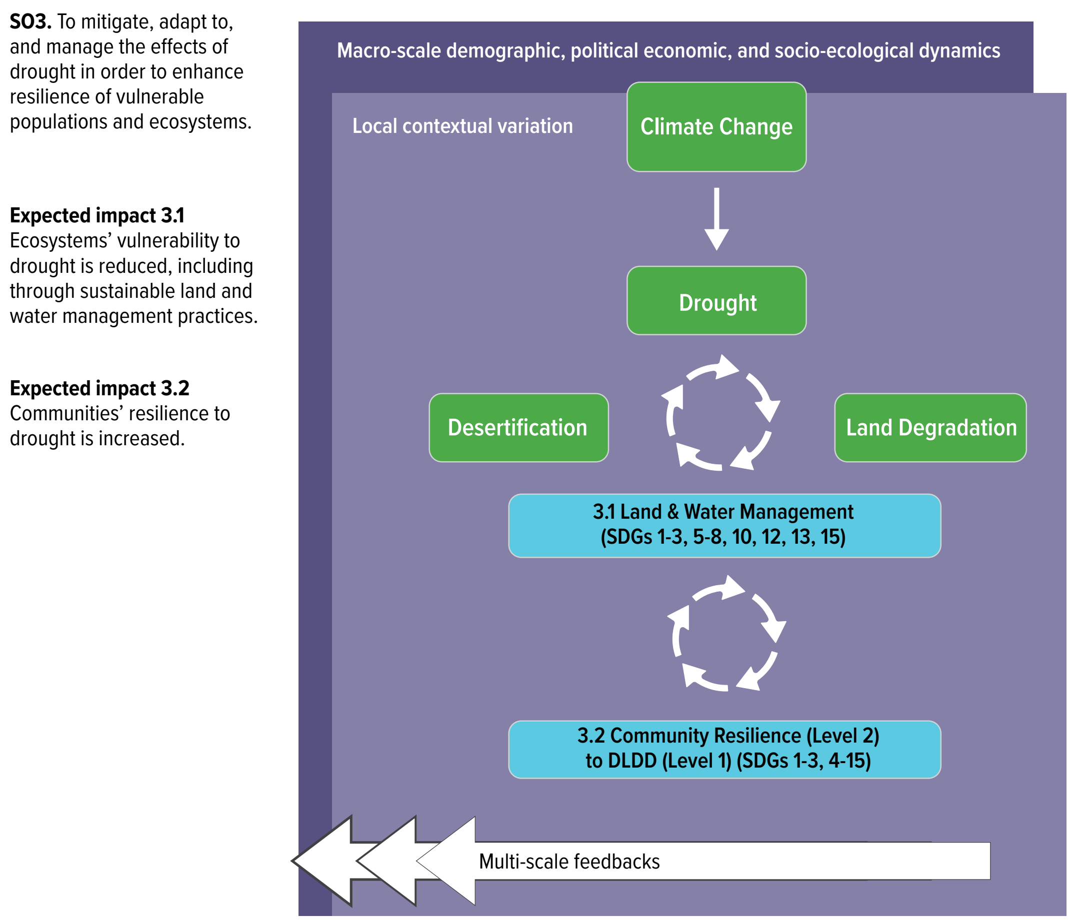


Figure 1. Strategic Objective 3 ecosystem (expected impact 3.1) and community (expected impact 3.2) vulnerability and resilience to drought, land degradation, and desertification (DLDD).

The UNCCD's established monitoring framework for SO3 utilizes a tiered approach comprised of three levels for monitoring drought (Table 1). This includes drought hazard (Level 1), drought exposure (Level 2), and drought vulnerability (Level 3) [1]. The framework establishes progress indicators and candidate metrics/proxies for the determination and reporting of each level. Consonant with Decision 11/COP.14, the UNCCD Secretariat has been requested to develop good practice guidance on the monitoring framework for SO3.

Table 1. Summary of the indicators and the basis for the metrics/proxies relevant to each of the three levels of proposed drought indicator and monitoring framework.

Level	Progress Indicator	Basis for Candidate Metrics/Proxies*
Level 1 – Simple Drought Indicator	Trends in the proportion of land under drought over the total land area	World Meteorological Organization Global Drought Indicator (standardized into classes) monitored and mapped monthly and aggregated for the United Nations Convention to Combat Desertification reporting period.
Level 2 – Simple Drought Exposure Indicator	Trends in the proportion of the population exposed to drought of the total population	Percentage of the population exposed to each drought class defined in Level 1.
Level 3 – Comprehensive Drought Vulnerability Indicator	Trends in the degree of drought vulnerability	Composite index of relevant economic, social, physical, and environmental factors that contribute to drought vulnerability
*The description provided for the candidate metrics/proxies should be considered preliminary as these will evolve through a multilateral process such as the World Meteorological Organization Global Multi-Hazard Alert System framework to help ensure progress towards the collaborative development of standards in methods and data supported by good practice guidance as well as national ownership of the reporting process.		

Improved member nation monitoring of SO3 is especially critical to UNCCD objectives as the successful achievement of SO3 catalyzes the implementation of SO1 and SO2 along with SDGs 1-15 (**Figure 1**). For the successful and expeditious achievement of these SDGs and UNCCD Objectives, it is imperative for member nations to avail themselves of standardized, state of the art methods and tools for assessing drought and understanding the socio-economic conditions of vulnerable communities in affected areas through the integration of free and open geospatial platforms such as Trends.Earth. Providing consistent global geospatial data to country Parties of the UNCCD has significantly lowered the reporting barrier and burden regarding efforts to achieve LDN [6].

I.2. Objectives of the report

Our primary objective is aimed at enhancing Trends.Earth functionalities to support country level implementation and reporting to the UNCCD on SO3 of the UNCCD 2018-2030 Strategic Framework (Decision 7/COP.13) [1]. To facilitate country-level SO3 monitoring and implementation within the Trends.Earth platform, we develop an approach for understanding human and ecosystem vulnerability to drought consistent with SO3. Secondarily, we develop a synthesis on global climate and weather datasets that can be used to better understand the impacts of drought towards LDN (and vice versa), including indicators on drought hazard, exposure, and vulnerability using global biophysical and socioeconomic datasets for understanding the socio-environmental conditions of vulnerable communities and ecosystems in affected areas. We then identify priority datasets, variables, and indices for monitoring drought in the context of SO3 and its two expected impacts, SO3.1 and SO3.2 (**Figure 2**). To integrate metrics of exposure, vulnerability, and resilience, the report introduces global socioeconomic and biophysical datasets to assess SO3 progress while allowing, to the extent possible, for the use of other national-level census or disaggregated data. The report assesses the potential for gender-disaggregation of global socioeconomic datasets to differentiate how men and women are affected by land degradation, drought, and poverty towards SO3 monitoring and implementation guidance. Lastly, we discuss integrated monitoring for SO3.1 and SO3.2 and consider limitations and the future potential of incorporating additional datasets into the framing and reporting of vulnerability to DLDD.

II. Background

II.1. Defining vulnerability and resilience to climate change and DLDD

As a brief introduction to the general topic, below we share some definitions of key terms and a summary of the broader issue of challenges and opportunities to building resilience to climate change and DLDD.

The Intergovernmental Panel on Climate Change (IPCC), the world's leading body on climate change and its impacts which is composed of climate scientists from around the world, is the primary source for our term definitions. Secondary definitions and additional explanations are also introduced.

The IPCC defines **climate change** as "a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer, and may be caused or influenced by natural or anthropogenic factors." **Drought** and the anthropogenic phenomena known as **land degradation** and the process of **desertification** (a process characterized by alterations in natural ecological regimes through a gradual and extreme transformation of previously productive ecosystems to more xeric ones occurring primarily in drylands environments) are closely related. These complex phenomena are driven by un-adapted human activity in conjunction with land and climatic constraints. Where inappropriate land use (e.g., monocultures) or unsustainable land management practices (e.g., deforestation, unsustainable agriculture, or water resource overexploitation) occur in conjunction with drought (and associated water shortages), the effects of the drought may be intensified leading to cascading effects resulting in land degradation and/or desertification.

Socio-ecological systems (SESs) are vulnerable when exposed to climatic changes and environmental changes such as land degradation and desertification. Under the IPCC framework (**Figure 3**), **vulnerability** is defined as the propensity or predisposition to be adversely affected by climate change and related processes, while scientists largely agree that vulnerability is a function of the sensitivity and adaptive capacity of those SESs [7–9]. **Sensitivity** is the impact of that environmental stressor on the SES. **Capacity** refers to both **coping capacity** (the ability of people, institutions, organizations, and systems, using available skills, values, beliefs, resources, and opportunities, to address, manage, and overcome adverse conditions in the short to medium term), and **adaptive capacity** (the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences) [4,10]. Vulnerability, sensitivity, and capacity are part of a larger framework that categorizes **risk**, or the potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values. Risk is often represented as the probability or likelihood of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur [4], thus the framework also incorporates elements of hazard and exposure. **Hazard**, as defined by the IPCC, is the potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources [4]. **Exposure** characterizes the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected [4]. In sum, vulnerability depends on exposure to a hazard and sensitivity to that exposure, including the susceptibility of individuals, human systems, and natural environments ensemble within a coupled natural-human system and their capacity to cope or adapt [11,12]. The intersection of hazard, exposure, risk, and disaster was encapsulated in the Sendai Framework, adopted at the Third United Nations (UN) World Conference on Disaster Risk Reduction in Sendai, Japan, on March 18, 2015. This framework outlines targets and priorities to prevent future and reduce existing disaster risk, specifically aiming to achieve substantial reduction of disaster risk and losses in lives, livelihoods and health and in the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countries over the next 15 years [13]. A specific priority identified in this report was to *"encourage the use of and strengthening of baselines and periodically assess disaster risks, vulnerability, capacity, exposure, hazard characteristics and their possible sequential effects at the relevant social and spatial scale on ecosystems, in line with national circumstances"*. Multifaceted risks to disasters are mitigated by human action through disaster risk management actions and climate change adaptation strategies, yet just what actions and strategies are effective remains an important area of research [4,14].

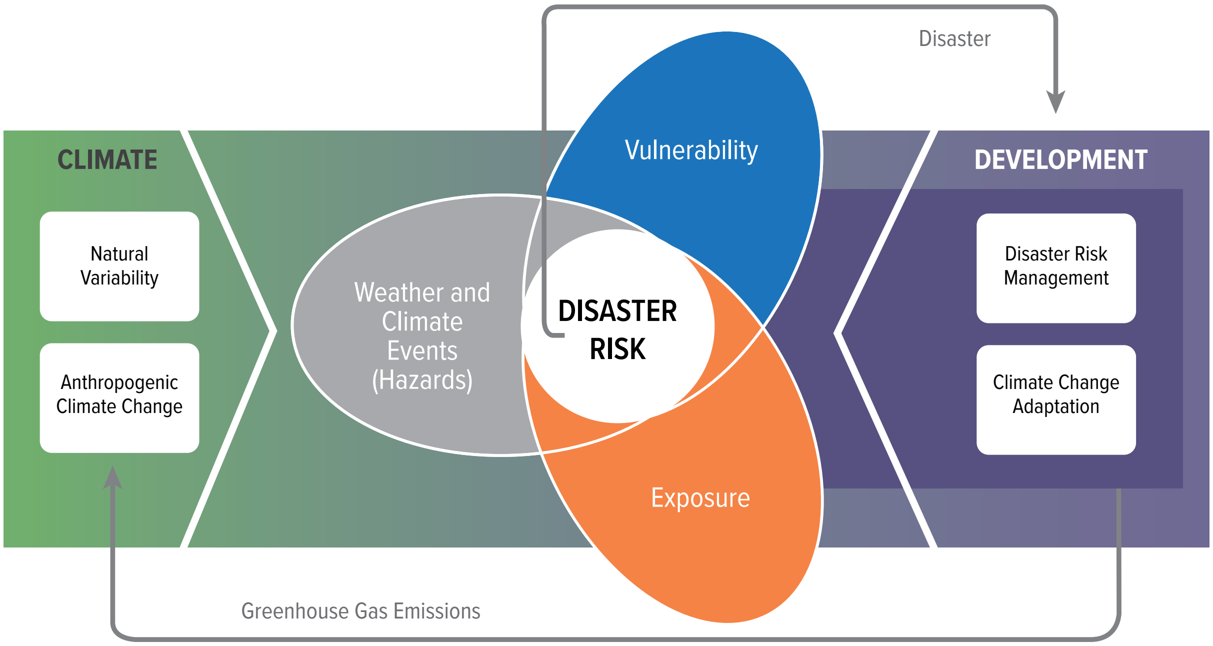
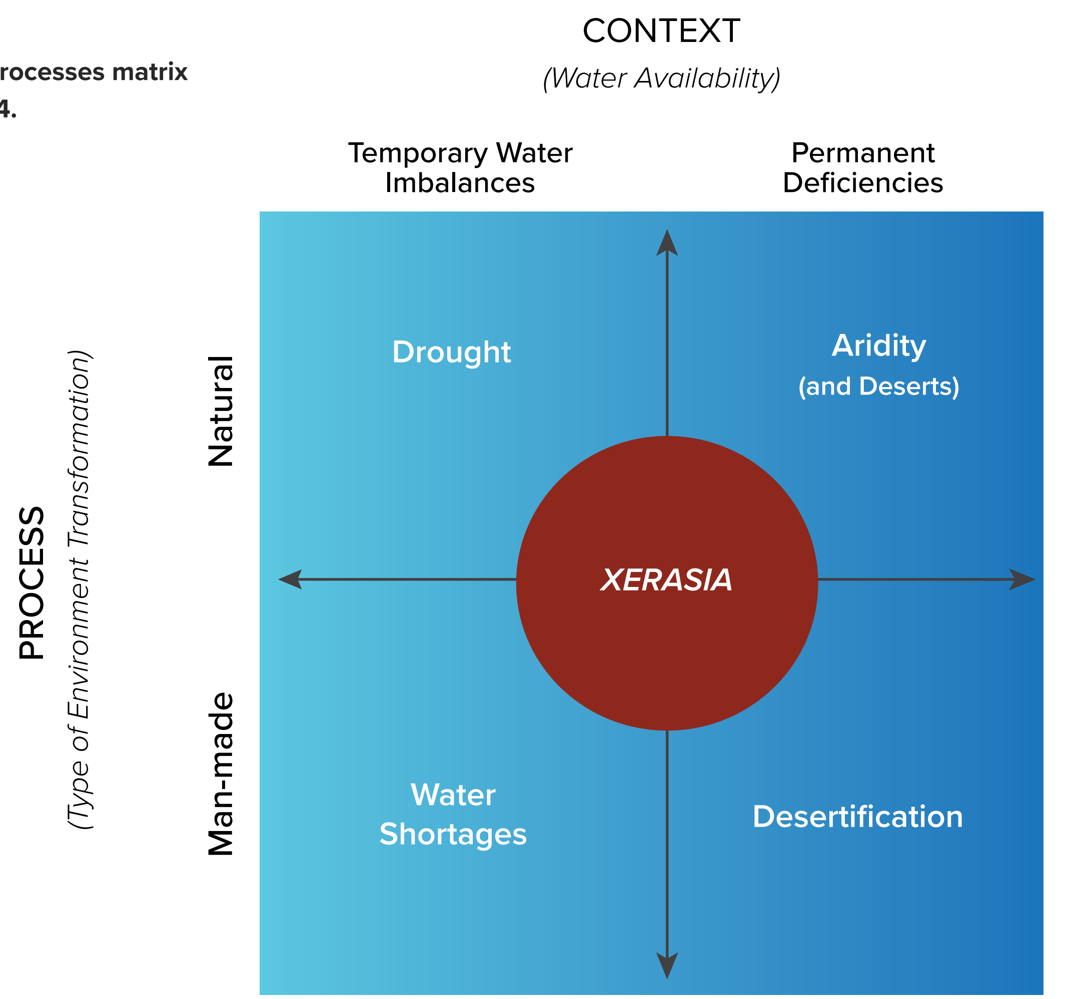


Figure 3. The IPCC Framework on risk to disaster conceptualized as an intersection of hazard (weather and climate events), exposure and vulnerability and mitigated by risk management and climate change adaptation strategies. Source: IPCC SREX, 2012.

Resilience, according to the IPCC, is defined as 'The capacity of social, economic, and environmental systems to cope with a hazardous event, trend, or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning and transformation." [4]. Necessary to building resilience is enhancing the capacity for a community to adapt, function, and even thrive in the face of challenging environmental conditions and changes [15].When we emphasize the land, its health, and resilience and the key role in worsening or lessening the impact of drought on human and socio-economic systems, **sustainable land management** (SLM) can reduce the impacts of droughts where land degradation would amplify them. Thus, when discussing resilience to drought and vulnerability reduction in the context of DLDD, SLM plays a crucial role. SLM was defined by the United Nations 1992 Rio Summit as "the use of land resources, including soils, water, animals and plants, for the production of goods to meet changing human needs, while simultaneously ensuring the long-term productive potential of these resources and the maintenance of their environmental functions." SLM includes practices that conserve natural resources, reduce emissions, and store carbon, among other benefits, for the primary goals of maintaining ecosystem functions and services, while also supporting human wellbeing. In a global context, SLM is an important approach to simultaneously support LDN and the SGDs.

To understand vulnerability and connections with drought and desertification a potentially useful framework when thinking about the integration of hazard, exposure, sensitivity, and adaptive capacity is through the concepts of aridity and desertification. **Aridity** is defined as a permanent, stable, and natural climatic condition that describes a region, while, in opposition, drought

Figure 4. The 'xerasia' processes matrix from Karavitis et al, 2014.



is a temporary climatic phenomenon that may occur unpredictably or following a more regular pattern. Droughts can lead to increased water demand and **water shortages** – temporary imbalances in water availability for human or ecosystem use that can be characterized at different spatial scales (i.e., local or regional) – which may be exacerbated in arid regions. This should be distinguished from **water scarcity**, which is commonly defined as a long-term imbalance of natural water availability and demand. Karavitis et al. [16] combined these processes and terminology into a framework termed 'xerasia' that highlights the overlapping boundaries among these four categories predicated on interdependencies, multiple feedback mechanisms and complex dynamics (**Figure 4**).

The take-home message is not only the complexity and interdependency of drought, water availability, and vulnerability but also the combined natural and anthropogenic causes leading to degradation outcomes. As we discuss below, socioeconomic, and demographic characteristics will ultimately define a population's relative vulnerability to various manifestations of drought and degradation while, concomitantly, accounting for the influences of human activities on drought frequency, occurrence, and spatial dynamics between drought, land degradation and vulnerability [12]. Ecosystem vulnerability will ultimately be defined by an ecosystem's response to drought and degradation in terms of ecosystem functions and regulatory processes in connection with biodiversity and nature protection [[17].

II.2. Introduction to drought types and monitoring approaches

Depending on its origin, effects, and consequences drought is typically classified into four main categories: meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought. More recently, a fifth type, termed ecological drought, has been defined. The IPCC refers to both agricultural and ecological drought as "soil moisture drought" but oftentimes these two are treated as independent types: agricultural drought is thought of as affecting agroecosystems, while ecological drought is thought of as affecting other natural or managed ecosystems, such as forests, rangelands or wetlands [14]. Soil moisture, hydrological, and socioeconomic droughts are often considered a follow-up to meteorological drought but place greater emphasis on human or social aspects of drought and the management of natural resources [18–20] (**Figure 5**).

Classification of drought into multiple types, based on the particular focal impacts of meteorological drought, highlights the interactions between the natural characteristics of drought magnitude and duration, and the numerous human activities and social demands that depend on precipitation to provide adequate water supplies [21]. In this context, we discuss in more detail the characteristics associated with all drought types and the general framework in which they are monitored from a hazard perspective.

Meteorological drought most commonly results from a natural period of precipitation deficit, a result of the persistent large-scale disruptions in global atmospheric circulation. Meteorological drought can also occur due to, or the severity can also be influenced by, other factors such as high winds, high temperatures, and low relative humidity [19] (**Figure 5**). Because it is predominantly a natural phenomenon, there is little, if anything, that can be done to prevent the occurrence of meteorological droughts. However, a recent study – the first of its kind – provided evidence of the connection between climate change and global drought patterns by finding alignments between drought and patterns of wetting and drying that are a characteristic response of the climate to greenhouse gas emissions [22]. Additionally, these models and other evidence presented by the IPCC support the conclusion that droughts are increasing in frequency and severity [4,22].

Precipitation data is most commonly used for meteorological drought hazard analysis, where drought is considered as the departure from normal precipitation for a specified period of time, or precipitation deficit with respect to average values. These data may also be analyzed in terms of drought duration and intensity in relation to cumulative precipitation shortages [19,23]. For example, the Standardized Precipitation Index (SPI) is commonly used to monitor meteorological drought over time scales of one or three months. SPI is expressed as standard deviations that the observed precipitation would deviate from the long-term mean, for a normal distribution and fitted probability distribution for the actual precipitation record (see section IV.1.1 for detailed description and equations). Since precipitation is not normally distributed, a transformation is first applied, followed by fitting to a normal distribution [24–26]. The SPI is a widely used index to characterize meteorological drought, or precipitation deficit, and was recognized through the Lincoln Declaration on Drought as the internationally preferred index for calculating and monitoring meteorological drought [27].

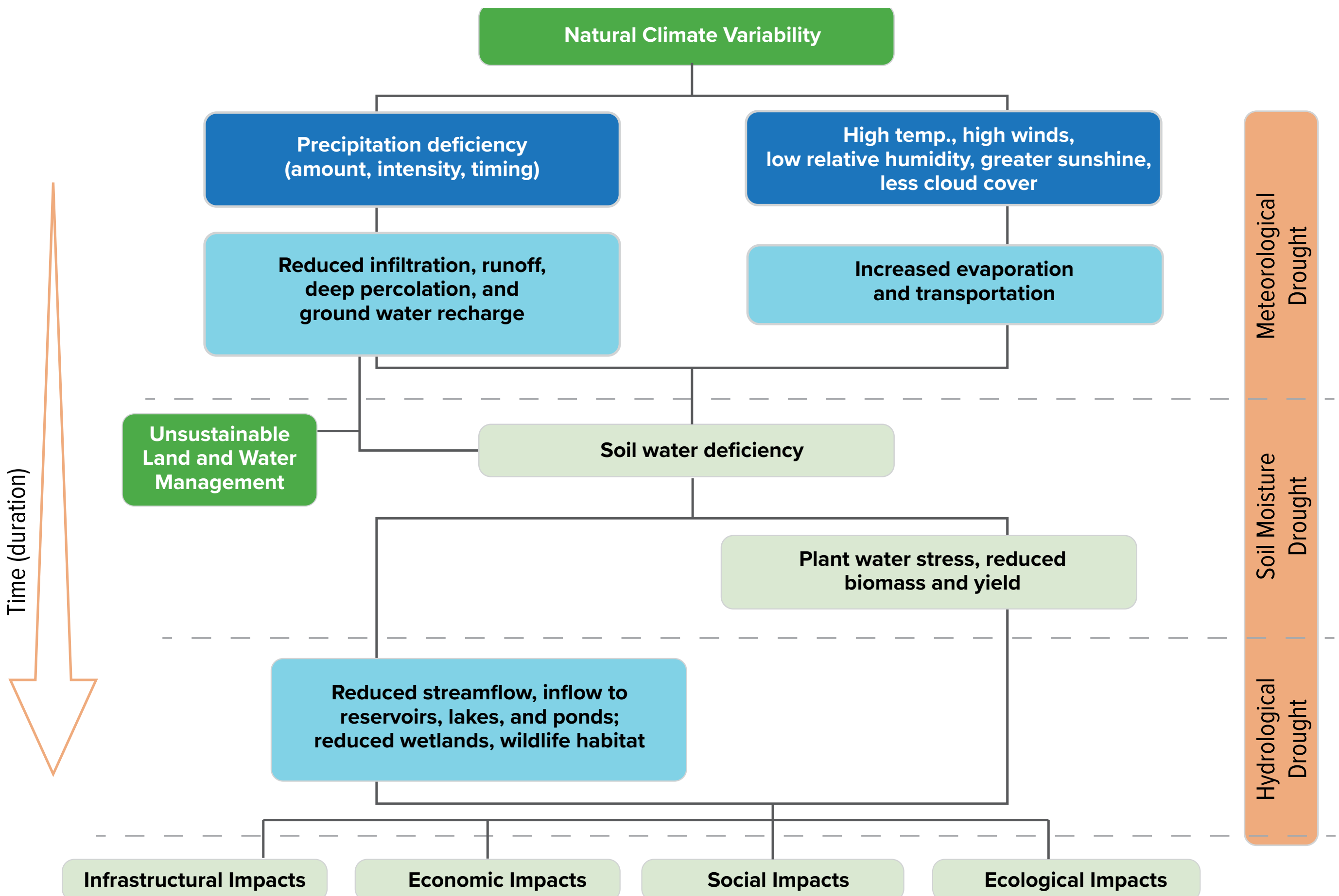


Figure 5. Drought types, causal factors, and their typical sequence of occurrence.

Soil moisture drought refers to both agricultural and ecological drought. **Agricultural drought** is more commonly defined by the availability of soil water to support crop and forage growth [19]. It references a period with declining soil moisture that subsequently causes crop failure or severely reduced grass growth and does not typically account for surface water resources [23]. Declines in soil moisture can be caused by precipitation deficit or differences in actual evapotranspiration (AET) and potential evapotranspiration (PET). Since plant water demands are dependent on prevailing weather conditions (temperature/ solar radiation, relative humidity, and the wind), biological characteristics of the specific plant and growth stage, and physical and biological properties of the soil, indices that combine precipitation, temperature, and/or soil moisture indicators are commonly employed to assess agricultural drought.

Ecological drought also results from a prolonged and widespread deficit in soil moisture or biologically available water that imposes multiple stresses in natural terrestrial and aquatic ecosystems. It is much less discussed and studied than other drought types. However, because meteorological droughts are predicted to become more frequent and severe in certain regions (such as the Mediterranean and Western Africa), this can lead to increases in wildfire and insect outbreaks, local species extinctions, forest diebacks, and altered rates of carbon, nutrient, and water cycling – all of which can have real consequences for ecosystems and human communities alike [4,22,28]. The monitoring of ecological drought largely depends on the type of ecosystem involved, where terrestrial vegetated ecosystems are typically assessed using a vegetation index (such as the Normalized Difference Vegetation Index (NDVI)), but drought stress may also be assessed using remotely-sensed land surface temperature [29]. For aquatic environments, monitoring approaches largely involve using in-situ data, but could also utilize terrestrial water storage data (e.g., Gravity Recovery and Climate Experiment (GRACE)) or other approaches used to monitor hydrological drought, described next.

Hydrological drought, while still influenced by precipitation deficiency, is better defined in terms of departure of surface and sub-surface water supplies from some average level in each timeframe. However, as water supplies are influenced by multiple other non-meteorological factors such as irrigation, recreation, tourism, flood control, hydroelectric power production, domestic water supply, protection of endangered species, and environmental and ecological preservation, attributing a decline in water supplies and resources to precipitation is not feasible. Furthermore, there are long lag times in precipitation deficits and the resulting decline in surface and/or subsurface water. Finally, in locations where water supplies are predominantly sourced from snowmelt, determination of drought severity is further complicated [19].

Streamflow data are widely used to analyze hydrological drought [23]. Hydrological drought is commonly assessed through hydrological modeling, but recently, remotely sensed satellite data such as remotely sensed rainfall estimates have been used with some degree of success to calculate hydrological drought indices like the Standardized Streamflow Index (SSFI) [30]. Remotely sensed reservoir surface area data has also been used to develop a Reservoir Area Drought Index (RADI) for hydrological drought monitoring [31]. Occasionally, hydrological drought may be prolonged enough to cause declines in groundwater, thus, the term groundwater drought has been used in scientific literature, with such drought types being assessed by decreases in groundwater level, storage, or recharge [23].

Socioeconomic drought is defined by an imbalance in water supply and demand and their resulting impacts on societies and economies. It is the least understood of all drought types. As such, socioeconomic drought indicators are much less developed than those for meteorological, agricultural, and hydrological drought. Because socioeconomic drought typically is a long-term drought, it can potentially be monitored using the same methods as other drought types but over a longer period, such as if SPI were calculated over a 12-month period it could be compared to human water demand in a region and used to monitor socioeconomic drought. However, because the human component is more inherent in socioeconomic drought than other drought types, the development of indicators specific to socioeconomic drought has recently received more attention in the scientific literature and may include measures of climate variability, local vulnerability/resilience, and water resources demand [20,32].

In summary, drought hazard monitoring most often integrates precipitation, temperature, and soil moisture data to create drought indicators, but includes other data types or combines data (such as in calculating evapotranspiration). Given that drought development is a slow and complex process, it is difficult to identify and quantify especially when attempting to use a globally applicable framework and, as such, drought is described using multiple indicators and variables, typically organized in order of computational (the level of technical expertise of end-users) and impact-related complexity. Because different indicators may emphasize different aspects of drought, indicators and data should be carefully selected with respect to the drought characteristic in mind. Additionally, some indicators have specific shortcomings, for example, in the context of climate change. For this reason, assessments of changes in drought characteristics (i.e., frequency, intensity, duration) with climate change should consider several indicators relating to frequency, intensity, duration, and areal extent, including a specific evaluation of their relevance to the addressed question to support robust conclusions.

II.3. Summary of UNCCD, WMO, & Conservation International work to date

II.3.1. United Nations Convention to Combat Desertification (UNCCD)

II.3.1.1 Background

The UNCCD has largely based its tiered monitoring framework for SO3 on the World Meteorological Organization (WMO) Global Multi-Hazard Alert System (GMAS) and the **Risk = Hazard x Exposure x Vulnerability** model. In decision 11/COP.14, the UNCCD has adopted a tiered drought indicator and monitoring framework [1] consisting of three complementary levels (**Table 1**).

In the UNCCD tiered framework for monitoring drought, the drought hazard indicator is the Level 1 indicator. This approach to calculating drought hazard requires a simple drought indicator calculated globally and based on well-established meteorological indices. Specifically, document ICCD/COP(14)/CST/7 describes an indicator "for which data are being regularly produced in most countries, which could be aggregated under a common framework consistent with international standards and be supported in terms of data collection, analysis and reporting by an existing multilateral process. Ideally the development of candidate metrics/proxies for this indicator would leverage ongoing collaboration among National Meteorological and Hydrological Services (NMHSs) to ensure that steps towards standardization are taken multilaterally with full consideration of national circumstances" [1]. This index would be used to quantify **drought hazard as the proportion of land under drought over the total land area**. Additionally, the candidate index should be aggregable in a cumulative way so that duration and intensity of drought would provide a measure of drought magnitude and a proxy for drought effects and impacts.

In the UNCCD framework, the drought exposure indicator is the Level 2 indicator. This simple approach to calculating drought exposure links the Level 1 (hazard) simple drought indicator with a commonly calculated and easy-to-use proxy indicator for drought exposure. Level 2 drought exposure is mentioned in document ICCD/COP(14)/CST/7 [1], and interpreted as "population exposed to drought." This would allow for monitoring of the SO3 progress indicator "Trends in the proportion of the population exposed to drought of the total population" and would be calculated as the percentage of population exposed to drought for each Level 1 drought class (**Table 2**). Using freely available fine spatial resolution gridded population data ensures that national census data has been mapped in a consistent way for each country. The UNCCD also mentions other factors, such as livestock density, crop cover, and water stress that could be used as proxies in the development of this indicator.

Table 2. Level 1 drought hazard indicator drought classes for severity mapping and monitoring defined in a statistically harmonized way, as proposed by the World Meteorological Organization.

Drought Class	Number of events in 100 years	Severity of event
No Drought		
D1 (Moderate Drought)	33	1 in 3 years
D2 (Severe Drought)	10	1 in 10 years
D3 (Extreme Drought)	5	1 in 20 years
D4 (Exceptional Drought)	2.5	1 in 50 years

The UNCCD Level 3 indicator for drought vulnerability, as defined in document ICCD/COP(14)/CST/7 should be built upon the Level 1 simple drought hazard indicator (a common and easily calculated global drought indicator) and the Level 2 simple drought exposure indicator (which links Level 1 with a common and easy-to-use proxy for drought exposure, such as population exposed to drought). This Level 3 indicator is necessary to more directly address SO3: to mitigate, adapt to, and manage the effects of drought to enhance resilience of vulnerable populations and ecosystems. Additionally, this indicator better allows for the identification of underlying causes of drought impacts and is essential in providing guidance for policy development and response protocols. Therefore, this indicator needs to be robust enough to encompass physical, social, economic, and environmental factors that affect community and ecosystem drought vulnerability and resilience. Currently, some advances have been made towards the development of a comprehensive drought vulnerability indicator, but there has yet to be a definitive solution in providing a global indicator that is comparable between countries but nationally relevant. Though this is the least developed part of the framework, it is a crucial component in the implementation of any framework for monitoring drought risk and subsequently informing policy or response initiatives. The UNCCD core principles (ICCD/COP(14)/CST/7) favor a harmonized index that can be standardized, where appropriate and feasible to account for variability in the causes and consequences of land degradation and sustainable land management, and in their capacity to measure and monitor impact. The indicators chosen should be sensitive to the contribution of DLDD.

II.3.1.2 Gaps and opportunities related to SO3

The current UNCCD framework does not currently account for the dimension of ecosystem exposure in the same way it does for human exposure. Without the accounting of ecosystem exposure the framework does not comprehensively facilitate the ability to measure progress towards SO-3.1 and Expected Impact 3.1 (*Ecosystems' vulnerability to drought is reduced, including through sustainable land and water management practice*) in the same capacity as it does for the human dimension of exposure. Therefore, the addition of a component to the Level 2 Exposure Indicator which measures ecosystem exposure would greatly enhance the framework.

Though the human exposure indicator for SO3 is well defined, more work is needed towards the development of the human dimensions of vulnerability in relation to DLDD for the Level 3 indicator – where, when, how, and under what circumstances human populations are relatively vulnerable or resilient to DLDD and how, in turn human agency feeds back in driving or mitigating DLDD. Additionally, the Level 3 indicator could be structured in such a way that it encompasses both human and ecosystem vulnerability to present a truly comprehensive assessment of drought vulnerability. The SO3 vulnerability framing, metrics, and methodology are insufficiently developed so far; therefore, understanding, and quantifying vulnerability to drought poses a great challenge, and the greatest opportunity for development and standardization of the UNCCD monitoring and reporting frameworks relating to drought. Emphasizing both human systems and ecosystems within the framework will more effectively monitor the interconnections between and among both systems, inform sustainable land and water management practices, and ultimately aid in reducing risk and increasing resilience of humans and land alike. Thus, there are significant opportunities for the UNCCD and partner organizations to develop standardized protocols and indicators for assessing and monitoring vulnerability of humans and ecosystems that are based on generic drought indicators, because they are valid for all types of exposed activities/elements and therefore do not alter with changes in the physical entities which are at risk [20]. Finally, the comprehensive drought vulnerability index could incorporate components of sensitivity and capacity (including both coping and adaptive) within the framework.

Additionally, there is a need and opportunity to provide guidance and recommendations on globally suitable and spatially explicit biophysical and socio-economic datasets to calculate the metrics included in support of drought monitoring across all levels of hazard, exposure, and, especially, vulnerability, which emphasize both exposure and vulnerability not just of people, but also of the land. Publicly available gridded datasets offer the most cost-effective approach to monitor and evaluate large scale Earth surface change. Finally, there is a need for guidance for countries to replace that data with their own data in a way that produces harmonized results on a global scale for inter-country comparisons.

II.3.2. World Meteorological Organization (WMO)

The WMO has been working on, and planning to implement, a GMAS to serve as a one-stop shop to support the humanitarian organizations of the UN, NMHSs and other global users, including the media, in monitoring hydrometeorological hazards (for example, drought, floods, heatwaves). The GMAS would address the need for both national and international organizations to monitor drought at national, regional, or global levels. Based on the United States (US) National Drought Monitoring Program and the European MeteoAlarm system, the GMAS is intended to take current weather warnings (wind, temperature, freezing rains, etc.) produced by the Hydrological and Meteorological services of various countries to help create weather alerts. The GMAS was developed in response to the Sendai

Framework for Disaster Risk Reduction 2015-2030 [13]. The WMO is actively developing a **Global Drought Index (GDI)** as a component of the GMAS, as no such system is currently in existence for globally monitoring and identifying drought within the GMAS or other WMO tools. WMO hopes to accomplish the integration of a European drought monitoring system by partnering with the meteorological and hydrological services divisions of several European countries and intends to expand this platform globally to begin reporting at the lowest level of meteorological drought hazard (Level 1). Current efforts are also focused on identifying an appropriate drought index to use as the basis for developing the GDI (although the Standardized Precipitation Index or SPI is a front runner since it is already endorsed by the WMO and meets many of the criteria that would be required for the GDI), and on providing recommendations on suitable dataset(s) (for example, station-based vs. remotes sensing-based). The WMO advises that drought indicators should be statistically based, to make it easier to integrate them into the GDI. The ultimate goal of the WMO is to standardize these drought indicators into 4 classes of drought intensity (based on the US Drought Monitor SPI index) for countries to report on drought hazard. However, this initiative is in its very early stages of development (Robert Stefanski, personal communication, 1 September 2020). In the long-term, the GDI and GMAS will enhance the abilities of nations and organizations to know when to prepare or respond to drought, based on the proposed risk matrix and associated color warning system for hydrometeorological hazards including drought (**Figure 6**).

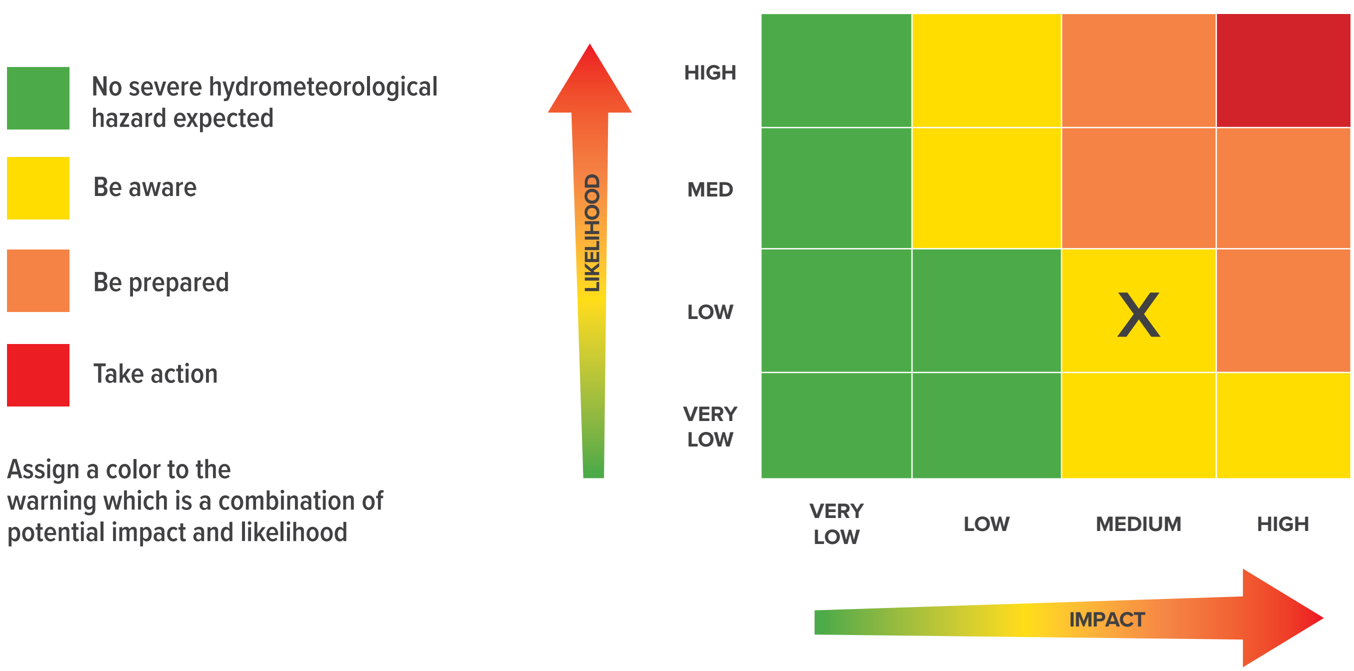


Figure 6. World Meteorological Organization Global Multi-Hazard Alert System (GMAS) proposed risk matrix. The X indicates an example of where the combination of potential impact and likelihood produces the warning level and associated color assignment. Source: Met Office, United Kingdom, and Tong & Cheng et al. (2018).

The UNCCD framework is aligned with the WMO GMAS framework, which is a methodology of aligning and standardizing national drought calculations in a coherent way to create an easy-to-understand global system of drought reporting based on a GDI. The SPI is recommended by the WMO to be used as an initial test because it meets the requirements of aggregation capacity (or the ability to be aggregated temporally, e.g., to match the UNCCD reporting period) and standardization. The Drought Hazard classes defined for the GMAS are based on the North American Drought Monitor with the exception that the Abnormally Dry class (D0) is removed (**Table 2**).

The WMO GMAS framework expresses the need to quantify exposure in terms of people and/or assets; and the need to quantify vulnerability in terms of people and/or assets with the goal of mapping a comprehensive indicator of drought risk across the globe [33]. As the GMAS in still in the early stages of development, there has yet to be a dataset or set of variables tested, validated, or otherwise defined for monitoring drought exposure. The WMO notes that institutional cooperation is crucial to provide good practice guidance on the most appropriate datasets, indices, and/or methods.

WMO's GMAS framework is centered around drought hazard reporting, thus representing complete gaps in enabling countries to report on metrics of exposure or vulnerability for either human populations or ecosystems. The creation of standardized methods for incorporating proxy data to monitor human and ecosystem dimensions of exposure and vulnerability are necessary at a global level and represent an area of opportunity for academic and organizational research.

II.3.3. Conservation International

Conservation International, through its open-source platform Trends.Earth, does not currently include any capabilities for monitoring drought in support of UNCCD SO3, although drought impacts on vegetation productivity can be analyzed through climate correction of the NDVI signal using different methods (e.g. Rain Use Efficiency, Water Use Efficiency, and Residual Trend Analysis) and datasets (soil moisture, precipitation, and evapotranspiration). Thus, the Trends.Earth platform, combined with this report, represents an avenue for providing datasets and tools that could be significant in the development of the WMO GMAS/GDI and UNCCD SO3 reporting tool, and can provide a testbed for data and indices that could be validated at global and national levels. Trends.Earth currently includes data for precipitation and soil moisture, but these datasets need to be re-evaluated for appropriateness for Level 1 drought monitoring. Additionally, indices and methods for monitoring Level 1 drought must be defined and proper tools to execute these analyses must be made available. Then, the framework for monitoring Level 2 and 3 droughts can be established following the proposed framework and guidance from UNCCD.

III. Monitoring Framework Recommendation for SO3: Drought Hazard, Exposure, and Vulnerability

III.1. Proposed drought monitoring approach

Our proposed drought monitoring approach integrated the current UNCCD Drought Monitoring Framework with an additional Level 2 indicator to better account for ecosystem exposure in addition to human exposure (**Figure 7**).

The Level 3 vulnerability indicator combines components of both ecosystems and humans to present a more comprehensive vulnerability index while accounting for both sensitivity and capacity of human and ecological systems. Within the following sections we present an overview of recommended datasets and indices to be used in each level of the framework, with detailed descriptions of those relevant indices and datasets in Sections VI and V, respectively. For indices not included in this report, we recommend the Handbook of Drought Indicators and Indices [32] as a practical source of information for biophysical drought hazard indicators.

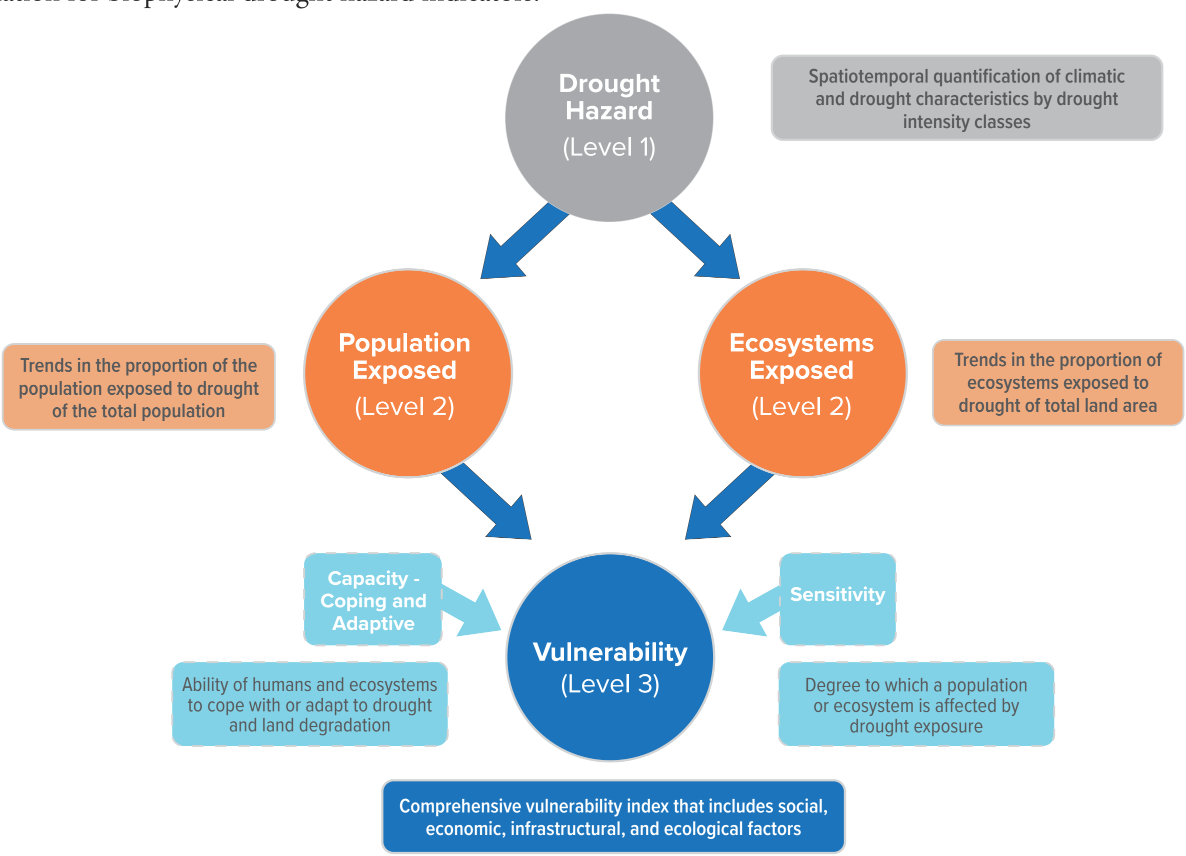


Figure 7. The UNCCD Drought Monitoring Framework is comprised of Level 1, 2, and 3 drought indicators (shown as circles in the figure); the Level 2 ecosystem exposure component is not currently included in the framework. Additionally, the light blue boxes show modifiers of vulnerability (sensitivity and coping/adaptive capacity) currently not included in the UNCCD Drought Monitoring Framework.

III.2. Monitoring drought hazard (Level I)

III.2.1. Recommendations on drought hazard indices

For Level 1, the bare minimum consideration in operational drought hazard monitoring should be based on a drought index that is derived from precipitation data. There are many indices that are used operationally on global, regional, or national levels [34]. Perhaps the most frequently employed is the Standardized Precipitation Index (SPI), widely used to characterize meteorological drought or precipitation deficit, and was recognized through the Lincoln Declaration on Drought as the internationally preferred index for calculating and monitoring meteorological drought [27]. SPI is calculated as standard deviations that the observed precipitation over a specified period would deviate from the long-term mean over periods of that duration considered over typically 30 years of data, for a normal distribution and fitted probability distribution for the actual precipitation record. The primary advantages for using the SPI for global drought monitoring, prediction, and risk assessment is that it is currently in use in many countries globally and is endorsed by the WMO [27]. Other key advantages are that the SPI represents both precipitation deficits and surpluses, and it can be calculated at different timescales (e.g., SPI-3, SPI-6, SPI-12, with the number indicating the number of months over which the index is calculated). Thus, it indirectly considers effects of accumulating precipitation deficits, which are critical for soil moisture and hydrological droughts.

While SPI is a strong contender for the WMO GDI, as a precipitation-only index, in some contexts it can fail to capture the complexity of drought conditions, such as temperature or soil moisture anomalies. More robust indices such as the Standardized Precipitation and Evapotranspiration Index (SPEI) could be used in place of or in conjunction with SPI. The SPEI is calculated using the same methodology as SPI but includes an evapotranspiration component in addition to the precipitation component and can be used to evaluate effects of climate change under multiple future scenarios [34] or provide a better determination on drought occurrence or severity. Laurent-Luchetti et al. [35] recommends for precipitation raw annual value or index of anomalies (specifically mentioned is SPI, # of months below an SPI threshold) or using a combination of precipitation and temperature calculated at the annual scale to highlight long term trends (e.g., SPEI).

The inclusion of a soil moisture-based drought index within a global drought monitoring tool provides an option for countries to replace the SPI or enhance a drought analysis with additional information that can detect deficiencies in soil moisture, and thus potentially provide more accurate monitoring of the onset, intensity, or duration of agriculture or ecological drought. Soil moisture, up to 5cm soil depth, is recognized as an Essential Climate Variable (ECV) by the WMO Global Climate Observing System and can be used as the input data for the SSI. Including soil moisture anomaly data in drought studies has been shown to correlate well with SPI-3 [36]. When comparing with drought characteristics, root zone soil moisture (RZSM) anomalies exhibit relatively larger drought duration, but smaller drought intensity compared with the meteorological-based drought indicators. Another benefit of including a soil-moisture-based index is to increase the ability of countries in areas with sparse or inaccurate meteorological data to detect and monitor drought.

Alternatively, a combination of meteorological- and soil moisture-based indices, such as SPI and Standardized Soil Moisture Index (SSI) might enhance the utility of drought hazard metrics for multiple stakeholders. SSI is highly compatible with both SPI and SPEI as it is calculated using the same methodology using soil moisture as an input. Because the SSI is computed using a similar statistical method as both the SPI and SPEI (in which the index quantifies observed values as a standardized departure from a selected probability distribution function that models the raw data) and because it also uses the same classification system for drought severity, it is most logical to utilize the SSI over other available soil moisture indices.

Though the WMO GDI has been developed based on a single input (i.e., precipitation), the existence of combined (or hybrid) drought indicators may be better suited for characterizing the evolution of droughts. Examples are the Combined Drought Indicator (CDI) [37], which combines information from precipitation deficit, soil moisture deficit, and vegetation stress. This

index is used operationally in the European Drought Observatory (EDO). Other examples include the Palmer Drought Severity Index (PDSI) [38], which is widely used operationally in the United States, and the Multivariate Standardized Drought Index (MSDI) [39], which is operationally implemented in the Global Integrated Drought Monitoring and Prediction System (GIDMaPS) [40].

In summary, the SPI, SPEI, and SSI are all highly compatible and complimentary indices that fit all the criteria for the WMO GDI and are easily aligned to the WMO Level 1 drought hazard indicator drought classes for severity mapping and monitoring (**Table 2**) in a statistically harmonized way. **Trends.Earth could include, at minimum, SPI, but could also include SPEI and SSI to provide multiple means for countries to assess drought hazard in an alternate or complimentary fashion that is consistent with the requirements of both the UNCCD and the WMO.**

III.2.2. Recommendations on precipitation, temperature, and soil moisture datasets

The selection of the data to be used for calculating the drought index is also a critical decision in effective operational drought detection and monitoring because drought metrics can vary significantly based on characteristics of the specific product including its retrieval technique, merging method, period of record, or spatial resolution [41]. Therefore, it is important to research how the choice of product may affect drought analysis and interpretation, including frequency of occurrence, spatial pattern, and severity.

Because there are potentially unlimited options in terms of available global precipitation datasets, there is a need to establish criteria for a suitable product for drought monitoring to provide guidance to countries when selecting a dataset. Based on inclusion and exclusion criteria described in Section V.1, there are few global datasets which meet all or most criteria. These include CHIRPS, CMAP, GPCP, and PERSIANN-CDR, which are all blended satellite-gauge products (**Table 3**; additionally, see Section V.2.1 for complete descriptions of these datasets and associated benefits and drawbacks to each). **We recommend that CHIRPS be utilized as the primary precipitation product for monitoring drought due to its extremely high spatial resolution, low latency, and multitude of temporal resolutions that make it effective in operational monitoring of both short- and long-term drought.** Moreover, it was specifically designed for drought monitoring, has been peer reviewed, literature has shown it to be effective, and it is currently employed for this purpose by multiple organizations including the Famine and Early Warning System Network (FEWS NET), ClimateSERV, and Trends.Earth. However, because there is no one dataset that will fit the needs of all nations or individuals using the Trends.Earth platform, it would be beneficial to provide guidance on alternate global (e.g., CMAP, GPCP, and PERSIANN-CDR) or national datasets.

Table 3. Coverage and spatiotemporal resolutions of selected major gridded precipitation, temperature, and soil moisture products.

PRECIPITATION					
Dataset	**Source**	**Spatial Resolution**	**Spectral Resolution**	**Temporal Coverage**	**Spatial Coverage**
CHIRPS 2.0	CHG UCSB	0.05º x 0.05º (~5.5 km at the Equator)	1981 – present	Daily, pentadal, dekadal, monthly, 2-monthly, 3-monthly, annual	50 N – 50 S
CMAP standard	NOAA CPC	2.5º x 2.5º (~278 km at the Equator)	1979 – present	Monthly, pentad	90 N – 90 S
GCPC v2.3 monthly	NASA GSFC	2.5º x 2.5º (~278 km at the Equator)	1979 – present	monthly	90 N – 90 S
PERSIANN-CDR	NOAA CDR Program / NOAA NCEI	0.25º x 0.25º (~278 km at the Equator)	1983 – present	1-hourly, 3-hourly, 6-hourly, daily	60 N – 60 S
TEMPERATURE					
Dataset	**Source**	**Spatial Resolution**	**Spectral Resolution**	**Temporal Coverage**	**Spatial Coverage**
BETP gridded land	Berkeley Earth Group	1º x 1º (~111 km at the Equator)	1753 – present	Daily, monthly	Global
CHIRTS-daily	CHG UCSB	0.05º x 0.05º (~5.5 km at the Equator)	1981 – present	daily	60°S – 70°N
CRUTEM4	CRU, Hadley Center	5º x 5º º (~555 km at the Equator)	1850 – present	Monthly	Global
CPC Global Daily	NOAA	0.5º x 0.5º (~55.5 km at the Equator)	1979 – present	Daily	Global
GISTEMP Land v4	NASA	2º x 2º (~222 km at the Equator)	1880 – present	Monthly, Seasonally, Annually	Global
NOAA GlobalTemp V5	NOAA	5º x 5º (~555 km at the Equator)	1880 – present	Monthly	Global
SOIL MOISTURE					
Dataset	**Source**	**Spatial Resolution**	**Spectral Resolution**	**Temporal Coverage**	**Spatial Coverage**
ERA5	ECMWF	0.28° x 0.28° (~31.1 km at the Equator)	1979 – present	Hourly	Global
ESA CCI v05.2	ESA	0.25° x 0.25° (~27.8 km at the Equator)	1980 – 2019	Daily	Global
MERRA-2	NASA	0.5° x 0.625° (~55.5 km x 58.75 km at the Equator	1980 - present	Hourly	Global
NASA-USDA Global Soil Moisture Data	NASA-USDA	0.25° x 0.25° (~27.8 km at the Equator)	2010 – present	3-daily	Global

Potential options for global temperature datasets that meet our criteria include Berkeley Earth gridded land, CPC, CHIRTS, GISTEMP Land, CRUTEM, and NOAA Global Temperature, though CRUTEM, GISTemp Land, and CHIRTS are most suitable for integration into Trends.Earth. CRUTEM and/or GISTemp Land contain values for both averages and anomalies, and thus can be used in a variety of applications (Table 3; additionally, see Section V.2.2. for complete descriptions of these datasets and associated benefits and drawbacks to each). For example, the raw values can be used in the calculation of the SPEI. These datasets may also be used to directly monitor raw annual values or temperature anomalies, a method recommended for monitoring changes in climate that may impact the frequency or severity of drought [35]. CHIRTS offers significant advantages in providing information in data-sparse regions because it combines satellite and gauge information and has a spatial resolution that is far superior to all other available datasets, and is complimentary to CHIRPS, our recommended precipitation dataset. As it is less common to include temperature data in drought hazard monitoring compared to precipitation, we suggest more testing is needed. **We recommend that CRUTEM, GISTemp Land, and CHIRTS be further evaluated for efficacy in drought hazard monitoring either through literature review or direct testing, with the one producing the most accurate results then implemented in Trends.Earth.**

There are currently multiple global soil moisture products available including ERA5, ESA CCI, MERRA-2, and the NASA-USDA Global Soil Moisture Dataset (**Table 3**; additionally, see Section V.2.3. for complete descriptions of these datasets and associated benefits and drawbacks to each). Of these products, the ESA CCI combined product utilizes both active and passive satellite microwave data, where active retrievals tend to perform better in more densely vegetated areas, and passive retrievals tend to perform better in more sparsely vegetated areas [42]. The robustness of this product for detecting and monitoring drought across different vegetation densities makes it worthy of inclusion in global drought monitoring toolboxes. However, ERA5 has shown overall higher correlation with in-situ observations and represents soil moisture at different depths within the soil column, which could facilitate analyses beyond the capacity of the other products which measure only the top-most layer. **We recommend that ESA CCI and ERA5 are equally suitable for inclusion in Trends.Earth and the inclusion of both would support a robust drought hazard monitoring toolbox.**

III.1.1. Additional considerations on how to monitor drought hazard

Drought hazard, as detailed in ICCD/COP(14)/CST/7, is recommended to be "a commonly calculated and easy-to-use global drought indicator for which data are being regularly produced in most countries, which could be aggregated under a common framework consistent with international standards and be supported in terms of data collection, analysis and reporting by an existing multilateral process." Currently, the WMO is working toward the development of a GDI that will be based on the SPI but allow countries to input nationally-employed indices (for example, Deciles Index from Australia [34]) which will then be fitted to a global drought classification. This will allow countries to use datasets and indices of their own choice while making it easier to analyze global patterns of drought occurrence (whether a drought has occurred, and when), severity (defined by the ranking in the drought classification), and duration.

While many countries have programs by which to quantify drought occurrence and severity, drought impacts are very rarely monitored or reported. Nevertheless, drought has short- and long-range impacts on virtually all types of activities related to water, economy, and society. Karavitis et al. [16] describe two methodological approaches that may be used to study and assess drought impacts. The first is a "cause and effect approach" in which drought operates on a certain activity, producing an impact. The second is an "interaction approach", suggesting that various processes (physical, economic, or societal) may influence an activity with impacts embedded and interrelated to that activity. The interaction approach is more favored, where first-order impacts are related to the hydrologic cycle (i.e., precipitation, runoff, stream flow). Second-order impacts tend to influence human activities such as agriculture, industry, urban populations, and transportation. The third-order impacts can be thought of as adaptations to both first- and second-order impacts (such as income losses, adjustments in lifestyle, water rationing). In the context of drought monitoring, the impacts should be categorized according to a distinct and comprehensive framework, leading towards potential responses in the decision-making process. Carrão et al. [20] suggest that it is most important to focus on generic drought indicators because they are valid for all types of exposed activities/elements and therefore do not alter with changes in the physical entities which are at risk.

III.3. Monitoring drought exposure (Level II)

III.1.1. Recommendations on population datasets for monitoring human drought exposure

Because the UNCCD drought exposure indicator is built upon the Level 1 hazard indicator by overlaying population data, within this section we discuss relevant population datasets (**Table 4**), as well as additional datasets that could be used to assess exposure beyond a population density metric (**Table 4**).

Using the overlaying population as a proxy for calculating drought exposure is a straight-forward method. Knowing how many people are directly affected by drought can help aid get allocated to the most needed areas, based on percent of population exposed and strength of that exposure (drought severity). This method can also serve as a proxy for socioeconomic drought [20]. **Either GPWv4 or WorldPop data would make a good candidate dataset to calculate this indicator – they meet the UNCCD criteria of being freely available, while being fine spatial resolution, gridded datasets that use a consistent method of mapping national census data; additionally, they allow for gender disaggregation.**

The gender disaggregation calculation for the Level 2 population indicator would be computed based on percent male and percent female in each grid cell. The outputs would include exposure information by gender (percent male and percent female) exposed to each Level 1 Drought Class. This would produce two comparable grids that could be aggregated to administrative boundaries if desired, where global and local spatial relationships between gender and drought occurrence and/or severity can be better quantified and visualized.

In addition to gender disaggregation, it may also be useful to disaggregate for urban vs. rural population exposure comparisons, which could be achieved using Global Human Settlement Layer data from the Joint Research Center (JRC) of the European Commission. The summary characteristics for these datasets are included in **Table 4**.

Table 4. Global Gridded Datasets for Monitoring Ecosystem Exposure to Drought and Human Drought Exposure Based on Population: Summary Characteristics. Settlement layers are included as a modifier for human exposure, which can be disaggregated by urban/rural populations.

Dataset	Source	Spatial Resolution	Temporal Coverage	Temporal Resolu-tion	Spatial Coverage	Source for National Level Population Totals	Gender disaggre-gation
Ecosystem Exposure							
Anthropogenic Biomes v1	NASA SEDAC/ CEISIN	5 arc minutes (~ 86 km at the Equator)	2001-2006	Annual	Global	N/A	No
Human Exposure Population Density							
GHS-POP	CIESIN, JRC	9 arc-seconds (~250 m at the Equator), 30 arc-seconds (~1 km at the Equator)	1975, 1990, 2000, 2015	Irregular	Global	UNPD estimates and projections	No
GPW v4	NASA SEDAC/ CEISIN	30 arc-seconds (~ 1 km at the equator)	2000, 2005, 2010, 2015, and 2020	Every five years	Global		Yes
GRUMP v1	CIESIN, IFPRI, The World Bank, CIAT	30 arc-seconds (~1 km at the Equator)	1990, 1995, 2000	Irregular	Global	UNPD estimates and projections	NO
LandScan Global Population Database	ORNL	30 arc-seconds (1 km at the Equator)	1998, 2000 – 2018	Annual releases, with 2019 planned for fall 2020	Global	US Census Bureau	No
WorldPop	WorldPop	3-arc seconds (~100 m)	2000-2020 globally and country-specific years	Annual	Global	Two versions: 1) Country-official estimates, and 2) UNPD estimates and projections	YES
World Population Estimate	ESRI	150 m [2016], 250 m [earlier]	2013, 2015, and 2016.	Irregular	Global	Country-official estimates with 134 countries processed further by Michael Bauer Research GmbH.	NO
Settlement Layers							
Global Human Settlement Layer – Built Up grid (GHS-BUILT)	European Commission JRC	30 x 30 m, 250 x 250 m, 1 x 1 km	1975, 1990, 2000, 2015	Irregular	Global	N/A	NO
Global Human Settlement Layer – Settlement Model (GHS-SMOD)	European Commission JRC	1 x 1 km	2015	Irregular	Global	N/A	NO

III.3.2. Additional considerations and recommendations for monitoring population drought exposure

In general, exposure data identify different types of physical entities including built assets, infrastructures, agricultural land, and people, among many others [20]. Generally, there are many difficulties relating to the identification, standardization, and combination of these disparate elements; thus, literature to date has primarily focused on socioeconomic indicators. A comprehensive measure of drought exposure would take into account not only the spatial distribution of the population, as described above, but would also include physical entities at risk, including agricultural yields/crop areas (agricultural drought), livestock (agricultural drought), industrial/domestic water stress or water availability (both hydrological drought), and vegetation (ecological drought) [20,35].

The UNCCD recommended framework for assessing and monitoring drought exposure is based solely on human population data, however, there are many other factors influenced by drought in the short-term, and land degradation/desertification in the long-term, that provide alternative or additional means of assessing drought exposure. Additional considerations we explore here in terms of human exposure are indicators relating to agriculture-/livestock-dependence, indicators relating to human health – namely respiratory disease risks from fine airborne particulate matter, exacerbated by drought and dust storms. Additional considerations for assessing drought exposure can include metrics of food security, mortality, and morbidity (including child) sub- or mal-nutrition metrics, assessments of livelihoods composition using various capitals (natural, social, physical, economic, and financial), reliance on surface vs. groundwater extraction for rainfed vs. irrigated agriculture, and other metrics that touch on a population's sensitivity and adaptive capacity. Using alternate proxies of exposure, such as livestock density, crop cover or reported annual yields, water stress, reliance on rainfed agriculture, or coping mechanisms (e.g., selling wood to survive drought periods, migration, wage labor etc.) makes gender disaggregation more complicated, as datasets relating to these factors do not inherently include a gender component. Thus, a method for integrating other exposure factors, like livestock density, with population data, including subsequent gender disaggregation, would need to be tested and validated before implementation.

Within our framework, we include many of these additional exposure indicators within our Level 3 vulnerability index described in Section III.4, to retain the simplicity of the current UNCCD Level 2 metric. These datasets, as well as other datasets relevant to the Level 3 indicator, are included in **Table 5** and discussed in detail in Section V. Finally, we explore indicators of ecosystem exposure which are calculated in a manner that is harmonious with the current Level 2 indicator for human exposure and defines trends in the proportion of ecosystems exposed to drought out of the total land area, broken down by drought severity.

III.3.2.1. Agriculture, livestock density, and water demand as additional indicators for drought exposure

In regions that are intensively exploited for agriculture and/or are expected to experience more frequent and intense drought due to climate change, assessing human drought exposure through agricultural data may indicate areas with higher risk of food insecurity where mitigation plans need to be established. Agricultural yields can be measured directly by yield data, where available, though at a global extent there are many issues with this method including data availability and the non-uniformity of available datasets. Alternative means of exposure monitoring include using precipitation as a proxy (for example, SPI-3 or SPI-6 which have been shown to correlate well with agricultural drought indices such as PDSI), cultivation area rates, or economic models [35]. Any of these methods would provide a means of assessing human exposure to agricultural drought. Carrão et al. [20] utilized the Global Agricultural Lands in the Year 2000 data collection as a proxy for crop areas, representing the extent and intensity of cultivated land use. We do not recommend this dataset only due to the fact that it is two decades out of date and may not represent current conditions but suggest that if an updated dataset is produced that it could be utilized. Agricultural drought exposure can also use livestock as a proxy – Carrão et al. [20] utilized the Gridded Livestock of the World (GLW), a collection that provides modeled livestock densities around the world.

The decrease in availability of water resources is perhaps one of the most obvious drought-related consequences on exposed populations, and when water availability is consistently decreased over long periods of time, hydrological drought can occur. Water resource availability can be modeled using results from hydrologic models; however, these can be difficult to construct where accurate data is not available. They represent a rather specialized area where many people may lack access to the resources or knowledge needed for successful implementation. Carrão et al. [20] utilized the Baseline Water Stress (BWS) dataset, an indicator of relative water demand (**Table 5**). An alternate proxy could be availability of drinking water. Most developing countries use well water, so the water level in the wells can serve as an indicator if that data is readily available. Additionally, through spatial interpolation methods, well water levels can be combined with additional information such as elevation and slope and transformed into gridded data representing groundwater.

We recommend, in order to keep the UNCCD Level 2 human exposure reporting metric as simple as possible, that these datasets not be utilized in the Level 2 indicator but could be reserved for building the Level 3 comprehensive vulnerability indicator. Summary characteristics of these datasets are presented in Table 5.

Table 5. Summary characteristics of select datasets for constructing drought vulnerability indices.

Dataset	Source	Spatial Resolution	Temporal Coverage	Temporal Resolution	Spatial Coverage	Gender disaggregation
ECOLOGICAL						
Land Management						
Intact Forested Landscapes (IFL)	IFL Mapping Team	Sub-national	2000, 2013, 2016	Irregular	Global	No
ESA CCI-LC (MRLC maps v207)	European Space Agency	300 m x 300 m	1992 to 2015	Annual	Global	No
Global Land Cover v3.0	Copernicus Global Land Service	100 m x 100 m	2015 to 2019	Annual	Global	No
Vegetative Productivity						
AVHRR/GIMMS	NASA	8 km x 8 km	1981 – 2015	Monthly	Global	No
MOD13Q1-coll6	NASA/USGS	250 m x 250 m	2000 – present	16-Day (composite)	Global	No
Soil Organic Carbon						
SoilGrids V 2.0	ISRIC	250 m x 250 m	2015	Static	Global	No
Pressure on Resources						
WorldPop	WorldPop	3-arc seconds (~100 m at the equator)	2000 - 2020	Annual	Global	Yes
Global Human Footprint v2	WCS & CIESIN	1 x 1 km	1995 - 2004		Global	No
Baseline Water Stress (BWS)	Water Resources Institute	National	2013	Static	Global	No
Protected Areas						
World Database of Protected Areas (WDPA)	UNEP & IUCN	Sub-national (vector and table)		Monthly updates; latest September 2020	Global	No
ECONOMIC						
Economic Welfare						
Geographically based Economic data (G-Econ) 4.0	Yale University & CIESIN	1º x 1º (~111 km at the Equator)	1990, 1995, 2000, 2005			No
Food Security						
FAOSTAT Food Security Indicators	FAO	National	2000 – 2020	Annual	Global	No
Food Insecurity Hotspots Dataset v1	NASA SEDAC/ CEISIN	250 m x 250 m	2009 – 2019	Annual	Regional*	No

Table 5 *continued*

Poverty						
Multidimensional Poverty Index (MPI)	OPHI	Household, sub-national, national	2010 - 2020	Annual	Quasi-global	Yes
Demographic and Health Surveys	The DHS Program	National, sub-national	1984 - 2020	Annual	Quasi-global	Yes
SOCIAL						
Human Development (Individual)						
Demographic and Health Surveys	The DHS Program	National, sub-national	1984 - 2020	Annual	Quasi-global	Yes
World Bank Development Indicators	World Bank	National	2000–2019	Annual	Global	No
WorldPop	WorldPop	3-arc seconds (~ 100 m at the equator)	2000 - 2020	Annual	Global	Yes
Institutional Coordination						
World Governance Indicators	World Bank	National	2009, 2014, 2019	Every five years	Global	No
Organization for Economic Cooperation and Development (OECD)						
Human Displacement						
World Bank Development Indicators	World Bank	National	2000–2019	Annual	Global	No
Migration Global Variables (Person)	IPUMS International	Person	1960 – 2018 (depending on variable and country)	Annual	Select nations	Yes
WorldPop Internal Migration Flows	WorldPop	Sub-national	2005 - 2010	N/A	LMIC	No
Human Health						
Global Annual PM 2.5 Grids from MODIS, MISR and SeaWiFS AOD with GWR, v1	NASA SEDAC	0.1° x 0.1° (~11.1 at the Equator)	1998 – 2016			
Data Integration Model for Air Quality (DIMAQ)	WHO	0.1° x 0.1° (~11.1 at the Equator)	2016			
INFRASTRUCTURAL						
Water Infrastructure						
Demographic and Health Surveys	The DHS Program	National, sub-national	1984 - 2020	Annual	Quasi-global	Yes
Wash Data	WHO/ UNICEF	National, House-hold	2000 – 2017	Annual	Global	No
Irrigation Potential						
Global Map of Irrigated Areas	FAO	5 arc-minutes (~ 86 km at the Equator)	2005	One year	Global	No

III.3.2.2. Impacts on human health: Global mortality and respiratory illnesses attributable to ambient air pollution and other risks due to land degradation, drought, and dust storms

Land degradation and desertification can impact human health through a variety of direct and indirect pathways. As water sources dry up, food is reduced, airborne pollution and dust storms are increased, and people are pressured to move away from inhospitable environments. Under these circumstances, human health impacts can include malnutrition, water and hygiene related diseases, foodborne illnesses, respiratory diseases, and other infectious diseases that expand with changing water resources and migrating human populations.

The World Health Organization (WHO) is beginning to monitor and quantify the global environmental burden of disease due to climate change, land degradation, and drought, with accelerating attention to these issues recently. First, they assembled a list of "climate-sensitive diseases" and launched a survey of member states to compile reported data on the status of each country's monitoring and mitigation activities for climate related illnesses, with a goal to support evidence-based decision making and encourage health system involvement in the UN Framework Convention on Climate Change (UNFCCC). The climate-health surveys have culminated in a collection of country profiles for 2015/16 and 2019/20 (in progress), accessible online[5].

Among the direct and indirect health impacts of land degradation and drought, one of the most studied, and easily quantifiable, stems from the contribution of drought to aerosolized atmospheric particulate matter and the risk this poses for respiratory health. According to the WHO, an estimated 6.5 million people die each year due to ambient air pollution and its health effects. Several spatially gridded datasets exist to monitor ambient concentrations of PM2.5 (a modeled estimate of the concentration of 2.5 μ and smaller fraction of airborne particulate matter, and a proxy for ambient air pollution). Two datasets to monitor PM2.5 that meet our criteria for inclusion are the NASA Socioeconomic Data and Applications Center (SEDAC) "Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, v1 (1998–2016)"[6] and the WHO "Data Integration Model for Air Quality (DIMAQ)"[7]. Both are freely available and have a spatial resolution of 0.1 x 0.1 degrees, but the latter includes estimates of uncertainty, while the former does not. Including gridded data on estimates of uncertainty is beneficial to decision-makers because the number of ground-based sensors varies widely across locations, making uncertainty variable and uneven, and the estimates more reliable in some regions than others.

One important consideration when monitoring health effects of drought and desertification, is the issue of attribution. That is, given the many interacting causes of disease, one needs to separate out the burden of disease resulting from one particular exposure, such as drought. Global health practitioners have used standardized methods to measure the "attributable fraction" of the total burden of each particular disease to each exposure, including detailed methods on how to attribute a fraction of respiratory disease to ambient air pollution [43,44]. What remains more nebulous is measuring the fraction of air pollution that is contributed by drought, desertification, and land degradation. Some estimates have suggested as much as 50% of tropospheric aerosols is made up of desert dust [45], but the contribution of deserts and desertification to atmospheric aerosols is less well known. Future studies of the impact of land use and land degradation on fine particulate matter pollution could be used to design optimized land use approaches to mitigate both desertification and PM2.5 pollution, with potential health benefits.

The Institute for Health Metrics and Evaluation[8] (IHME) is a Seattle (Washington, US) based institute compiling quantitative, spatially explicit (at least to country level and sometimes to sub-country levels), and gender disaggregable health metrics for more than one thousand diseases across the world. IHME has recently incorporated new data on estimates of health burden

5 https://www.who.int/globalchange/resources/countries/en/

6 https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod

7 https://www.who.int/airpollution/data/modelled-estimates/en/

8 http://www.healthdata.org

due to temperature extremes and ambient air pollution, among other relevant environmental risks [46]. The newest release of the Global Burden of Disease estimates[9], will be published by IHME in collaboration with the WHO[10] in mid-October 2020. With each release, data are compiled back several decades, allowing for change-over-time analyses. Global health data, including the Global Burden of Disease estimates and some relevant environmental risk factors (e.g., temperature extremes, ambient air pollution), can be explored and downloaded from the Global Health Data Exchange[11]. These data could become integral to monitoring and reporting the health impacts of land degradation, desertification, and drought by member nations to the UNCCD.

III.3.2.3. Ecosystem exposure: an overlooked component of the UNCCD Drought Monitoring Framework

Though the current UNCCD Drought Monitoring Framework does not directly address the exposure of ecosystems to drought, this information is critical in the early detection of potentially damaging changes in ecosystem functions and safeguards the sustainable use of ecosystems and their services, support ecosystem management, and aid the analysis of weaknesses that make an ecosystem vulnerable to drought, or its capacity to recover after being exposed [17].

The exposure of an ecosystem expresses the degree of change that it is projected to experience, and, according to the abruptness of the change the terms disturbance and stress are applied in situations that are abrupt and continuous, respectively [17]. More simply, exposure describes the fact that an ecosystem is in contact with a stressor (in this case, drought). Differing methods of calculating exposure are presented in scientific literature, including determining the probability of occurrence of the disturbance or its spatial proximity to the ecosystem, alternatively it is suggested to determine the threatened area [47]. In the probability calculation, the exposure of an ecosystem towards a certain stressor is determined by the quality of the stressor (e.g., its persistence or pervasiveness) and the qualities of the affected ecosystems. At a global scale, it is possible to implement the Anthropogenic Biomes dataset. The Anthropogenic Biomes dataset (**Table 4**) describes globally-significant ecological patterns within the terrestrial biosphere caused by sustained direct human interaction with ecosystems, including agriculture, urbanization, forestry and other land uses circa 2001-2006 [48]; the direct accounting of human land use and land management activity within this dataset makes it well-suited for drought monitoring in the context of DLDD. However, in order to harmonize this indicator with SO1, using the land cover classes that countries need to report on as part of SO1 (tree covered, grassland, crops, wetlands, urban, other, and water), represents a better opportunity to create linkages between the land degradation assessment and ecosystem exposure are easy to compute and more straightforward to interpret and communicate. **Therefore, we recommend that ecosystem exposure could be calculated as the proportion of each land cover class used in SO1 reporting that is affected by drought, further classified according to drought severity class.** Using a proportion, rather than a probability, is also more harmonious with the current UNCCD population exposure metric.

III.4. Monitoring drought vulnerability (Level III): Towards a comprehensive drought vulnerability indicator

III.4.1. Overview of existing drought vulnerability indices: strengths and limitations

There are a variety of ways to define and measure drought vulnerability. First, social vulnerability is linked to the level of well-being of individuals. Economic vulnerability is highly dependent on the economic status of individuals. Infrastructural vulnerability comprises basic infrastructures needed to support production of goods and sustainment of livelihoods. Ecosystem vulnerability is focused on habitats and food supplies on which plants, animals, and humans depend. Because of the complexity

9 http://www.healthdata.org/gbd

10 Data collection tools - WHO

11 http://ghdx.healthdata.org

inherent in monitoring vulnerability, no single factor on its own can sufficiently characterize all the varied livelihood outcomes that societies need to be resilient to desertification, land degradation, and drought.

The JRC has developed a framework which integrates 15 economic, social, and infrastructural components related to drought vulnerability derived from global data sources; see Section IV for methodological details and the 15 components in this index [20]. This framework recommends that drought vulnerability indicators should encompass orthogonal social, infrastructural, and economic factors that are generic and valid for any region [20]. What this framework lacks is an appropriate accounting of relevant environmental factors that influence ecosystem vulnerability. It also focuses on summary data, aggregated at country or sub-country levels, such as World Bank data, rather than focusing on spatially gridded datasets.

The framework has been tested on a regional basis [32], indicating that there is potential to upscale to a global level following testing and validation. Blauhut et al. [32] assesses drought vulnerability using factors intended to capture components of exposure, sensitivity, and adaptive capacity. While this study was conducted only across the European Continent, its methodology more comprehensively addresses SO3 than the JRC's framework, in that it includes environmental factors which influence ecosystem vulnerability. Because the datasets, and thus some of the factors included in the Blauhut study are specific to Europe, the specific factors and datasets are not presented in this report, as they may not be translatable to a global scale. However, Blauhut's study framework can be utilized to partially guide the development of a comprehensive global drought vulnerability indicator.

Two additional drought vulnerability frameworks that have been proposed are: the Drought Vulnerability Index (DVI) developed by Naumannn et al. [49], and the Standardized Drought Vulnerability Index (SDVI) developed by Karavitis et al. [16]. These indices each have a slightly different approach to vulnerability, and therefore each has slightly different strengths and limitations for application in the UNCCD framework.

For example, as with the framework used by Carrão et al [20], most of the elements used in the existing DVI and SDVI frameworks rely on summary data per country, such as World Bank and UN Development Program (UNDP) Human Development Index (HDI) data for each country. For SDVI, regional applications have also incorporated some gridded data, such as gridded land cover, NDVI, and land-surface model data.

The DVI uses 17 factors that are grouped to address renewable natural capital (e.g., water availability), economic capacity (e.g., gross domestic product per capita), human and civic resources (e.g., the adult literacy rate), and infrastructure and technology (e.g., fertilizer consumption). The SDVI is slightly different than the other frameworks, in that it quantifies vulnerability by separating the risks and the impacts: Vulnerability = Risk identification x Impacts assessment, which deviates slightly from the Drought Risk = Hazard x Exposure x Vulnerability framework used by the UNCCD and Carrão et al. [20]. Both the DVI and SDVI have been applied for specific regions but not yet globally (DVI originally applied to Africa, SDVI to Greece and then the US).

In the final sections of Part III, we explore recommendations for potential approaches for a new, global, drought vulnerability index that would remain simple to implement for country Parties of the UNCCD and be comparable across regions or globally. Building on the approaches presented in the JRC's drought vulnerability framework [20], Blauhut et al. [32], and the DVI approach, we incorporate similar elements of vulnerability, but here we focus on data elements that are spatially gridded (or at least available at a fine-grained subnational level), and for the human population elements, those that are gender-disaggregable. Additionally, we include a spatially explicit component for determining ecosystem vulnerability in order to more holistically address vulnerability of both humans and ecosystems within the monitoring framework. We then expand on the technical details of each of the recommended datasets in Part V. As with any proposed drought vulnerability assessment framework, our recommended approach needs to be tested and validated at national to global levels, to ensure that results can be accurately reproduced independently so that the national ownership criterium can be satisfied [1].

III.4.2. Recommendations on moving towards a comprehensive drought vulnerability monitoring framework, using gender-disaggregable and spatial data

We recommend that the drought vulnerability monitoring use a framework that builds on exposure of populations and ecosystems to drought hazard and captures factors from social, infrastructural, and economic components. We also recommend that this index more comprehensively address ecosystem components in terms of habitats and food supplies on which plants, animals, and humans depend in a way that captures facets of land management and land degradation. **To the extent that it is possible, and data are available, we recommend the use of contemporary, spatially gridded, or sub-national, and gender-disaggregable datasets and that the indicators chosen are generic and valid for any region.** We present specific details about potential datasets, indicators, and their effect on increasing or decreasing vulnerability on **Table 6**. Of these datasets, only WorldPop and Demographic and Health Surveys (DHS) are gender-disaggregable at this time.

Our framework for the drought vulnerability index consists of four components: Ecological, Economic, Social, and Infrastructural (**Table 6**). Each component is broken into multiple aspects that relate to drought management. For each indicator we suggest, we include how that metric would be measured, and what influence that would have on overall vulnerability if the value for the metric were to increase. For each indicator/metric, we suggest at least one potential data source, however, guidance for replacing these datasets with other global or national data should be possible, with national data replacement allowing countries to meet the ownership requirement. These datasets best meet the inclusion/exclusion criteria outlined in Section V.1 but should be further evaluated before implementation in Trends.Earth.

Table 6. Towards a comprehensive drought vulnerability monitoring framework: recommended datasets and indicators for global drought vulnerability monitoring.

Component	Aspect Related to Drought Management	Indicators	Unit of measure	Influence on Vulnerability	Potential Data Sources	Justification
Ecological	Land Management	Fragmentation	Percentage of Intact Ecosystem Loss or Fragmentation	Increase	Intact Forested Land-scapes	
		Alteration	Percentage of Land Covers Converted to More Vulnerable Classes	Increase	ESA CCI (or Copernicus)	Daldegan et al, 2020; Trends.Earth
	Vegetative Productivity	NDVI, EVI2, or MSAVI	Percent Reduction in Vegetative Produc-tivity	Increase	AVHRR/GIMMS (or MOD13Q1-coll6)	Daldegan et al, 2020; Trends.Earth
	Soil Organic Carbon	Changes in Carbon Stocks	Percent Reduction in Soil Organic Carbon	Increase	SoilGrids V 2.0	Daldegan et al, 2020; Trends.Earth
	Pressure on resources	Population Density	inhabited per grid cell	Increase	WorldPop	Nauman et al., 2014
		Global Human Footprint	0 - 100 (extremely rural to extremely urban)	Increase	Wildlife Conservation Society, and Center for International Earth Science Information Network - Columbia University	Nauman et al., 2014 (rural population per grid cell); Carrao et al, 2016 (% rural population)
	Protected areas	Total protected areas	km2 per grid cell	Decrease	World Database of Protected Areas	Blahut et al., 2016 included European-based measures of protected areas
		Protected area management effectiveness	Protected Area Management Effectiveness Score	Decrease	World Database of Protected Areas	Blahut et al., 2016 included European-based measures of protected areas
Economic	Economic welfare	Geographically based Economic data (G-Econ)	GDP per capita	Decrease	Yale, and Center for International Earth Science Information Network - Columbia University	Nauman et al., 2014; Carrao et al, 2016
	Food security	Food Insecurity	Prevalence of Moderate and Severe Food Insecurity based on Food Insecurity Experience Scale (FIES) or Integrated Food Security Phase Classification (IPC)	Increase	FAOSTAT Food Security Indicators or NASA Food Insecurity Hotspots Dataset v1	Nauman et al., 2014 and Carrao et al, 2016 both used agricultural GDP; FIES is SDG Indicator 2.1.2
	Poverty	Multidimen-sional Poverty Index (where available)	0 - 1	Increase	Oxford Poverty and Human Development Initiative, University of Oxford	Carrao et al, 2016 (poverty headcount ratio at US$1.25/day)

Table 6. Continued

Component	Aspect Related to Drought Management	Indicators	Unit of measure	Influence on Vulnerability	Potential Data Sources	Justification
Social	Human development (individual)	Adult literacy rate	%	Decrease	Demographic and Health Surveys (DHS)	Nauman et al., 2014
		Life expectancy at birth	years	Decrease	World Bank	Carrao et al, 2016
		Population ages 15-64	% of total	Decrease	WorldPop	Carrao et al, 2016
	Institutional coordination	Government effectiveness	ranges from -2.5 to 2.5 (weak to strong)	Decrease	World Governance Indicators	Carrao et al, 2016
		Disaster prevention preparedness	US$/year/capita	Decrease	Organization for Economic Cooperation and Development (OECD)	Carrao et al, 2016
	Human displacement	Refugee	% of total population	Increase	World Bank	Nauman et al., 2014; Carrao et al, 2016
	Human health	Air Quality	micrograms per cubic meter of ground-level fine particulate matter (PM2.5)	Increase	NASA SEDAC Global Annual PM 2.5 Grids	SDG Target 11.6
Infrastructural	Water infrastructure	Safe drinking water	Percent of Population Using Safely Managed Drinking Water Services	Decrease	WASH or Demographic and Health Surveys (DHS)	Nauman et al., 2014
		Sanitation	Percent of population with Access to Safely Managed Sanitation	Decrease	WASH	Nauman et al, 2014 (Total water use; % of renewable); Carrao et al, 2016 (% retained renewable)
		Hygiene	Percent of Population with Access to Basic Handwashing Facilities	Decrease	WASH	
	Irrigation Potential	Agricultural irrigated land	Percent of total agricultural land	Decrease	FAO Aquastat Global Map of Irrigated Areas	Nauman et al., 2014; Carrao et al, 2016

III.5. Overall recommendations and conclusions: integrating indices of hazard, exposure, and vulnerability to monitor SO3 expected impacts

The integrated vulnerability index we propose in this report combines **hazard**, defined as the spatiotemporal quantification of climatic and drought characteristics by drought intensity classes, **human exposure**, defined as the density of human populations experiencing drought, **ecosystem exposure**, defined as the areal extent of ecosystems experiencing drought, and **vulnerability**, defined as the degree to which humans, socio-economic systems, and ecosystems are affected by drought exposure (**Figure 8**). Using this framework, vulnerability is therefore conceptualized as the overlap of hazard and exposure. Exposure of humans is given by population density, modified by gender classes (where the gender-disaggregated data is readily available) and/or rural vs. urban populations, while exposure of ecosystems is given by areal extent under a given drought class by ecosystem types. The vulnerability index integrates social, ecological, economic, and infrastructural components as shown in **Table 6**. Although not explicitly detailed in this report, we recommend that future monitoring efforts attempt to capture both components of sensitivity and adaptive capacity within the vulnerability monitoring framework.

At a minimum, Trends.Earth could include a global precipitation dataset and the Standardized Precipitation Index (SPI) for drought hazard monitoring, though including additional data and indices relating to soil moisture and temperature would increase a nation's ability to effectively monitor drought hazard by type (soil moisture, agricultural, ecological, or hydrological drought). Additionally, there are not yet any defined datasets or framework for calculating drought exposure in Trends.Earth, thus the integration of datasets, indices, and methods for monitoring Level 1 drought must first be defined. Then, the framework for monitoring Level 2 drought can be established, which should include, at a minimum, a population dataset and method to derive a proxy indicator for human exposure, and if desired, an ecosystems type dataset by which to monitor ecosystem exposure. Following the determination of the Level 2 index, the framework for monitoring Level 3 drought can be established in accordance with the proposed framework and guidance from UNCCD as given in ICCD/COP(14), including testing and validation at the national level.

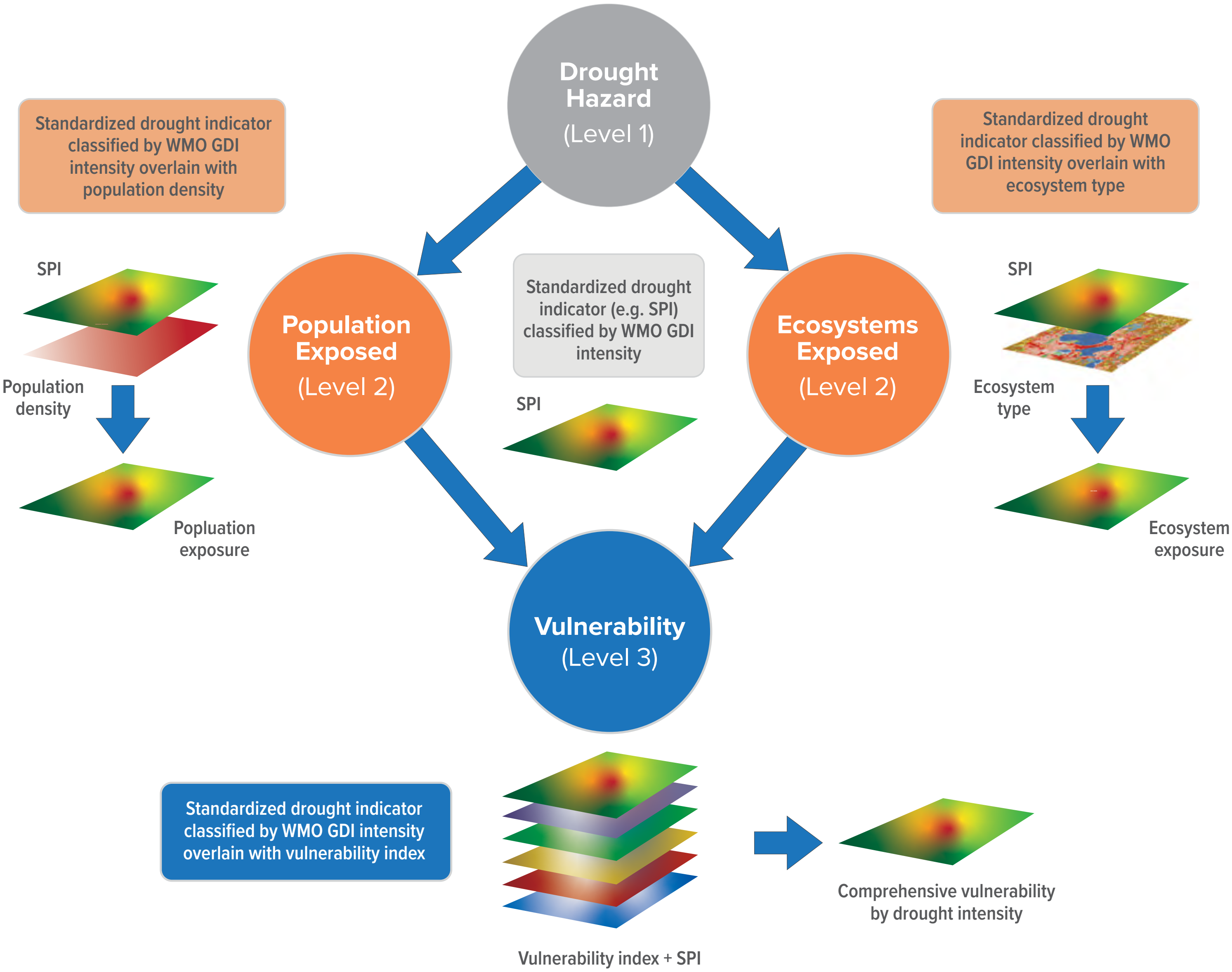


Figure 8. Integrative Drought Monitoring Including Comprehensive Vulnerability of Human Systems and Ecosystems to Drought and Land Degradation.

IV. Relevant Indices

IV.1. Biophysical indices for drought hazard detection and monitoring

IV.1.1. Standardized Precipitation Index – SPI

The SPI quantifies observed precipitation as a standardized departure from a selected probability distribution function that models the raw data. The raw data can be fitted to a gamma or a Pearson Type III distribution, and then transformed to a normal distribution. The transformed precipitation data are then used to compute the dimensionless SPI value, defined as the standardized anomaly of the precipitation.

The detailed equations for computing this index are described in the following steps using the gamma distribution:

1. The transformation of the precipitation value into SPI has the purpose of:
   a. Transforming the mean of the precipitation value adjusted to 0;
   b. Standard deviation of the precipitation is adjusted to 1.0; and
   c. Skewness of the existing data must be readjusted to zero.

When these goals have been achieved the standardized precipitation index can be interpreted as mean 0 and standard deviation of 1.0.

2. Mean of the precipitation can be computed as:

$$Mean = \bar{X} = \frac{\sum X}{N}$$

where N is the number of precipitation observations.

3. The standard deviation for the precipitation is computed as:

$$s = \sqrt{\frac{\sum (X - \bar{X})^2}{N}}$$

4. The skewness of the given precipitation is computed as:

$$Skew = \frac{N}{(N-1)(N-2)} \sum \left(\frac{X - \bar{X}}{s} \right)^3$$

5. The precipitation is converted to lognormal values and the statistics U, shape and scale parameters of gamma distribution is computed:

$$\log mean = \bar{X}_{ln} = ln(\bar{X})$$

$$U = \bar{X}_{ln} - \frac{\sum ln(X)}{N}$$

$$shape\ parameter = \beta = \frac{1 + \sqrt{1 + \frac{4U}{3}}}{4U}$$

$$scale\ parameter = \alpha = \frac{\bar{X}}{\beta}$$

6. The resulting parameters are then used to find the cumulative probability of an observed precipitation event. The cumulative probability is given by:

$$G(x) = \frac{\int_0^x x^{a-1} e^{\frac{-x}{\beta}} dx}{\beta^{\alpha} \Gamma(\alpha)}$$

7. Since the gamma function is undefined for x = 0 and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x)=q+(1-q)G(x)$$

where the probability from q is zero.

8. The cumulative probability $H(x)$ is then transformed to the standard normal random variable Z with mean zero and variance of one:

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad 0<H(x)\leq 0.5$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad 0.5<H(x)\leq 1.0$$

where

$$t = \sqrt{\ln\left(\frac{1}{H(x)^2}\right)} \quad 0<H(x)\leq 0.5$$

$$t = \sqrt{\ln\left(\frac{1}{1-H(x)^2}\right)} \quad 0.5<H(x)\leq 1.0$$

$c_0 = 2.515517$

$c_1 = 0.802583$

$c_2 = 0.010328$

$d_1 = 1.432788$

$d_2 = 0.189269$

$d_3 = 0.001308$

The dimensionless SPI values are interpreted as the number of standard deviations by which the observed anomaly deviates from the long-term mean and are typically labeled categorically based on condition (i.e., extremely wet, extremely dry, normal) as shown in **Table** 7. A drought occurs when the SPI is consecutively negative, and its value reaches an intensity of -1 or less and ends when the SPI becomes positive.

Table 7. Drought categories based on Standardized Precipitation Index.

Description	Precipitation Category
2.0 or more	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2.0 or less	Extremely dry

The key benefit of the SPI is that it is simple to calculate and understand, given that the shortage of precipitation is the most comprehensible definition of drought. It uses only precipitation data as an input, where 30 to 50 years of data are recommended [50]. It is comparable across different time scales, typically being calculated over periods of one to 36 months; this also allows for SPI to be simultaneously assessed over a multitude of time scales to address both short-term and long-term drought. Additionally, it is more comparable across different regions than the PDSI [51]. However, because the SPI does not account for evapotranspiration, it is less able to capture the effects of temperature increases resulting from climate change. Other limitations include its inability to account for precipitation intensity (and thus impacts in terms of runoff, streamflow, and water availability), and its sensitivity to the quality and quantity of the input data [51]. Because SPI requires a long period of input data, some newer remotely sensed precipitation datasets (such as CMORPH, GSMaP, and IMERG) may not cover a suitable time period for reliable calculations of SPI.

There are several variations of the SPI that have been developed to account for potential shortcomings in the standard equation. The nonstationary SPI (nSPI) fits the precipitation data to a nonstationary gamma distribution. Russo et al [52]show the nSPI to be more robust than the SPI in predicting precipitation changes in Europe. Li et al [53] report that the nSPI with climate indices as covariates outperformed the traditional SPI in the Luanhe River basin, China. The SPI-GEV fits the precipitation data to a generalized extreme value (GEV) distribution rather than a gamma distribution [52]. Farahmand and AghaKouchak [54] suggest that a non-parametric approach to calculating SPI is superior because parametric approaches may lead to inconsistent results at continental to global scales.

The SPI is endorsed by the WMO and is widely implemented in drought studies. A freely available, downloadable program to calculate SPI is available through the National Drought Mitigation Center at the University of Nebraska[12], additionally the calculations can be performed in Microsoft Excel using available functions, or with free code in the statistical package R.

IV.1.2.Standardized Precipitation Evapotranspiration Index – SPEI

A more recently developed index by Vicente-Serrano et al. [55] at the Instituto Pirenaico de Ecologia in Zaragoza, Spain, the Standardized Precipitation Evapotranspiration Index (SPEI) uses the basis of the SPI but includes an evapotranspiration calculation using temperature data. The intensity scale is both positive and negative, allowing it to represent both wet and dry events. Because it includes temperature data, it can be compared to the self-calibrating Palmer Drought Severity Index (scPDSI). The SPEI requires serially complete monthly precipitation data and can be applied to any case where SPI would be applied. The potential evapotranspiration (PET) calculation uses the Thornewaithe equation as it is the simplest approach to calculate PET [56], and has the advantage of only requiring data on monthly-mean temperature.

$$\mathrm{PET} = 16K \left(\frac{10T}{I}\right)^{m}$$

where T is the monthly-mean temperature in °C, I is a heat index, which is calculated as the sum of 12 monthly index values i, where i is derived by the equation

$$i = \left(\frac{T}{5}\right)^{1.514}$$

and m is a coefficient depending on I: $m = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.79 \times 10^{-2} + 0.492$; and K is a correction coefficient computed as a function of the latitude and month,

$$K = \left(\frac{N}{12}\right)\left(\frac{NDM}{30}\right)$$

with NDM representing the number of days of the month and N is the maximum number of sun hours. With a value for PET, the difference between the precipitation P and PET for the month i is calculated using

$$D_i = P_i - PET_i$$

to provide a simple measure of the water surplus or deficit for the analyzed month. SPEI is calculated as

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

where

$$W = \sqrt{-2\ln(P)} \quad \text{for} \quad P \leq 0.5$$

and P is the probability of exceeding a determined D value, $P = 1 - F(x)$, the probability distribution of the D series according to the log-logistic distribution. If $P > 0.5$, then P is replaced by $1 - P$ and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

The full, detailed calculations and methodological description are described in Vincente-Serrano et al. [55], though code to perform the calculations in the statistical package R is publicly available and can be obtained online[13], making it a fairly user-friendly option. Additionally, the code allows the method to calculate PET to be performed with either the Thornwaite, Penman-Monteith, or Hargreaves equations.

12 http://drought.unl.edu/droughtmonitoring/SPI/SPIProgram.aspx.

13 https://rdrr.io/cran/SPEI/man/spei.html

The SPEI is a strong index with many advantages. It has many of the same advantages of SPI including the ability to analyze a variety of climatic regimes and is comparable across space and time because it is standardized. Due to the inclusion of temperature data, it is more robust than indices that use only precipitation and can be used to evaluate the effects of climate change under multiple future scenarios [34]. It is also directly comparable to SPI because it uses the same drought category classification (**Table** 7). SPEI has been implemented in multiple global drought monitoring toolkits including the SPEI Global Drought Monitor, which uses the Thornwaithe equation to calculate PET, and the Global SPEI Database (or SPEIbase), which uses the more robust Penman-Montieth method to calculate PET[14]. A recent publication stated that "SPEI should be the first choice for use in monitoring global-warming related drought" [57].

As with other indices calculated monthly, its ability to detect rapidly developing conditions is limited. Also, like other indices that require serially complete data, its use may be limited if data are not available.

IV.1.3.Standardized Soil Moisture Index (SSI)

The Standardized Soil Moisture Index (SSI) is computed in a nearly identical manner to the SPI. Soil moisture datasets used are summed and averaged, respectively, monthly, and successively averaged (soil moisture) over a given number of months (e.g., SSI-1, SSI-3, etc) that are referred to as accumulation periods or time scales. A statistical distribution function is fitted to the rainfall/soil moisture values for the different months of the year. The percentile value from this probability distribution is then transformed to the corresponding value in the standard normal cumulative probability distribution function, to obtain the standardized drought index [24,26,58].

Using a gamma distribution to fit the soil moisture data to the standard normal distribution makes this soil index highly comparable to SPI and has been implemented in multiple studies [58,59]. This approach also allows the SSI drought categories to mirror those of the SPI (**Table** 7). The SSI requires less input that almost all other drought indices which incorporate soil moisture because it does not require any additional data. SSI has been implemented in global drought monitoring in conjunction with SPI, i.e. GIDMaPS [40].

When computing the SSI (or any soil moisture index for that matter), the user should take care to use datasets that have been verified, as soil moisture data can sometimes be misleading. Users should pay attention to the accuracy, robustness, and reliability of soil moisture datasets.

IV.1.4.Recommendations on drought indices

The SPI is the most likely candidate for assessing drought on global and local scales because it can be computed on different timescales, is endorsed by the WMO, and used by multiple national drought monitoring agencies. For non-technical users it is the simplest to implement and easiest to understand. In a global assessment of the performance of different drought indices for monitoring drought impacts on several hydrological, agricultural, and ecological response variables including streamflow, soil moisture, forest growth, and crop yield, Vicente-Serrano et al. [60] found superior capability of the SPI and the SPEI drought indices. This is partially since they can be calculated on different time scales than the Palmer indices to capture the drought impacts on the aforementioned variables. **For this reason and others discussed previously, we recommend the SPI be implemented as the primary index for global drought monitoring within Trends.Earth.** Additionally, we suggest the SPEI and SSI can be incorporated to supplement the capacity of nations to assess and monitor drought given their direct comparability to the SPI and potential to detect characteristics of climate change and/or drought types other than meteorological drought.

IV.2. Review of existing integrated drought vulnerability indices

IV.2.1.Joint Research Centre of the European Commission framework for drought vulnerability

The JRC framework for monitoring drought risk as described in Carrão et al. [20] adopts an approach for

14 https://spei.csic.es/

assessing drought vulnerability that was initially proposed by the United Nations Office for Disaster Risk Reduction (UNDRR – formerly the United Nations International Strategy for Disaster Reduction or UNISDR) that reflects the state of the individual and collective social, economic, and infrastructural factors of a region [61]. This methodology has also been operationally implemented within the JRC Global Drought Observatory (GDO) to document and map global risk of drought impact for agriculture. The authors state that the factors that have been included do not represent a complete description of vulnerability in relation to a specific exposed element but can be viewed as the foundation for building a regional plan for reducing vulnerability and facilitating adaptation.

The methodology used in Carrão et al. [20] follows the concept that individuals and populations require a range of "(semi-) independent" factors characterized by a set of proxy indicators to achieve positive resilience to impacts. The methodology uses a two-step composite model that derives from the aggregation of 15 proxy indicators (**Table 8**) that represent social, economic, and infrastructural vulnerability at each geographic location (a similar methodology as the DVI, discussed subsequently) and are derived from both at the national level and very high spatial resolution gridded data. This process involves first combining the indicators presented in **Table 8** for each factor using a Data Envelopment Analysis (DEA) model, a deterministic and non-parametric linear programming technique that can be used to quantify the relative exposure of a region to drought from a multidimensional set of indicators. Secondly, arithmetically aggregating the individual factors resulting from the DEA model into a composite model of drought vulnerability such that:

$$dv_i = \frac{Soc_i + Econ_i + Infr_i}{3}$$

where Soc_i, $Econ_i$, and $Infr_i$ are the social, economic, and infrastructural vulnerability factors for region i.

Additionally, the authors make a comparative assessment between the weighting and aggregation scheme used in their methodology and those used in other composite drought vulnerability indicators such as the DVI, HDI, and Multi-dimensional Poverty Index (MPI) and state that their model is more robust and better able to represent the unknown regional vulnerability rankings.

Table 8. Proxy indicators for vulnerability to drought used in Carrao et al. 2016. With the exception of gROADS and FAO's Irrigated Agricultural Lands which are both gridded data, all data are available only at the national level.

Indicator	Source	Link
ECONOMIC		
Energy consumption per capita (millions Btu per person)	US Energy Information Administration (U.S. EIA)	http://www.eia.gov/
Agriculture (% of GDP)	World Bank	http://data.worldbank.org/products/wdi
GDP per capita (current US$)	World Bank	http://data.worldbank.org/products/wdi
Poverty headcount ratio at $1.25 per day (PPP) (% of total population)	World Bank	http://data.worldbank.org/products/wdi
SOCIAL		
Rural population (% of total population)	World Bank	http://data.worldbank.org/products/wdi
Literacy rate (% of people age 15 and above)	World Bank	http://data.worldbank.org/products/wdi
Improved water resources (% of rural population with access)	World Bank	http://data.worldbank.org/products/wdi
Life expectancy at birth (years)	World Bank	http://data.worldbank.org/products/wdi
Population ages 15-64 (% of total population)	World Bank	http://data.worldbank.org/products/wdi
Refugee population by country or territory of asylum (% of total population)	World Bank	http://data.worldbank.org/products/wdi
Government effectiveness	Worldwide Governance Indicators (WGI)	http://info.worldbank.org/governance/wgi/index.aspx#home
Disaster prevention & preparedness (US$/year/capita)	Organization for Economic Cooperation and Development (OECD)	http://stats.oecd.org/
INFRASTRUCTURAL		
Agricultural and irrigated land (% of total agricultural land)	Food and Agricultural Administration (FAO)	http://www.fao.org/nr/water/aquastat/main/index.stm
% of retained renewable water	Aqueduct	http://www.wri.org/our-work/project/aqueduct
Road density (km of road per 100 sq.km. of land area)	gROADSv1	http://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1

IV.2.2. Drought Vulnerability Index – DVI

The Drought Vulnerability Index (DVI) was developed by Naumannn et al. [49] to assess drought vulnerability in Africa using factors related to renewable natural capital, economic capacity, human and civic resources, and infrastructure and technology. The selection of variables and weights reflects the assumption that a society with institutional capacity and coordination, as well as with mechanisms for public participation, is less vulnerable to drought. The definition of the factors was based on the relevance of each indicator for policy development and the entire statistical structure of the dataset (**Table 9**). For each factor, a normalization scheme was necessary prior to data aggregation, as most of the single indicators have different measurement units. Each component is assessed as a geometric mean of a set of indicators inferred from variables that can be obtained in public databases and therefore contrasted by stakeholders.

The DVI is calculated similarly to the HDI, where each factor can be viewed as a dimension. Overall drought vulnerability is calculated as a weighted aggregation of the factors as:

$$DVI_i = \sum_{(k=1)}^{4} W_k C_i k$$

where W_k are the weights assigned for the k component (with $\sum W^k = 1$) and $C_{i,}k$ are the components for each country. The DVI gives the relative vulnerability of a country with respect to all the countries considered in the computation. The scores of the DVI range on a scale of 0 to 1, where 0 represents the lowest vulnerability and 1 is associated with the highest vulnerability.

Table 9. Vulnerability Factors used in the Drought Vulnerability Index (DVI).

Component	Aspect relevant to drought management and type of influence	Indicator	Data source
1. Renewable natural	Water management, positive influence	Agricultural water use (% of total) Irrigation water withdrawals (millions of m3 year-1 per grid cell)	Aquastat World Water Assessment Program, World Water Development Report II. https://wwdrii.sr.unh.edu/index.html
	Water management	Total water use (% of renewable)	FAO, Aquastat, CRU
	Water management	Irrigated area (% of cropland) Irrigation-equipped area (km2 per grid cell) Agricultural area (km2) Rural population, year 2000 (people per grid cell) and Total population, year 2000 (people per grid cell)	Aquastat World Water Assessment Program, World Water Development Report II. https://wwdrii.sr.unh.edu/index.htm
	Water availability	Average precipitation 61-90 (mm year-1)	Aquastat GPCC (Global Precipitation Climatology Center, DWD)
	Pressure on resources	Population density (inhab km-2)	Aquastat World Water Assessment Program, World Water Development Report II.
2. Economic capacity	Economic welfare	GDP per capita USD	UNDP Human Development Index World Statistics Pocketbook (United Nations Statistics Division)
	Food security	Agricultural value added/GDP%	Aquastat
	Economic welfare	Energy use (kg oil equivalent per capita)	World Bank World Statistics Pocketbook (United Nations Statistics Division)
	Collective capacity	Population living below USD 1.25 PPP per day	UNDP Human Development Index

Table 9 continued

3. Human and civic resources	Human development (individual level)	Adult literacy rate (%)	UNDP Human Development Index
	Human development (individual level)	Life expectancy at birth (years)	UNDP Human Development Index
	Collective capacity, institutional coordination	Government Effectiveness (ranges from approximately -2.5 (weak) to 2.5 (strong) governance performance)	World Bank
	Collective capacity, institutional coordination	Institutional capacity (0 to 1)	DEWFORA
	Collective capacity	Population without access to improved water (%)	World Bank
	Human displacement	Refugees (% of total population)	UNHCR
4. Infrastructure and technology	Development	Fertilizer consumption (kilograms per hectare of arable land)	World Bank, Fertiliser consumption total in Tons from Faostat, Arable land in Kha from Aquastat
	Water management potential	Water infrastructure (storage as proportion of total RWR)	Aquastat

IV.2.3. Standardized Drought Vulnerability Index — SDVI

The Standardized Drought Vulnerability Index (SDVI) was developed by Karavitis et al. [16] in an effort to link drought characteristics to impacts by incorporating water supply information, demand data, and the state of relevant water infrastructure and climatic parameters. Within this framework, vulnerability is quantified as **Vulnerability = Risk identification x Impacts** assessment and includes measures of hazard and exposure as variables, which differs from the **Drought risk = Hazard x Exposure x Vulnerability** utilized by the UNCCD and Carrão et al. [20] where hazard and exposure are considered as separate, although not independent, elements. However, in both cases, vulnerability occurs only when drought hazard is present. SDVI assesses impacts of different drought types.

Each factor is broken down into levels of vulnerability ranking from 0 to 3, where 0 is less vulnerable and 3 is extremely vulnerable. The scaled vulnerability factors are then used to compute a final vulnerability value per area as the average scaled value of the factors as:

$$SDVI=\sum_{i=1}^{6}\frac{Factors'\ Scale\ Value}{6}$$

with all factors being weighted equally. The equal weighting method was shown to be more effective than more complex weighting methods [62]. The final SDVI values are ranked into six equal interval classes from 0.0 to 3.0, with the lowest rank representing non-vulnerable areas and the highest rank representing exceptionally vulnerable areas.

SDVI was originally developed using data from Greece and has also been implemented in the United States with modifications that incorporated gridded land cover, NDVI, and land-surface model data among other spatial non-gridded data [63].

IV.3. Recommendations on drought vulnerability indices

We recommend that the creation of the Level 3 vulnerability index should draw on components of ecosystem and human exposure and incorporate elements of capacity and sensitivity. We find that none of the indices presented in this section is a one-size-fits-all solution, moreover there is a divide between how drought vulnerability is addressed, where it is primarily considered in terms of humans or ecosystems. Where indices incorporate both it is in a limited capacity. Thus, more work is needed to develop a truly comprehensive vulnerability index.

V. Relevant Datasets

V.1. Inclusion/exclusion criteria for datasets

Using document ICCD/COP(14).CST/7 as a reference as well as expert knowledge, we created a series of inclusion and exclusion criteria for datasets included in our report and described in more detail in the sections below (**Table 10**).

Table 10. Inclusion and Exclusion Criteria for Datasets to Inform Drought Monitoring.

Criteria & Description
Fidelity to SO3 and SDG indicator 15.3: in ICCD/COP(14) referred to as Sensitivity of the indicator to the SO.
Comparability of candidate metrics/indices with consideration for development and implementation of international standards in underlying data, methodologies, and guidance (modified from criteria in ICCD/COP(14)). An example would be MERRA-2 data which has a rectangular spatial resolution, making it less directly comparable.
Data Validity and Reliability: Datasets have been assessed for accuracy/uncertainty and ability to detect droughts and/or changes in weather/climate. Additionally, the preference is to exclude gauge-only and satellite-only precipitation products because they can be less accurate than satellite-gauge products. There is still a lack of available satellite-gauge products (such as CHIRTS, which is available only through 2016 and is not updated regularly), therefore the preference is to include only gauge-based products. Reanalysis products provide invaluable information on time scales ranging from daily to interannual variability. However, they may often be unable to characterize long-term trends. In Golian et al [51], precipitation reanalysis products were the least consistent in capturing the number of drought events. In Funk et al. [61], the MERRA-2 reanalysis temperature product was excluded from the analysis due to several observed instances in which there were large, unexpected shifts in the maximum temperature values estimated by the MERRA-2 system.
Readiness/Adaptability: Datasets do not require special permission to access and can be freely downloaded from the internet. (could be considered component of Readiness per ICCD/COP(14))
Global coverage: Datasets should have quasi-global to global coverage, including most inhabited land areas. (component of Readiness per ICCD/COP(14))
Spatial resolutions: The spatial resolution should be the finest available. Golian et al [51] reports that drought indices are sensitive to spatial resolution and the prediction of severe or exceptional drought can be reduced significantly when using coarser resolution products.
Temporal range: Goes to 2000 at least for soil moisture and has a minimum 30-year record for precipitation/temperature as recommended for some common drought indices (e.g. SPI) and WMO guidance for climate studies. (could be considered component of Readiness/Adaptability per ICCD/COP(14)). For climatological studies, the WMO guidance generally requires at least 30 years of historical weather data [62]. The use of longer precipitation records is also recommended by McKee et al. [63] and Wu et al [64] for calculation of the SPI. The period of record can significantly affect the prediction of drought characteristics including percent grids under severe or exceptional drought, with even records of almost 40 years underestimating drought extent in mid- and low latitudes [51]. Newer satellite-based products such as CMORPH or IMERG do not have a period of record sufficient to satisfy the WMO requirement for utilization in climate studies.
Temporal resolution: The dataset should be available at a temporal resolution that makes it easy to assess both short-term and long-term changes in climate and weather. A product that is available at multiple temporal resolutions including daily, monthly, and annually is ideal, but if desired temporal resolutions are available, a daily product that can be easily aggregated to monthly or annual products is preferable. Sub-daily products are not required. (Most indices will be calculated at monthly or multi-monthly timesteps e.g. SPI-1, SPI-3, SPI-6, etc). (could be considered component of Readiness/Adaptability per ICCD/COP(14))

Table 10. Continued

Criteria & Description
Data Type: Because gauge-based gridded products generally have more uncertainty associated with them partially due to inconsistencies in gauge density, a blended satellite-gauge product is most desirable for precipitation, temperature, and soil moisture where available. For socioeconomic data, the order of preference from most desirable to least desirable is gridded, sub-national, and national.
Feasibility of Trends.Earth integration (user-friendly): Datasets that are easier to work with are preferable. For example, gridded precipitation datasets can be derived from gauge, satellite, satellite with gauge correction, or reanalysis products. Reanalysis products are less straight-forward and more difficult to work with, so these are not preferred. (component of Readiness per ICCD/COP(14))
Update frequency: The dataset should be actively updated on a regular basis, meaning datasets that are no longer operational or do not have an easily identified timeframe for subsequent releases are excluded. For both biophysical and socioeconomic datasets, those that are updated at least yearly are preferred. (could be considered component of Readiness/Adaptability per ICCD/COP(14))
Gender disaggregation: Socio-economic data and indicators with gender disaggregation will be preferred. (component of Readiness/Adaptability per ICCD/COP(14))
Capacity to create ownership at the national level (component of Readiness/Adaptability per ICCD/COP(14)): where we provide guidance for countries to replace with their own data, thereby allowing them to validate, accept, or reject the recommended data.

V.2. Biophysical datasets and indices for drought monitoring, drought hazard, and climate extremes: Precipitation, temperature, & soil moisture

V.2.1. Precipitation

This section includes only satellite-gauge products that have at least 30 years of record, near-global coverage, and are currently operational and regularly updated.

V.2.1.1. CHIRPS (currently used in Trends.Earth)

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) is a quasi-global rainfall dataset with a temporal coverage spanning over 35 years (**Table 3**). CHIRPS incorporates an in-house climatology called CHPclim, multiple high spatial resolution geostationary thermal infrared (TIR) satellite sources, and in-situ station data though a modified inverse distance weighting algorithm [66]. CHIRPS was explicitly designed for monitoring agricultural drought and environmental change over land in regions with complex topography, changing observation networks, and deep convective precipitation systems that correspond well with cold cloud duration (CCD) estimates.

Because sub-monthly timesteps are required for monitoring agricultural drought, the primary timestep is calculated in pentads (5-day periods) and subsequently re-scaled to other timesteps such as daily and monthly. Final products are released shortly after the 20th of the following month for which they are calculated, resulting in a low latency for release of operational products. The global product is calculated at a 0.05-degree spatial resolution, the finest of any product available. CHIRPS data is free to download with unrestricted use.

Validation results indicate good performance for drought monitoring in locations such as the Middle East, North Africa, North America, Europe, and Asia. However, large biases in certain countries such as Colombia and Peru exist that could inhibit effective remote monitoring of drought and environmental change [66].

A study by Tote et al. [67] used CHIRPS to estimate dekadal rainfall values in Mozambique, concluding that its dependence on 0.25 degree TRMM (Tropical Rainfall Measuring Mission) data may contribute to its tendency to overpredict the frequency of rainfall events because the values were averaged over larger areas. The overprediction of rainfall events made this dataset the least useful for drought monitoring of those compared in the study; however, it outperformed other products in terms of rainfall amount estimation both during the cyclone season and over the entire seasonal cycle, indicating some utility in monitoring drought effect on agricultural production and in flood monitoring.

In another study, Bayissa et al. [68] found good correlation between CHIRPS and monthly station data in Ethiopia, and noted its utility as an alternate source of rainfall information in developing grid-based drought monitoring tools to aid in developing early warning systems. Additionally, CHIRPS was found to be in good agreement for gauge-based drought predictions at moderate to severe drought thresholds (SPI of -1 and -1.5; **Table 7**) and performed well in terms of predicting the spatial distribution of the number of drought events [41]. Finally, in a study with limited gauge data and over rugged topography in Ethiopia, CHIRPS was shown to outperform all other products including CMAP, GPCP, and PERSIANN at all temporal and spatial scales when evaluated against ground observations [69].

Finally, CHIRPS has even been used to estimate hydrological drought, and accurately captured the beginning, end, and duration of this drought event; however, several deviations were found in severity and intensity estimation of the drought event [30]. In this study, CHIRPS was also found to outperform PERSIANN-CDR.

CHIRPS is well-suited for drought monitoring given its high spatial and temporal resolutions and its effectiveness is substantially supported in scientific literature. Currently, CHIRPS is used in multiple operational drought and climate monitoring initiatives including FEWS NET, ClimateSERV, and Trends.Earth.

V.2.1.2. CMAP Standard

The CPC (Climate Prediction Center) Merged Analysis of Precipitation (CMAP) values are derived from a gauge analysis with microwave and infrared observations from polar orbiting and geostationary satellites [70]. In the CMAP standard product, overlapping satellite-based estimates are weighted according to their fit with the gauge-based analysis, which is assumed to have the most accurate values. CMAP is provided at 2.5-degree spatial resolution in monthly and pentadal increments with a slightly longer temporal coverage than CHIRPS. CMAP products are updated irregularly. CMAP was originally developed to support the analysis of annual and interannual variability in large-scale precipitation.

One study which assessed meteorological drought over Saudi Arabia found good agreement between observation and CMAP data for both the wet and dry seasons, but noted that its coarse resolution limited ability to detect nuances in spatial patterns of precipitation that were better resolved using higher spatial resolution Climate Research Unit (CRU) data [71]. In the Gebremichael et al. [69] study, CMAP was found to perform very poorly, having extremely large error biases. Overall, the use of CMAP in the calculation of drought indices is much less common within the scientific literature, making it more difficult to assess its effectiveness for this specific purpose. Additionally, there are newer products available such as CHIRPS and PERSIANN that are likely more accurate for the common periods of record, due to greater uniformity of input data sources and more advanced satellite-derived products [72].

V.2.1.3. GPCP (currently used in Trends.Earth)

The Global Precipitation Climatology Project (GPCP) monthly data is derived from a combination of Global Precipitation Climatology Center (GPCC) rain gauge stations, passive microwave (PMW) and infrared (IR) satellite observations and sounding observations and is provided at a 2.5-degree spatial resolution from 1979 to present. It was originally developed to improve understanding of seasonal to inter-annual and longer-term variability of the global hydrological cycle. GPCP is currently one of the most used precipitation datasets for regional and global climate studies [73]. GPCP provides uncertainty estimates due to random errors and is updated regularly.

In the previously mentioned study by Golian et al [41], GPCP showed similar effectiveness to CHIRPS at predicting moderate drought using the SPI and in predicting the spatial distribution of number of drought events, but performed worse when predicting the severe to exceptional drought categories (**Table 10**). The coarse spatial and temporal resolution of the GPCP product may limit its ability to capture spatial details and dynamics of extreme precipitation events [74] or complex terrain [69], and can be insufficient to operationally monitor and characterize drought [75]. Like CMAP, other newer products may have benefits that make them more accurate [72].

V.2.1.4. PERSIANN-CDR (currently used in Trends.Earth)

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) was developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at University of California, Irvine [74]. The PERSIANN algorithm primarily relies on satellite infrared (IR) brightness temperature data from geostationary satellites to estimate rainfall rate, updating its parameters using PMW observations from low-orbital satellites and an artificial neural network approach trained on National Centers for Environmental Prediction (NCEP) stage IV hourly precipitation data to calculate final precipitation values. PERSIANN-CDR (for Climate Data Record) has been bias-corrected using GPCP monthly data and is described as a product suitable for global climate studies at a scale relevant to extreme drought events.

PERSIANN-CDR provides daily rainfall estimates at a spatial resolution of 0.25 degrees beginning in 1983 (**Table 4**), with monthly estimates that are consistent with GPCP v2.2 when degraded to a 2.5-degree resolution. The data is free to download and open access.

Several national or regional studies have also utilized PERSIANN-CDR for detecting drought events. In China, PERSIANN-CDR was found to perform similarly to a gridded gauge-based product in terms of capturing spatial and temporal patterns in drought in areas where the gauge network was denser, but found large differences in areas where gauge networks were less dense or the terrain was more complicated [75]. In Ethiopia, Bayissa et al. [68] found weak performance in terms of agreement with ground observations. In Iran, PERSIANN-CDR was used to calculate ten WMO standard extreme precipitation indices and found good correlation with gauge observations of consecutive dry days (CDD), though it tended to underestimate absolute daily precipitation when compared with gauges [76]. In Hawaii and the United States Affiliated Pacific Islands (USAPI) region, Luchetti et al. [77] expressed high confidence in using this data to accurately represent ENSO-specific rainfall patterns of wet and dry anomalies despite some disagreements with gauge data. Finally, this product outperformed multiple other products including CMAP and GPCP in the Gebremicael et al. [69] study, though it was outperformed by CHIRPS.

Overall, PERSIANN-CDR meets the operational requirements of the WMO for calculating a precipitation-based drought index and assessing drought. It has been shown to be effective in representing spatiotemporal patterns of precipitation under diverse climatic types and complex terrain, with inconsistencies with ground observations primarily in regions with low gauge density where interpolated data is less accurate.

V.2.1.5. Recommendations on global climate and weather datasets for precipitation

We recommend that CHIRPS be the primary precipitation product used to monitor drought within Trends.Earth due to its extremely high spatial resolution, low latency, and multitude of temporal resolutions that make it effective in operational monitoring of both short- and long-term drought. Moreover, it was specifically designed for drought monitoring and is currently employed for this purpose by multiple organizations. However, for areas where CHIRPS has been shown to be less successful at detecting drought or predicting drought occurrence and severity, we recommend that additional datasets be accessible such as PERSIANN-CDR and GPCP in the event that there is not a national or regional product that is more suitable for use. We recommend that CMAP undergo more testing specifically for drought monitoring before being employed for operational use.

V.2.2. Temperature

All of the products included here are derived from gauge data, with the exception of CHIRTS-daily which is derived from gauge plus European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA5) data.

V.2.2.1. BETP Gridded Land

Berkeley Earth is an independent U.S. non-profit organization focused on environmental data science, which provides gridded land temperature products including averages, minimums, and maximums on daily and monthly timesteps from 1753 until present (**Table 4**) [78,79]. The Berkeley Earth Temperature Product (BETP) data is derived from weather station thermometer data and was originally produced for climate analysis. The methodology used to calculate the final product allows for inclusion of short or discontinuous temperature records and uses a statistical method known as Kriging to interpolate the station data as well as an iterative weighting process to reduce the influence of statistical outliers [79]. Comparison of global temperature increases calculated using Berkeley Earth data were found to be comparable to results from other gridded temperature products including products by NOAA, NASA, and at the Hadley Center/CRU. The daily product is, at this time, considered experimental. Because this dataset contains values for both actual temperature and temperature anomalies, it has multiple uses in the context of drought monitoring including assessing temperature anomalies in relation to drought and in the calculation of drought indices such as SPEI.

To our current knowledge, the Berkeley Earth products have not explicitly been used in the calculation of a drought index or to determine drought hazard. Additionally, the product has not been widely evaluated at the national scale in many regions so the efficacy of this product in detecting changes in temperature or warming trends may be unknown. In the high latitudes of Canada, it was found to systematically underestimate regional warming [80], potentially because the BEPT data did not include key observational data from that region. Thus, more research would be needed to determine the efficacy of these products in detecting and monitoring spatiotemporal variations in temperature and drought on global and regional levels. We recommend that this product be considered in future research projects to that effect given its extensive temporal coverage and relatively fine spatial resolution in comparison to other gridded temperature products (**Table 4**).

V.2.2.2. CHIRTS-daily

CHIRTS-daily is a global 2-m maximum temperature (Tmax) product that combines the monthly Climate Hazards Center Infrared Temperature with Stations (CHIRTSmax) dataset [64] with the ERA5 reanalysis to produce routinely updated data to support the monitoring of temperature extremes (**Table 4**). CHIRTSmax is derived from monthly average MERRA-2 2-m maximum air temperature estimates, the GridSat B1 TIR dataset, and CRU station data. CHIRTS was developed to address the dearth of accurate information supporting the monitoring and evaluation of extreme temperatures in many food-insecure regions for climate change studies, climate extreme analyses, and early warning applications. The monthly CHIRTS data is available only through 2016, even though aggregation of the daily data to monthly data (which goes to present day) is feasible.

A potential limitation of the CHIRTS-daily data is that, while the ERA5 has been shown to have robust performance with respect to spatial covariance and daily anomalies, ERA5 shows significant cool bias globally, which is most pronounced in Africa. This cool bias results in underrepresenting the number of extreme hot days globally, and most notably in Africa[15]. However, the low latency of ERA5 enables CHIRTS-daily to be released with minimal delay. Additionally, this is the only blended satellite-gauge product of those discussed within this report, where the inclusion of satellite data can provide valuable information in data-sparse regions. Finally, the spatial resolution of the dataset is the finest available, making this an attractive choice for drought monitoring.

V.2.2.3. CPC Global Daily

The Climate Prediction Center (CPC) Global Daily temperature product is built upon a gridded climatology with orographic consideration [81]. Gridded analysis of temperature anomaly is defined by interpolating

15 https://www.chc.ucsb.edu/data/chirtsdaily

station values through the Shepard algorithm, a distance-weight technique with directional correction. Gridded analyses of total temperature are computed by adding the anomaly to the CRU climatology [82]. Recently, the CPC Global Daily temperature product has been used in the development of high-resolution gridded datasets in data-sparse regions [83] and to generate high temperature extreme data [84]. There are substantially few applications which use this data in the calculation of a drought index such as SPEI, making it difficult to assess its qualifications for this purpose.

V.2.2.4. CRUTEM: averages plus anomalies land air temp

The CRU Temperature data (CRUTEM) have been developed by the CRU (University of East Anglia) in conjunction with the Hadley Centre -UK Met Office [85,86]. This dataset is derived from near-surface land air temperatures recorded at weather stations of the Global Historical Climatology Network (GHCN). It has been developed and maintained by the CRU since the early 1980s and is updated at roughly monthly intervals. CRUTEM provides hemispheric and global land air temperature averages and anomalies as monthly and annual values at five-degree spatial resolution. This is one of the most notable global temperature datasets, used widely by the WMO, IPCC, and many scientific studies that monitor global warming. One reason for its widespread use is that it has a detailed analysis of errors and uncertainties at multiple time and space scales from grid cells to global mean [87]. A drawback to using this dataset is that data from 1961 – 1990 are expressed only as anomalies and would require a series of calculations to obtain actual temperatures before they could be implemented in operational drought monitoring platforms such as Trends.Earth.

V.2.2.5. GISTEMP Land

The Goddard Institute for Space Studies (GISS) Surface Temperature Analysis (GISTEMP) recalculates consistent temperature anomaly series from 1880 to present using the Global Historical Climatology Network (GHCN) station data (**Table 4**) [88]. The data are primarily used to investigate regional and global patterns and trends concerning temperature anomalies. GISTEMP data are used in NASA's annual global temperature update, in partnership with NOAA. GISTEMP is reported to be a reliable index for current and future climate research [89] and could be useful in monitoring temperature anomalies across the globe. However, there are currently no published papers that directly assess the feasibility of using this dataset for drought monitoring. Additionally, because the data values are anomalies and not actual temperatures, this dataset should not be used to calculate evapotranspiration within a drought index such as SPEI.

V.2.2.6. NOAA GlobalTemp

NOAA GlobalTemp, formerly MLOST (Merged Land–Ocean Surface Temperature Analysis), combines monthly land surface air temperatures primarily from the Global Historical Climatology Network (GHCN-M) version 3 with sea surface temperatures (SSTs) of the ERSSTv3b (Extended Reconstructed Sea Surface Temperature v3b) analysis into a comprehensive global surface temperature dataset spanning 1880 to the present at monthly resolution, on a 5x5 degree latitude-longitude grid [90,91]. It is one of the primary datasets used to monitor global and regional temperature variability and trends. Like GISTEMP, interpolation of the station records is performed to provide broad spatial coverage, however, the

methodology is unique because land and ocean domains are treated separately. Data-sparse areas are masked to prevent reliance on the highly smoothed reconstruction estimates, leading to limited coverage in polar regions and portions of Africa and South America. Values are provided as temperature anomalies, relative to a 1971–2000 monthly climatology, following the WMO convention.

V.2.2.7. Recommendations on global climate and weather datasets for temperature

We recommend that NOAA GlobalTemp and CRUTEM are most suited for further analysis as to their suitability for monitoring drought within Trends.Earth, due to their values being provided as both absolute values and anomalies, and their proven reliability as datasets used to monitor global and regional temperature variability and trends. Additionally, the inclusion of CHIRTS will provide reliable alternatives for the calculation of SPEI because it meets the criteria of having serially and spatially complete data that are analysis-ready (unlike NOAA GlobalTemp which has gaps in coverage and CRUTEM which requires transformation of certain years from anomaly values to absolute values). Additionally, CHIRTS has the finest available spatial resolution and is the only fused satellite-gauge product. The inclusion of CHIRTS will enable SPEI to be calculated using the complimentary datasets of CHIRPS and CHIRTS. We recognize that there is a deficit in the scientific literature that directly assesses and compares the suitability of global gridded temperature datasets for drought monitoring and suggest that this area of research is worthy of exploration. Additionally, the development of additional blended satellite-gauge temperature products will greatly enhance the ability of the world community to assess and monitor drought globally, and especially in regions where observational data is scarce or not updated regularly.

V.2.3. Soil moisture

Globally gridded soil moisture products from observational data are not well developed, thus most global soil moisture data is obtained from satellite information, land surface models (LSMs), or reanalysis products.

V.2.3.1. ERA5 (ERA-Interim is currently used in Trends.Earth)

The ERA5 reanalysis replaced the highly successful ERA-Interim reanalysis that was started in 2006. It embodies a detailed record of the global atmosphere, land surface, and ocean waves from 1950 onwards [92]. ERA5 includes values for soil moisture and is created in part from observational data using a thermodynamical orographic adjustment. The product has a spatial resolution of 0.28 x 0.28 degrees with global coverage. ERA5 is available within 5 days of real time which ranks it highly in terms of operational readiness and combined with its long and consistent climate record, make it suitable for climate extremes monitoring. In one study, ERA5 showed overall higher correlation with in-situ observations compared to four other products including MERRA-2 [93]. At individual sites, ERA5 showed considerable fidelity in the annual cycles in soil moisture. ERA also represents soil moisture values at different depths in the soil column, potentially making it more useful for monitoring the effects of longer-term droughts (i.e., agricultural/ecological drought).

V.2.3.2. ESA CCI soil moisture combined product

The European Space Agency Climate Change Initiative (ESA CCI) produces three separate global soil moisture products derived from active, passive, and combined (active plus passive) microwave satellite sensors that span over 40 years in time. Active and passive datasets are merged into the combined product using a decision tree that selects either one of the products alone or uses the arithmetic mean of both during a particular period based on the assumption that active retrievals tend to perform better in more densely vegetated areas, whereas passive retrievals tend to perform better in more sparsely vegetated areas [42]. The combined product is thus more suitable for monitoring drought over larger areas where differences is vegetation density are an absolute certainty.

The ESA CCI-SM (soil moisture) product seems to better represent the soil wetness conditions in a study in India than the MERRA-2 LSM [58]. However, because it detects dryness only in the upper layer of the soil column (usually associated with warmer-than-average conditions), the derived indices may be more comparable with SPI calculated over a short period, as for meteorological drought. Largest uncertainties are in the early period of the CCI-SM product and were noted by Nicolai-Shaw et al. [94].

V.2.3.3. MERRA-2 (currently used in Trends.Earth)

The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), is the latest atmospheric reanalysis of the modern satellite era produced by NASA's Global Modeling and Assimilation Office (GMAO). MERRA-2 assimilates observation types not available to its predecessor, MERRA, and includes updates to the Goddard Earth Observing System (GEOS) model and analysis scheme so as to provide a viable ongoing climate analysis beyond MERRA's terminus [95]. MERRA-2 soil moisture data is currently included in Trends.Earth, however, peer-reviewed studies have shown that other products including ERA5 and ESA-CCI outperform MERRA-2 [58,93].

V.2.3.4. NASA-USDA Global Soil Moisture Data

The NASA-USDA (United States Department of Agriculture) Global soil moisture data provides global soil moisture information at 0.25 x 0.25 degree spatial resolution. These datasets include surface and subsurface soil moisture (mm), soil moisture profile (%), surface and subsurface soil moisture anomalies (-). The dataset is generated by integrating satellite-derived Soil Moisture Active Passive (SMAP) and Soil Moisture Ocean Salinity (SMOS) soil moisture observations into the modified two-layer Palmer model using Ensemble Kalman Filter (EnKF) data assimilation approach. The assimilation of the satellite-derived soil moisture observations helped improve the model-based soil moisture predictions, particularly over poorly instrumented areas of the world that lack good quality precipitation data. In Sazib et al. [36] RZSM anomalies calculated in part from NASA-USDA soil moisture data were well correlated with SPI-3 but less so with SPI-6 and SPI-9.

V.2.3.5. Recommendations of soil moisture datasets

We recommend further exploration of the ESA-CCI combined product for drought monitoring because it utilizes both active and passive satellite microwave data, where active retrievals tend to perform better in more densely vegetated areas, and passive retrievals tend to perform better in more sparsely vegetated areas [42]. The robustness of this product for detecting and monitoring drought across different vegetation densities makes it worthy of inclusion in global drought monitoring toolboxes. Additionally, we recommend ERA5 as a backup option, as it has shown overall higher correlation with in-situ observations and represents soil moisture at different depths within the soil column, which could facilitate analyses beyond the capacity of the other products which only measure the top-most layer.

V.3. Datasets for monitoring human population exposure to drought

V.3.1. Human population density

V.3.1.1. Gridded Population of the World – GPW, version 4

The Gridded Population of the World (GPW) collection is a gridded global population dataset developed by the Centre for International Earth Science Information Network (CIESIN) at Columbia University. Now in its fourth version (GPWv4), this spatially disaggregated layer is gridded with an output resolution of 30 arc-seconds (approximately 1 km at the equator) and incorporates inputs such as population census tables & national geographic boundaries, protected areas, and water bodies. The input data are weighted and extrapolated to produce population estimates (counts and densities) for the years 2000, 2005, 2010, 2015, and 2020. A set of estimates adjusted to national level population predictions from the United Nation's World Population Prospects report are also produced for the same set of years. Rasters are also available for basic demographic characteristics (age and sex), data quality indicators, and land and water areas. Summary characteristics of GPWv4 are shown in **Table 4**.

The strengths of GPWv4 are that the population estimation method of areal-weighting is straight-forward, i.e., 'lightly modelled', therefore providing fidelity to the input census data. Therefore, this dataset can be analyzed in conjunction with other datasets such as land cover and elevation without concern for endogeneity [96]. However, the disadvantage of using areal-weighting as the spatial disaggregation method leads to a high variability of grid-level estimates. Consequently, for counties where the input (e.g., administrative) units are relatively large, the precision of population estimates for individual grids within that unit can be compromised [96].

V.3.1.2. Global Rural-Urban Mapping Project (GRUMP)

The Global Rural-Urban Mapping Project (GRUMP) collection is a gridded global population dataset developed by CIESIN in collaboration with the International Food Policy Research Institute (IFPRI), the World Bank, and Centro Internacional de Agricultural Tropical (CIAT). The Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) consists of eight global datasets: population count grids, population density grids, urban settlement points, urban-extents grids, land/geographic unit area grids, national boundaries, national identifier grids, and coastlines. All gridded datasets are available at a resolution of 30 arc-seconds (~1km at the equator), with population estimates normalized to the years 1990, 1995 and 2000 based on UNPD estimates and projections. Summary characteristics of GRUMP v1 are shown in **Table 4**.

The strengths of GRUMP v1 are that the population estimation method of binary dasymetric mapping is straight-forward, i.e., 'lightly modelled', therefore providing fidelity to the input population data while accounting for settlement extents. For instance, GRUMPv1 built upon the GPWv3 by the creation of a population density and population count grid that distinguishes between urban and rural areas. However, the main limitation of GRUMPv1 is the lack of contemporary data & no gender disaggregation.

V.3.1.3. Global Human Settlement Layer – Population (GHS-POP)

The Global Human Settlement Layer – Population (GHS-POP) is a gridded global population dataset developed by the JRC in collaboration with CIESIN. All gridded datasets are available at a resolution of 9 arc-seconds and 30 arc-seconds (~ 250m & ~1km at the equator), with population estimates normalized to the years 1975, 1990, 2000 and 2015 based on UNPD estimates and projections. These population estimates were disaggregated from GPWv4 based on the Global Human Settlement Layer (GHSL) for each corresponding target year. Summary characteristics of GHS-POP are shown in **Table 4**.

V.3.1.4. LandScan Global Population database

The LandScan Global dataset is a gridded global population dataset developed by the Oak Ridge National Laboratory (ORNL). This spatially disaggregated layer is gridded with an output resolution of 30 arc-seconds (approximately 1 km at the equator) and incorporates inputs such as population census tables & national geographic boundaries, roads, land cover, built structures, urban areas, infrastructure, and environmental data. The input data are modelled to produce annual population estimates for the years 1998, 2000 - 2018. Summary characteristics of LandScan are shown in **Table 4**.

The strengths of LandScan are that the population estimation method of dasymetric mapping is multivariate, i.e., 'highly modelled', therefore tailored to match data conditions and geographical nature of each individual country and region. The main disadvantage is that LandScan lacks gender disaggregation.

V.3.1.5. Esri's World Population Estimate

The World Population Estimate datasets, a collection of gridded global population datasets, were developed by the Environmental Systems Research Institute (Esri). This spatially disaggregated layer is gridded with an output resolution of 150 meters in 2016 & 250 m for earlier datasets and incorporates inputs such as population census tables & national geographic boundaries, roads, land cover and water bodies. The input data are modelled to produce annual population estimates for the years 2013, 2015 – 2016. Summary characteristics of World Estimate are shown in **Table 4**.

The strength of Esri's World Population Estimate is that the population estimation method of dasymetric mapping is multivariate, i.e.,. 'highly modelled', therefore tailored to match data conditions and geographical nature of each individual country and region. One disadvantage is that one would need a subscription to Esri ArcGIS Online, organizational account, or an ArcGIS Developer account to access this dataset. However, Esri does provide free account access to certain non-profits or other qualifying entities so this limitation can potentially be overcome.

V.3.1.6. WorldPop

The WorldPop collection is a global gridded high-resolution geospatial dataset on population distributions, demographics, and dynamics. WorldPop's spatially disaggregated layers are gridded with an output resolution of 3 arc-seconds and 30 arc-seconds (approximately 100 m & 1 km, respectively at the equator) and incorporates inputs such as population census tables & national geographic boundaries, roads, land cover, built structures, urban areas, night-time lights, infrastructure, environmental data, protected areas, and water bodies. The input data are modelled to produce annual population estimates for the years 2000-2020 and some select country-specific years. A set of estimates adjusted to national level population predictions from the UNPD are also produced for the same set of years. Summary characteristics of WorldPop are shown in **Table 4**.

The strengths of WorldPop are that the population estimation method of dasymetric mapping is multivariate, i.e., 'highly modelled', therefore tailored to match data conditions and geographical nature of each individual country and region. Gender information is also available. The weakness of WorldPop is that the utilization of such complex interpolation models with sparse census data may lead to highly uncertain and imprecise population estimates in some sub-national and rural regions. In spite of the aforementioned limitation, WorldPop remains the most ideal gridded population dataset as it satisfies all our inclusion criteria, including spatial resolution, global coverage, frequency of data updates, and inclusion of a gender-disaggregated component.

V.3.1.7. Recommendations on population density datasets

Based on the population density datasets for monitoring drought exposure discussed in this review, we recommend that progress towards SO3 should take advantage of WorldPop as the spatially gridded datasets of choice that meet all our inclusion/exclusion criteria. Some pros of the WorldPop datasets include: 1) the finest gridded resolution (~100m) currently available for national-level population estimates for the entire continent; 2) the efficacy of the multivariate population estimation ensures that the dataset is tailored to match data conditions and geographical nature of each individual country and region; 3) availability of gender-structured global population count datasets for all countries in the world, for each year 2000-2020. Some limitations of these datasets include their "highly-modelled" nature and the relatively higher spatial resolution that might affect the overall computational processing times.

V.3.2. Urban vs. rural exposures: Settlement layers

V.3.2.1. Global Human Settlement Layer – Built Up grid (GHS-BUILT)

The Global Human Settlement Layer – Built Up (GHS-BUILT) is a gridded global settlement dataset developed by the JRC. All gridded datasets are available at a resolution of 30 m, 250 m and 1 km, with the classification of built-up presence normalized to the years 1975, 1990, 2000 and 2014 (**Table 4**). Landsat imagery was used to estimate the proportion of building footprint and impervious surfaces within each grid cell for each corresponding target year. This dataset is open access.

V.3.2.2. Global Human Settlement Layer – Settlement Model (GHS – SMOD)

The Global Human Settlement Layer – Settlement Model (GHS-SMOD) is a gridded global settlement dataset developed by the JRC and gridded at a resolution of 1 km (**Table 4**). This dataset incorporates GHS-BUILT built-up density and GHS-POP population grid as inputs to create classes (urban center, urban cluster, and rural) derived from combinations of population density, size, and density of built-up, normalized to the years 1975, 1990, 2000 and 2015. This dataset is open access.

V.3.2.3. Recommendations on Settlement Layers Datasets

To the extent possible, we recommend the integration of the GHS – SMOD settlement dataset indicating Urban vs. Rural Exposures, as it incorporates aspects of GHS – BUILT and at a manageable resolution of 1 km. End-users should be aware that the latest year that GHS – SMOD has been normalized to is 2015. Furthermore, GHS – SMOD is not disaggregated by gender.

V.4. Datasets on monitoring ecosystem exposure to drought

V.4.1 Anthropogenic Biomes

The Anthropogenic Biomes of the World, Version 1 (also called Anthromes or Human Biomes) is distributed by CIESIN and available through the NASA SEDAC. It describes globally significant ecological patterns in the terrestrial biosphere that are caused by direct and sustained human interaction with ecosystems. These interactions include agriculture, urbanization, forestry, and other land uses. Conventional biomes are categorized based on global vegetation patterns related to climate (e.g., tropical rainforests, grasslands, tundra). This dataset provides a contemporary view of the terrestrial biosphere that directly accounts for the human alteration that has fundamentally altered global patterns of ecosystem form, process, and biodiversity.

This dataset was produced using a multi-stage mapping procedure based on population (urban, non-urban), land use (percent area of pasture, crops, irrigation, rice, and urban land), and land cover (percent area of trees and bare earth). The input datasets include Landscan population data, land use data, and land cover data. A detailed description of the methodological procedure is published in Ellis and Ramankutty [48]

V.5. Datasets for monitoring population and ecosystem vulnerability to drought

V.5.1. Ecological

V.5.1.1. Intact Forested Landscapes

The Intact Forested Landscape (IFL) concept and its technical definition were introduced by a diverse team (including Greenpeace, The University of Maryland, and Transparent World, with support from the World Resources Institute and World Wildlife Foundation Russia) to help create, implement, and monitor policies concerning the landscapes alteration and fragmentation at the regional-to-global levels. The essence of the IFL method is to use freely available medium spatial resolution satellite imagery to establish the boundaries of large undeveloped forest areas, so called IFLs, and to use these boundaries as a baseline for forest degradation monitoring [97–99].

The most recent update in 2017 employed the latest available cloud-free Landsat composite data from 2016 and annual forest cover change products produced by the Global Land Analysis and Discover lab. Therefore the 2017 dataset represents conditions as close as possible to the end for the year 2016 and beginning of the year 2017.

V.5.1.2. ESA CCI (MRLC maps v 207)

The European Space Agency Climate Change Initiative-Land Cover (ESA CCI-LC[16]; Multi-Resolution Land Characteristics - MRLC maps v207) is produced by the ESA Climate Office and includes annual global land cover maps at 300 m spatial resolution from 1992 to 2015. This dataset utilizes the UN Land Cover Classification System (LCCS), which supports the conversion of the 22 land cover classification values into Plant Functional Types distribution required by Earth System Models.

These maps are derived from a unique baseline MRLC map that is created using a classification chain applied on the entire MEdium Resolution Imaging Spectrometer (MERIS) Full Resolution (FR) and Reduced Resolution (RR) archive from 2003 to 2012. Independently from this baseline, MRLC changes are detected at 1 km based on a time series of annual global classifications generated from the Advanced Very High-Resolution Radiometer High Resolution Picture Transmission System (AVHRR HRPT; 1992 - 1999), Satellite Pour l'Observation de la Terre Vegetation (SPOT-Vegetation; 1999 - 2012) and Project for On-Board Autonomy-Vegetation (PROBA-V; 2013 - 2015). The temporal trajectory of each pixel is systematically analyzed to depict major changes using a simplified classification consisting of cropland, forest,

16 http://www.esa-landcover-cci.org/

grassland, wetlands, settlements, and other lands; other is further divided into shrubland, sparse vegetation, bare area, and water. Changes detected at 1 km are re-mapped at 300 m where MERIS FR or PROBA-V data are available.

The ESA CCI-LC dataset has been used to analyze built settlement expansion [100], map the SDG 6 water scarcity indicator [101], and is the default land cover dataset provided by the UNCCD to countries for reporting on SDG indicator 15.3.1 [5]. This high-resolution dataset also can be used to map land use conversions across the globe and has been implemented for this purpose in Trends.Earth.

V.5.1.3. Copernicus Global Land Cover

The Copernicus Global Land Cover product is derived from the Project for On-Board Autonomy-Vegetation (PROBA-V) sensor and is a medium-resolution land cover product that primarily targets land cover detection and change. The land cover data is provided from 2015 – 2019 in conjunction with vegetation continuous field layers that provide proportional estimates of vegetation cover for several land cover types. The version 3.0 annual 100m spatial resolution land cover classes were mapped with high temporal stability across years and an overall mapping accuracy just over 80 percent[17].

This product is widely utilized for a variety of applications including deforestation, desertification, urbanization, land degradation, loss of biodiversity and ecosystem functions, water resource management, agriculture and food security, urban and regional development, and climate change.

V.5.1.4. AVHRR/GIMMS

The AVHRR/GIMMS dataset was created from the Global Inventory Monitoring and Modeling System (GIMMS) project. The data is assembled from different AVHRR sensors and accounts for various deleterious effects, such as calibration loss, orbital drift, volcanic eruptions, etc. This dataset provides global values for the Normalized Difference Vegetation Index (NDVI), which is a simple indicator that can be used to study vegetation condition or productivity using multispectral remote sensing data. It is computed using the equation:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

where *NIR* represents the near-infrared band and *Red* represents the red band.

AVHRR data is used to generate NDVI-based images of the planet's land surface on a regular basis, thereby creating image series that portray seasonal and annual changes to vegetation worldwide. AVHRR NDVI data are available in a consistently processed database at an 8 km re-sampling grid covering the entire planet. The latest version of the GIMMS NDVI dataset spans the period July 1981 to 2015 and is termed NDVI3g (third generation GIMMS NDVI from AVHRR sensors). This dataset is currently available in Trends.Earth for the computation of the SDG 15.3 land degradation indicator [5,102].

V.5.1.5. MOD13Q1-coll6

The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) Version 6 data[18] are generated every 16 days at 250 m spatial resolution as a Level 3 product (meaning that product accuracy has been assessed and the uncertainties in the product are well established by independent measurements in a systematic and statistically robust way that represents global conditions). The MOD13Q1 product provides two primary vegetation layers. The first is the NDVI which is referred to as the continuity index to the existing AVHRR derived NDVI. The second vegetation layer is the Enhanced Vegetation Index (EVI), which has improved sensitivity over high biomass regions, and is computed using the equation:

$$EVI = G \times \frac{(NIR - Red)}{(NIR + C1 \times Red - C2 \times Blue + L)}$$

where *NIR* represents the near-infrared band, *Red* represents the red band, and *Blue* represents the blue band. *L* is the canopy background adjustment that

17 https://land.copernicus.eu/global/products/lc

18 https://lpdaac.usgs.gov/products/mod13q1v006/

addresses non-linear, differential NIR and red radiant transfer through a canopy, and *C1*, *C2* are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the MODIS-EVI algorithm are L=1, $C1$ = 6, $C2$ = 7.5, and G (gain factor) = 2.5. The algorithm chooses the best available pixel value from all the acquisitions from the 16-day period. The criteria used is low clouds, low view angle, and the highest NDVI/EVI value. This dataset is currently available in Trends.Earth for the computation of the SDG 15.3 land degradation indicator [5,102].

V.5.1.6. SoilGrids V 2.0

SoilGrids[19] are produced by ISRIC – World Soil Information (legally registered as the International Soil Reference and Information Centre) and use state-of-the-art machine learning methods to map the spatial distribution of soil properties across the globe. The prediction models are fitted using over 230,000 soil profile observations and a series of environmental covariates including climate, land cover, and terrain morphology. SoilGrids global soil property maps include data at six standard depth intervals at spatial resolution of 250 m. Prediction uncertainty is quantified by the lower and upper limits of a 90 percent prediction interval. The additional uncertainty layer is the ratio between the inter-quantile range and the median[20]. The SoilGrids maps are publicly available under the CC-BY 4.0 License.

Maps of the following soil properties are available: pH, soil organic carbon content, bulk density, coarse fragments content, sand content, silt content, clay content, cation exchange capacity (CEC), total nitrogen, soil organic carbon density and soil organic carbon stock. This soil organic carbon stock data is currently available in Trends.Earth for the computation of the SDG 15.3 land degradation indicator [5,102].

V.5.1.7. WorldPop

See Section V.3.1.6 for a description of WorldPop data.

V.5.1.8. Global Human Footprint

The Global Human Footprint Dataset was developed by the Wildlife Conservation Society and CIESIN in 2005. Now in its second version, this spatially gridded dataset of 1 km resolution reflects the Human Influence Index (HII) created from nine global data layers covering human population pressure, land use, infrastructure, and access, all normalized by biome and realm spanning from the time period of 1995-2004.

V.5.1.9. Baseline Water Stress (BWS)

The Baseline Water Stress (BWS) layer, developed as part of the World Resources Institute's (WRI's) Aqueduct Water Risk Atlas, is an indicator that measures the ratio of total water withdrawals relative to the annual available renewable surface water supplies. A higher percentage means more water users are competing for limited water supplies, with percentages typically ranked following **Table 11**. This dataset is available globally at the national and subnational levels (except for Greenland and Antarctica). One significant disadvantage of this dataset is that it is at this time over 10 years outdated, with no indication of future releases by which the United Nations or member nations could rely on it for monitoring and reporting of UNCCD SOs. This dataset does not allow gender disaggregation.

Table 11. Baseline Water Stress (withdraws / available flow).

Low	< 10%
Low to medium	10 – 20 %
Medium to high	20 – 40 %
High	40 – 80 %
Extremely high	> 80 %
Arid & low water use	Available blue water and water withdrawal less than 0.03 and 0.012 m/m2 respectively

19 https://www.isric.org/explore/soilgrids

20 https://soilgrids.org

V.5.1.10. World Database on Protected Areas (WDPA)

The World Database on Protected Areas (WDPA) is a global spatial dataset on terrestrial and marine protected areas (**Table 4**). The WDPA is a joint project between UN Environment Programme (UNEP) and the International Union for Conservation of Nature (IUCN). The compilation and management of the WDPA is carried out by UNEP World Conservation Monitoring Centre (UNEP-WCMC), in collaboration with governments, non-governmental organizations, academia and industry. The data are updated monthly and are made available online through the Protected Planet website where the data are both viewable and downloadable as a shapefile of polygons, among other non-spatial formats.

V.5.2. Economic

V.5.2.1. Geographically based Economic data (G-Econ)

The Global Gridded Geographically Based Economic Data (G-Econ) was originally produced by Yale University and later enhanced by CIESIN. Now in its 4th version, this dataset contains derived one-degree grid cells (~111 km resolution at the equator) of Gross Domestic Product (GDP) data for both Market Exchange Rate (MER) and Purchasing Power Parity (PPP) for the years 1990, 1995, 2000 and 2005. MER is the exchange rate between local and U.S. dollar currencies for a given time interval established by the market. PPP is the exchange rate between a country's currency and U.S. dollars adjusted to reflect the actual cost in U.S. dollars of purchasing a standardized market basket of goods in that country using the country's currency.

V.5.2.2. FAOSTAT Food Security Indicators

The FAOSTAT Food Security Indicators provide data relating to food availability, access, stability, and utilization at the national level from 2000 - 2020. The indicators are revised annually based on the new information received from nations and international organizations. Statistics are subject to the general quality assurance framework of FAO with accuracy varying by indicator depending on the sampling design and size and accuracy

Table 12. Metrics included in the FAOSTAT Food Security Indicators database.

AVAILABILITY	
Average dietary energy supply adequacy	Percent (3-year average)
Average value of food production	Constant 2004-2006 i$/cap (3-year average)
Dietary energy supply used in the estimation of prevalence of undernourishment	Kcal/cap/day (3-year average)
Share of dietary energy supply derived from cereals, roots, tubers	Kcal/cap/day (3-year average)
Average protein supply	g/cap/day (3-year average)
Average supply of protein of animal origin	g/cap/day (3-year average)
ACCESS	
Rail line densities	Total route in km per 100 km2 of land
Gross domestic product per capita, PPP, dissemination	Constant 2011 international $
Prevalence of undernourishment	Percent
Number of people undernourished	Million
Prevalence of severe food insecurity in the total population	Percent
Prevalence of moderate of severe food insecurity in the total population	Percent
Number of severely food insecure people	Million
Number of moderately or severely food insecure people	Million
STABILITY	
Cereal import dependency ratio	Percent (3-year average)
Percent of arable land equipped for irrigation	Percent (3-year average)
Value of food imports in total merchandise exports	Percent (3-year average)
Political stability and absence of violence/terrorism	Index
Per capita food production variability	Constant 2004-2006 thousand international $ per capita
Per capita food supply variability	Kcal/cap/day
UTILIZATION	
Percentage of population using safely managed drinking water services	Percentage
Percentage of population using a least basic drinking water services	Percentage
Percentage of population using safely managed sanitation services	Percentage
Percentages of population using at least basic sanitation services	Percentage
Percentage of children under 5 years of age affected by wasting	Percentage
Percentage of children under 5 years of age who are stunted	Percentage
Percentage of children under 5 years of age who are overweight	Percentage
Prevalence of obesity in the adult population (18 years and older)	Percentage
Prevalence of anemia among women of reproductive age (15 – 49 years)	Percentage
Prevalence of exclusive breastfeeding among infant 0-5 months of age	Percentage
Prevalence of low birthweight	Percentage

of the basic variables that make up the indicator. The data are reasonably comparable over time by country if methodology and classification have not changed, but there is limited geographic comparability between countries. The complete list of indicators and their associated measurements included in this dataset are shown in **Table 12**. The prevalence of moderate and severe food insecure of the total population is computed using the Food Insecurity Experience Survey (FIES, **Figure 9**).

Figure 9. The Food Insecurity Experience Scale (FIES) questionnaire.

During the last 12 months, was there a time when, because of lack of money or other resources:
1. You were worried you would not have enough food to eat?
2. You were unable to eat healthy and nutritious food?
3. You ate only a few kinds of foods?
4. You had to skip a meal?
5. You ate less than you thought you should?
6. Your household ran out of food?
7. You were hungry but did not eat?
8. You went without eating for a whole day?

V.5.2.3. NASA Food Insecurity Hotspots Dataset v1

The Food Insecurity Hotspots Dataset is produced by NASA SEDAC and hosted at CIESIN. This dataset contains the level of intensity and frequency of food insecurity over the 10 years between 2009 and 2019, as well as hotspot areas that have experienced consecutive food insecurity events, based on FEWS NET Food Security Data. The gridded data (250 x 250 m) are based on subnational food security analysis provided by FEWS NET (Famine Early Warning Systems Network) for selected countries in five regions including Central America and the Caribbean, Central Asia, East Africa, Southern Africa, and West Africa. The classification is based on the Integrated Food Security Phase Classification (IPC), where food insecurity is defined as Minimal, Stressed, Crisis, Emergency, and Famine. This dataset is updated as needed, making it difficult to rely on planned releases. The biggest advantage of this dataset is that it is gridded, and thought it does not cover the entire globe, it is focused on regions that are likely to experience food insecurity.

Table 13. Dimensions, Indicators, Deprivation Cutoffs, Weights and SDG Areas addressed in the Multi-Dimensional Poverty Index (MPI). Source: OPHI (2018). Global Multidimensional Poverty Index 2018: The Most Detailed Picture to Date of the World's Poorest People**. Oxford Poverty and Human Development Initiative, University of Oxford.**

DIMENSIONS OF POVERTY	INDICATOR	SDG AREA	DEPRIVED IF...	WEIGHT
Health (1/3)	Nutrition[1]	SDG 2	Any person under 70 years of age for whom there is nutritional information is undernourished.	1/6
	Child Mortality[2]	SDG 3	Any child has died in the family in the five-year period preceding the survey.	1/6
Education (1/3)	Years of Schooling[1]	SDG 4	No household member aged 10 years or older has completed six years of schooling.	1/6
	School attendance[3]	SDG 4	Any school-aged child* is not attending school up to the age at which he/she would complete class 8.	1/6
Living Standards (1/3)	Cooking Fuel	SDG 7	A household cooks with dung, agricultural crop, shrubs, wood, charcoal, or coal.	1/18
	Sanitation[4]	SDG 11	The household's sanitation facility is not improved (according to SDG guidelines) or it is improved but shared with other households.	1/18
	Drinking Water[5]	SDG 6	The household does not have access to improved drinking water (according to SDG guidelines) or safe drinking water is at least a 30-minute walk from home, roundtrip.	1/18
	Electricity	SDG 7	The household has no electricity.	1/18
	Housing[6]	SDG 11	The household has inadequate housing: the floor is of natural materials or the roof or walls are of rudimentary materials.	1/18
	Assets	SDG 1	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck.	1/18

1 Adults 20 to 70 years are considered malnourished if their Body Mass Index (BMI) is below 18.5 m/kg. Those 5 to 20 are identified as malnourished if their age-specific BMI cutoff is below minus two standard deviations. Children under 5 years are considered malnourished if their z-score of either height-for-age (stunting) or weight-for-age (underweight) is below minus two standard deviations from the median of the reference population. In a majority of the countries, BMI-for-age covered people aged 15-19 years, as anthropometric data was only available for this age group; if other data were available, BMI-for-age was applied for all individuals above 5 years and under 20 years.

2 Child mortality draws on information from women aged 15-49. If this information is missing, and if the male in the household age 15-59 reports no child mortality, that record is included.

3 Data source for age children start compulsory primary school: DHS, MICS and national country reports, United Nations Educational, Scientific and Cultural Organization, Institute for Statistics database, Table 1. Education (full dataset) [UIS: http://data.uis.unesco.org/].

4 A household is considered to have access to improved sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared. If survey report uses other definitions of "adequate" sanitation, we follow the survey report.

5 A household has access to clean drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring or rainwater, and it is within 30 minutes' walk (round trip). If survey report uses other definitions of "safe" drinking water, we follow the survey report.

6 Deprived if floor is made of mud/clay/earth, sand, or dung; or if dwelling has no roof or walls or if either the roof or walls are constructed using natural materials such as cane, palm/trunks, sod/mud, dirt, grass/reeds, thatch, bamboo, sticks, or rudimentary materials such as carton, plastic/polythene sheeting, bamboo with mud/stone with mud, loosely packed stones, adobe not covered, raw/reused wood, plywood, cardboard, unburnt brick, or canvas/tent.

V.5.2.4. Multidimensional Poverty Index – MPI

The Multidimensional Poverty Index (MPI) is an international measure of acute multidimensional poverty covering over 100 Low- and Middle-Income Countries (LMIC). The MPI was proposed by Alkire and Foster [103](2007) –and then further described in Alkire and Santos [104,105] - as a result of a joint effort of the Oxford Poverty and Human Development Initiative (OPHI), University of Oxford and the Human Development Report (HDR) from the Office of the UNDP. It has been published annually by OPHI and in the HDRs since 2010 [106].

The MPI assesses poverty at the individual level, measuring deprivation instead of possession and "shows the number of people who are multidimensionally poor (suffering deprivations in 33% of weighted indicators) and the number of deprivations with which poor households typically contend" [106]. Detailed methodology of assembling the MPI can be found in Alkire and Santos [104]. The MPI ranges between 0 and 1, where 0 is multidimensionally not deprived and 1 is multidimensionally deprived. The DHS questionnaires typically report all the necessary information needed to create the MPI, with some exceptions for older surveys. Using the DHS microdata, the index can be constructed by different population subgroups at household or cluster level as well as at higher levels (Region, Country). It can be also decomposed by dimension to show how the structure of poverty differs between different groups.

V.5.3. Demographic Health Surveys (DHS) Wealth Index

The Demographic and Health Surveys (DHS) wealth index is a composite measure of a household's cumulative living standard, based on data collected in the DHS Household Questionnaire. This questionnaire includes questions concerning the household's ownership of several consumer items such as a television, bicycle, car; dwelling characteristics such as flooring material; type of drinking water source; toilet facilities; and other characteristics that are related to wealth status. The DHS Wealth Index is generated using a statistical procedure known as Principal Components Analysis (PCA) where individual households are placed on a continuous scale of relative wealth. The resulting asset scores are standardized in relation to a standard normal distribution with a mean of zero and a standard deviation of one. These standardized scores are then used to create the break points that define wealth quintiles as: Lowest, Second, Middle, Fourth, and Highest. Each quintile value can be reproduced as a weighted average of urban/rural rates (weighted by proportions urban/rural) or the male/female rates (weighted by the proportion male/female). The Wealth Index is presented in the DHS Final Reports and survey datasets as a background characteristic. While the DHS Wealth Index is calculated using household characteristics, it is available at the individual level for men, women, and children up to 5 years old within each respective household. Further the Wealth Index can be summarized at the household-cluster level (point format), first subnational level and national level (polygon format). Specific information on the calculation of the wealth index for each DHS, including the syntax used and the factor loadings can be found in the Wealth Index Construction Page [107,108].

V.5.4. Social

V.5.4.1. Demographic and Health Surveys (DHS)

Since 1984, the Demographic and Health Surveys (DHS) Program has collected, analyzed and disseminated data on areas such as fertility, family planning, maternal and child health, gender, HIV/AIDS, malaria and nutrition through more than 400 surveys in over 90 countries, primarily in LMIC [109] The DHS program is funded by the U.S. Agency for International Development (USAID) with contributions from other donors and individual countries and is implemented by ICF, Incorporated.

The DHS collects and provides cluster-randomized survey data by first-order sub-national regions (for example at province or state level) and urban/rural strata. More recent surveys now provide geocoded data for individual household-clusters. The availability of GPS coordinates for DHS clusters provides highly resolved locational information that can be linked with other geospatial variables for further analysis.

Of the variables included, we selected Adult Literacy Rate as a measure of individual human development; this indicator was also used in Naumann et al [49].

V.5.4.2. World Development Indicators (WDI)

World Development Indicators (WDI)[21] is the primary World Bank collection of development indicators, compiled from officially recognized international sources. It presents the most current and accurate global development data available, and includes national, regional, and global estimates. In many cases, this represents the best available source of information that countries could use for deriving socio-economic indicators or can be used as validation for other data sources.

V.5.4.3. WorldPop

See Section V.3.1.6 for a complete description of WorldPop data. In addition to the gender disaggregation strength already discussed, WorldPop can additionally be disaggregated by age. The metric we have selected, "population between ages 15 – 64, is a measure of the working population, or the population contributing to the labor market.

V.5.4.4. World Governance Indicators

The Worldwide Governance Indicators (WGI) project reports aggregate and individual governance indicators for over 200 countries and territories over the period 1996–2019, for six dimensions of governance including political stability and absence of violence, government effectiveness, regulatory quality, voice and accountability, rule of law, and control of corruption. These aggregate indicators combine the views of many enterprises, citizen, and expert survey respondents in industrial and developing countries. They are based on over 30 individual data sources produced by a variety of survey institutes, think tanks, non-governmental organizations, international organizations, and private sector firms. Available at the national level, this dataset is the only one we were able to locate that represents this data type. Because national governance is inherently a national-level metric, the necessity for a lower level of spatial resolution is not necessary. We have selected the government effectiveness score that was used in Carrão et al. [20].

V.5.4.5. WHO "Data Integration Model for Air Quality (DIMAQ))

The World Health Organization (WHO) Data Integration Model for Air Quality (DIMAQ) is reported to be freely available at a spatial resolution of 0.1-degrees and include uncertainty estimates that are not available in alternate air quality datasets. Including gridded data on estimates of uncertainty is beneficial to decision-makers because the number of ground-based sensors varies widely across locations, making uncertainty variable and uneven, and the estimates more reliable in some regions than others. However, the website currently seems to have only country-level data available; despite a thorough investigation we were unable to locate the gridded data, ranking this dataset low in terms of "ease of access". Additionally, the update frequency for this dataset is uncertain. This would have been our recommended dataset for air quality due to the inclusion of uncertainty information, but due to difficulty of access and update uncertainty we recommend the NASA SEDAC Global Annual PM 2.5 Grids, described next.

V.5.4.6. NASA SEDAC Global Annual PM 2.5 Grids

The NASA SEDAC "Global Annual PM 2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, v1 (1998–2016)" data is available at 0.1-degree spatial resolution. It does not include uncertainty estimates as does the WHO DIMAQ data, but is our recommended air quality dataset since it is expected to be updated on a regular basis and is much easier to locate and access in a spatially gridded format than DIMAQ. The data values are given in micrograms per cubic meter of ground-level fine particulate matter (PM2.5).

V.5.5. Infrastructural

V.5.5.1. WASH

Established in 1990, the World Health Organization/United Nations Children's Fund (WHO/UNICEF) Joint Monitoring Program (JMP) global database includes estimates of progress in household drinking

21 https://databank.worldbank.org/source/world-development-indicators

Table 14. WHO/UNICEF Joint Monitoring Program indicators used for global monitoring of WASH service levels in households.

<table>
<tr><th>SERVICE TYPE</th><th colspan="2">JMP SERVICE LADDERS</th></tr>
<tr><td rowspan="5">Drinking Water

1. Improved or unimproved; surface water

2. Basic & limited services

3. Safely managed services

3a – accessibility

3b – availability

3c – quality</td><td>Safely Managed</td><td>Drinking water from an improved water source that is located on premises, available when needed and free from faecal and priority chemical contamination</td></tr>
<tr><td>Basic</td><td>Drinking water from an improved source, provided collection time is not more than 30 minutes for a round trip, including queuing</td></tr>
<tr><td>Limited</td><td>Drinking water from an improved source for which collection time exceeds 30 minutes for a round trip, including queuing</td></tr>
<tr><td>Unimproved</td><td>Drinking water from an unprotected dug well or unprotected spring</td></tr>
<tr><td>Surface Water</td><td>Drinking water directly from a river, dam, lake, pond, stream, canal or irrigation canal</td></tr>
<tr><td colspan="3"></td></tr>
<tr><td rowspan="5">Sanitation

1. Improved or unimproved; open defecation

2. Basic & limited services

3. Safely managed Services

3a – emptying of on-site facilities

3b – treatment and disposal of excreta from onsite facilities

3c – treatment of wastewater</td><td>Safely Managed</td><td>Use of improved facilities that are not shared with other households and where excreta are safely disposed of in situ or transported and treated offsite</td></tr>
<tr><td>Basic</td><td>Use of improved facilities that are not shared with other households</td></tr>
<tr><td>Limited</td><td>Use of improved facilities shared between two or more households</td></tr>
<tr><td>Unimproved</td><td>Use of pit latrines without a slab or platform, hanging latrines or bucket latrines</td></tr>
<tr><td>Open Defecation</td><td>Disposal of human feces in fields, forests, bushes, open bodies of water, beaches or other open spaces, or with solid waste</td></tr>
<tr><td colspan="3"></td></tr>
<tr><td rowspan="3">Hygiene

1. Facility or no facility

2. Basic & limited handwashing facility</td><td>Basic</td><td>Availability of a handwashing facility on premises with soap and water</td></tr>
<tr><td>Limited</td><td>Availability of handwashing facility on premises without soap and water</td></tr>
<tr><td>No Facility</td><td>No handwashing facility on premises</td></tr>
<tr><td colspan="3"></td></tr>
<tr><td>Menstrual Hygiene

1. Special attention to the needs of women and girls

1a – private place to wash and change

1b – use of menstrual hygiene products

1c – exclusion due to menstruation</td><td></td><td></td></tr>
</table>

water, sanitation, and hygiene since 2000 that have been calculated from data produced by national authorities. The JMP monitors Water, Sanitation, and Hygiene (WASH) at the household level in addition to schools and health care facilities, with reporting focused on inequalities in service levels between rural and urban, sub-national regions, and rich and poor and other population sub-groups where data permit. The JMP database includes over 5,000 national data sources with information on WASH in households including nationally representative household surveys, censuses, and administrative reports.

JMP uses a standardized classification and estimation method to facilitate comparisons between countries, regions, and the world (**Table 14**). Estimations start with the identification of nationally representative data pertaining to water use and sanitation and the prevalence of handwashing facilities in the home. Administrative data and household surveys are used to incorporate service level data. Data harmonization is supported using a set of core questions for water, sanitation, and hygiene[22]. Then, a simple linear regression is used to estimate the populations using different levels of services using the JMP ladders.

V.5.5.2. Demographic and Health Surveys (DHS) safe drinking water access

The main source of drinking water for members of each household is collected through the Demographic and Health Survey and classified as improved and unimproved sources, following the WHO/UNICEF Joint Monitoring Programme (JMP) on Water and Sanitation guidelines[23]. Improved water sources include piped water into the dwelling, yard, or plot; a public tap/standpipe or borehole; a protected well or protected spring water; rainwater; and bottled water. Unimproved water sources include unprotected wells or springs, water delivered by tanker trucks, and surface water. Pertinent indicators depicting source of drinking water are in a form that can be gender-disaggregated and summarized into georeferenced clusters of households contained within each respective country's first sub-national administrative units.

V.5.5.3. FAO's Global Map of Irrigation Areas

The Global Map of Irrigation Areas (**Table 4**) was produced by the FAO and shows the amount of area equipped for irrigation around the year 2005 in percentage of the total area on a raster grid with a resolution of 5 arc-minutes (~10 km at the equator). Additional map layers show the percentage of the area equipped for irrigation that was used for irrigation and the percentages of the area equipped for irrigation that was irrigated with groundwater, surface water or non-conventional sources of water.

V.6. Recommendations on datasets for monitoring drought vulnerability

One of the largest challenges in mapping drought vulnerability in a spatially explicit manner is the lack of gridded data. Some relevant data is only available at the country level or as sub-national polygons. We recommend that the datasets chosen for the comprehensive vulnerability index should address multiple facets of drought vulnerability including effects on ecological, economic, infrastructural, and social dimensions. In **Table 6** we present a comprehensive index based on these dimensions that defines not only the recommended datasets, but the specific metrics that are relevant within these datasets and their overall effect on vulnerability to drought (i.e.,. when a value for a metric increases, will vulnerability increase or decline?). The specific metrics and the dimension which they represent were defined based on extensive literature review of drought vulnerability literature as previously described, with our recommendations for datasets representing our best attempt to locate gridded or sub-national data. However, because some metrics have yet to be mapped at anything below country level, we also include a limited number of country-level datasets within our recommendations. We suggest that these data be tested before implementation and recommend that nations replace the proposed country level datasets with sub-national or gridded data if they are available. Furthermore, we recommend that governments, not-for-profit organizations, and academia develop

22 https://washdata.org/report/jmp-2018-core-questions-household-surveys

23 http://www.unwater.org/publication_tag/jmp/

datasets or methods for deriving sub-national or gridded data for key variables that currently only exist at the country level.

One other challenge in terms of the datasets presented is the capacity for gender disaggregation. As only WorldPop, GPWv4, MPI, and DHS data have a gender disaggregable component, we recommend that progress towards SO3 should take advantage of these datasets where they are available and relevant to the analysis; additionally, we recommend the exploration of additional methods for gender disaggregation of other data types. Using water data as an example, gender disaggregation of individual indicators can utilize the United Nations Educational, Scientific, and Cultural Organization (UNESCO) World Water Assessment Programme (WWAP) Toolkit on Sex-Disaggregated Water Data, as currently the majority of the water-related indicators presented here are not in a form that can be gender-disaggregated [110].

VI. Recommendations on Monitoring Progress Towards SO3

Within this section, we discuss final recommendations on the integration of global and country specific geospatially explicit datasets on climatological and socio-economic indicators with bearing on SO3 and associated expected impacts in Trends.Earth.

Importantly, drought mitigation towards reducing vulnerability and increasing resilience is a matter of national security in many countries disproportionately impacted by climate change and variability. In reducing their vulnerability to drought and land degradation, countries are increasingly considering and implementing sustainable land and water management practices and have the unique opportunity to leverage and learn from other member countries through networks such as the World Overview of Conservation Approaches and Technologies (WOCAT), a notable project partner working collaboratively with Trends.Earth.

This report provides a summary review of the publicly available global geospatial datasets and pertinent variables and indices therein that enable the assessment of Strategic Objective (SO3) of the UNCCD 2018-2030 Strategic Framework, and its two expected impacts: *Ecosystems' vulnerability to drought is reduced, including through sustainable land and water management practices* (SO3.1), and *Communities' resilience to drought is increased* (SO3.2). Our overall summary recommendation is that Trends.Earth supports a comprehensive framework for monitoring drought vulnerability that builds on exposure of populations to drought hazard and captures factors from social, infrastructural, economic, and ecosystem components. To the extent that it is feasible, and data are available, we recommend that the datasets used are contemporary, spatially gridded, or sub-national, and gender-disaggregable and that the chosen indicators are generic and valid for any region. However, in keeping with the existing UNCCD vulnerability framework, we did not include recommendations on incorporating and quantifying sensitivity and adaptive capacity, two important mitigating factors of vulnerability with bearing on resilience considered key by the IPCC in their reporting and assessments and we advise that further consideration from the UNCCD be given to this in future iterations of its vulnerability framework.

VI.1. Expected impact 3.1: Ecosystems' vulnerability to drought is reduced, including through sustainable land and water management practices

The sustainable management of land and water resources to accomplish a reduction in ecosystem and population vulnerability and increase resilience to drought, land degradation, and desertification (DLDD) can be done only through collaborative efforts that, on the one hand, are supported by freely available global geospatial datasets, and, on the other hand, are led by bottom-up, community-driven efforts to manage and steward sensitive resources and ecosystems. Since drought is often a natural occurrence, it cannot be avoided entirely, though it is possible in some instances to reduce associated land and water resource degradation. Nations and individuals can potentially limit the frequency and severity of drought with sustainable land management that reduces carbon emissions, deforestation, wetland loss, and other drivers of climate change. However, in the context of global consumption pathways, sustainable land management to reduce carbon emissions falls short, and from the perspective of developing nations, this does not map the full picture. In cases like this, the concept of resilience and the aspect of vulnerability adopted by the UNCCD framework is very useful in analyzing the underlying socio-economic drivers that make a society more or less vulnerable to the effects of drought.

Below we discuss some ways that integrated land and water management, community, and ecosystem vulnerability can be measured and monitored.

VI.1.1. Ecosystem vulnerability (SO3-1)

Ecosystem vulnerability is a matter of serious concern to nations worldwide. Using our proposed integrative vulnerability framework that incorporates common measures of land management and quality (see **Figure 8**) in tandem with additional covariates on ecosystem use and protection, such as the WDPA[24], we can begin to devise measures of ecosystem vulnerability. Especially when combined with measures of human pressure or population density using, e.g., WorldPop, and their relative changes over time and the relative level of sustainability and protection afforded by each management activity, we can begin to quantify, in a globally consistent and standardized approach, the level of resilience of various ecosystems of global importance. A drought hazard index such as SPI could be a useful starting point; it accounts for timing when it is calculated for multiple points in time and intensity based on the Global Drought Index (GDI) drought hazard categories. Subsequently, using a vegetation index like NDVI, two-band Enhanced Vegetation Index (EVI2), or the Modified Soil-Adjusted Vegetation Index (MSAVI), and especially multi-step temporal changes in those vegetation indices (VI) would provide a measurement of vegetation condition as a proxy for land management practices (VIs will have low values where vegetation is in poor health or low density). Because VIs assesses both natural and human systems, their use has implications for management in agricultural systems, managed forests, rangelands, and other human-environment systems. NDVI is a logical choice since it is widely used and featured in Trends.Earth, with EVI2 showing substantial promise for improved monitoring [102].

In addition, Water Use Efficiency (WUE) is useful in calibrating vegetative productivity time series to separate the impacts of climate and land use/management activities [111]. WUE is quantified as the ratio of above-ground net primary productivity (ANPP) to evapotranspiration – this provides a measure of insight into the ecological functioning of the land surface and determines how AANP across biomes may respond to alterations in hydroclimatic conditions induced by drought. AANP can be represented by a VI such as NDVI or EVI, with EVI exhibiting better correlation with WUE time series.

VI.1.2. Sustainable land & water management (SO3-1)

VI.1.2.1. Sustainable water management (SO3-1)

In addressing the goal of sustainable water resources management, aside from the datasets discussed at length in the prior section of this report, additional datasets can rely on the use of remotely sensed terrestrial water data from the NASA satellite GRACE. GRACE-derived datasets can be used to study reservoir levels, groundwater resources availability or depletion rates, and would provide a first approximation for more complex drought factors as it would be more closely tied to hydrological and socioeconomical drought which are more difficult to quantify and for which there are much fewer global spatially explicit datasets available. GRACE would be a good choice since it also can help assess both ecosystem and community vulnerability (through terrestrial water losses due to drought in wetlands, reservoirs, etc.).

Moreover, many studies have assessed water management using secondary derived datasets typically available at the country level, including Carrão et al. [20]. The principal dataset used for this was the FAO's Aquastat, which provides a global information system on water resources especially focused on agricultural water management[25]. Several variables available in Aquastat address both land and water management. Users can choose to focus on respective indicators depending on their reporting thematic focus and geographic scale.

VI.1.2.2. Sustainable land management (SO3-1)

The sustainable management of lands and associated water resources is an important consideration for the Tools4LDN project overall as evidenced by the inclusion of the World Overview of Conservation Approaches and

24 https://www.protectedplanet.net/en/thematic-areas/wdpa

25 http://www.fao.org/aquastat/en/

Technologies (WOCAT) as a project partner. Launched in 1992, WOCAT has been spearheading efforts to compile, document, evaluate, share, disseminate, and apply sustainable land management (SLM) knowledge with users globally. As such, the toolsets, approaches, datasets, and resources available in the WOCAT partner repository represent an important component of SLM implementation, monitoring and reporting. In addition, exploratory, globally available data-driven approaches such as the World Food Programme - Vulnerability Analysis and Mapping (WFP-VAM) [124] represent an important starting point for assessing the performance of the current and past rainfall seasons, the timing and intensity of drier or wetter than average conditions, and their impact on vegetation status, thus allowing for the establishment of baseline condition assessment. As with ecosystem vulnerability monitoring, a hazard index such as SPI would be a logical start, followed by a vegetation index such as NDVI to monitor changing vegetation vitality to serve as a proxy for land management practices. Since NDVI can be used for both natural and human systems, it is suitable for monitoring the management of agricultural systems, managed forests, rangelands, and other human-environment systems [102]. Due to the correlation between drought and ecosystem health, by employing good land management practices such as those discussed in detail in the WOCAT database, communities can work towards reducing their vulnerability to the effects of drought on local ecosystems. Monitoring change would enable users to ascertain if a given place or region is less impacted or suffers no effect from a drought occurrence following the implementation of land management practices; where before the land management practices were implemented there were negative effects.

VI.1.3. An integrated SO3-1 index

The integrated vulnerability index we propose in this report combines **hazard**, defined as the spatiotemporal quantification of climatic and drought characteristics by drought intensity classes, **human exposure**, defined as the proportion of human populations experiencing drought, **ecosystem exposure**, defined as the proportion of ecosystems by area experiencing drought, and **vulnerability**, defined as the degree to which populations and socio-economic sectors are affected by drought exposure (**Figure 8**). Vulnerability is therefore conceptualized as the overlap of hazard and human exposure by population and gender or ecosystem exposure by type and area and integrates social/ecological/economic/infrastructural components as shown in **Table 6**.

VI.2. Expected impact 3.2: Communities' resilience to drought is increased

The combination of hazard, exposure, and various ecological, socio-economic, and infrastructural components outlined in our **Figure 8** highlights the state-of-the-art knowledge on population and ecosystem vulnerability to DLDD and proposes a way forward for effective integration, as copiously illustrated throughout the report. In our report we discuss the advantages and disadvantages to using global geospatially-explicit datasets to analyze the proportion of land, ecosystems and populations (and their approximate gender breakups) exposed to drought and land degradation, as well as the effects of drought on ecological, social, economic, and infrastructural sectors of countries' economies through integrated indices that combine precipitation, temperature and soil moisture datasets with socio-demographic and poverty metrics. While the freely accessible, global, and relatively reliable temporal and spatial resolution geospatial datasets recommended in this report are an important step forward towards improving reporting on SO3.1 and 3.2 in an integrative vulnerability framework, we also caution that the proposed vulnerability framework presented has limitations. Specifically, there is ample literature focused on the dimensions and operationalization of vulnerability that rely on conceptualizations of sensitivity and adaptive capacity as metrics that modify and mitigate a population or ecosystem's vulnerability to DLDD. In this report, we are condensing those two concepts of sensitivity and adaptive capacity into vulnerability in line with UNCCD partner work that does not explicitly account for them.

Another important concept with bearing on reducing community vulnerability and increasing resilience is ecological drought. Ecological drought is still something of an emerging area of research with much of the context centered around coupled human and natural systems (CHANS) and thus explicit links to vulnerability, sensitivity, adaptive capacity, and exposure calculated from spatio-temporally explicit datasets. There are also feedbacks between degraded ecosystems and drought, such as between vegetation degradation and changes in evapotranspiration regimes, which can initially reduce but then cause further drying of air and soils and lead to more degraded conditions, prolonged periods of drought and a potentially inescapable positive feedback loop of drought and degradation. Areas with low precipitation are particularly vulnerable to drought and desertification as vegetation becomes a non-renewable resource, unlike areas where high precipitation leads to rapid vegetative regeneration. Therefore, low rainfall and high temperatures make certain geographic regions more prone to land degradation. Even slightly higher rates of anthropogenic and livestock pressure can lead to rapid degradation and subsequent desertification.

VI.2.1. SO3-2 community resilience

As droughts continue to increase in frequency and severity, the need to understand community vulnerability and resilience to drought is only growing. Social scientists have extensively researched climate change and drought impacts on communities and households, community ability to respond successfully to environmental changes (including degradation) and resulting varying levels of vulnerability, as well as actual responses to these impacts that lead to varying levels of community resilience. What remains less clear is to what extent and under what circumstances various combinations of human behaviors and activities, across the SDG suite of objectives, provide optimal resilience and to what extent and under what conditions this community resilience feeds back into the local ecology to provide enhanced ecosystem resilience. To increase our understanding of the complex processes underlying communities' response to drought impacts, there is a need to incorporate open-source gender-disaggregated gridded population datasets and socio-economic variables (such as the MPI), where available. Since drought is a natural climatic occurrence, we cannot completely eliminate or eradicate its effects, but we can reduce associated land degradation and impacts on humans and ecosystems by developing our understanding of spatially disaggregated socio-economic and demographic vulnerability datasets and indicators that support the development of resilience pathways. One can then associate gridded population distributions with ecosystem-based outcomes to make inferences about human behaviors and activities towards determining to what extent and under what conditions this resilience influences land management. In so doing, we can potentially limit the impact of drought with good land management that reduces carbon emissions, deforestation, wetland loss, or other drivers of climate change.

Finally, in order to decrease community vulnerability to drought, we must ultimately address the "vulnerability drivers" or the causes of the relative vulnerability as well as the coping capacity or the ability of communities to adapt [112]. Many resilience building efforts globally have suggested that piecemeal incremental adjustments are insufficient, and that adaptation should consider systemic transformations that address deep-rooted structures and processes influencing social vulnerability by restructuring across various political-economic and environmental contexts [112]. To maximize community resilience and to create enduring resilience plans, necessary local capacity and skillsets must be developed (see, e.g., Moser [29]) based on drought and degradation monitoring that can inform policies and programs.

VI.3. Limitations, attribution, and future considerations

The measures, indices, and databases presented here are intended to serve as best practices for monitoring SO3 using Trends.Earth. The selection criteria are purposefully narrow: global coverage, sufficient temporal resolution to measure change meaningfully, sufficient spatial scale to measure sub-national patterns, and the capacity for gender disaggregation, among others. These criteria are intended to increase uniformity and standardization for all UN member nation end users. However, available data that meet these criteria are relatively few and this is especially the case for human data. We therefore highlight the importance of member nations and end users to review this report in the context of the variability in data availability and ability to process data from one place to another. This report focuses on what is possible globally but does not elaborate on what may be possible in places where richer data relating to SO3 targets are available. While we discuss some of these cases in the report, a case-by-case assessment should be made for each end user's context and needs.

Given that the data is an imperfect reflection of reality, the context is important to understand potential attribution of degradation and drought and their relative effects on ecosystems and people. Take the case of SO3.1, sustainable land management. If analysis of the time series of VIs suggests an increase in biomass or landscape greenness over time accompanied by a change in land management, it can be inferred that the land management may have played a role in the greening signal measured via remote sensing. However, that signal alone may not be enough to determine a causal or correlative attribution between greening and land management. Other factors would need to be accounted for, including trends in SPI, SSI, and an on-the-ground understanding of the land management to, at least qualitatively, suggest attribution. Would our knowledge of human-land systems suggest that the given land management change would increase greening? If so, it would appear more likely that the land use change was a driver of the VIs of ecosystem health. Or, if the land use would anticipate landscape browning, why was the converse observed? These are the kinds of critical contextual questions that must be included when assessing the relative attribution of management systems to change (or stasis) in ecosystem vulnerability. In some places, vegetation greening is actually driven by drought (for instance, woody encroachment in savannas may appear in remote sensing data as greening but could actually be leading to less productivity and higher vulnerability for people and ecosystems who both cannot access necessary resources. Similarly, increased irrigation can increase NDVI during a drought period - this has happened in fact in recent years in parts of Northern Mexico. No measure currently exists that is an unassailable, direct, one-to-one relationship among all the complex components that comprise human and ecosystem vulnerability and resilience. Context is critical.

Potential exists for enhancing monitoring of the UNCCD's Strategic Objectives. This report focuses on how monitoring in support of SO3 can be improved based on freely available global data. There is potential for new data sources and the improvement of existing ones. Remotely sensed imagery has vastly improved over the past couple of decades and will likely permit a spatial granularity that would have seemed unimaginable a few years ago, with considerably high-resolution remote sensing data currently available commercially. As technology advances, today's expensive cutting-edge products will be tomorrow's publicly available data. But there is also the opportunity to innovate, leveraging extant publicly available datasets, such as those presented here. Various spatial statistical methods enable the conversion of data of relatively low spatial resolution to data of higher resolution, with associated location-specific data value probability ranges. Despite ongoing challenges of data scarcity in some remote rural areas within nations, future efforts could usefully develop and disseminate a tool, along with best practices for its use, that enhances the spatial coverage of some of the data presented here.

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