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Operationalizing an integrative socio-ecological framework in support of global monitoring of land degradation

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Abstract

Despite sustained global efforts to avoid, reduce, and reverse land degradation, estimates of land degradation nationally and regionally vary considerably. Land degradation reduces agricultural productivity, impacts the provision of vital ecosystem services, and disproportionately affects vulnerable populations. The 2030 Agenda for Sustainable Development, through Sustainable Development Goal 15.3, sets out to achieve land degradation neutrality (LDN) by improving the livelihoods of those most affected and building resilience in areas affected by or at risk from degradation. The United Nations Convention to Combat Desertification (UNCCD) leads the charge in creating a spatially explicit framework for monitoring and reporting on LDN goals that countries can integrate into their land planning policies. However, it remains difficult to operationalize the integration of biophysical indicators of land degradation with climatic and socio-economic indicators to assess the impact of land degradation on vulnerable populations. We present an integrative framework that demonstrates how freely available global geospatial data sets can be leveraged through an open-source platform (Trends.Earth) to simplify and operationalize monitoring and reporting on progress towards achieving LDN. Then, we summarize a suite of data sets and approaches that can be used to understand and quantify the socio-ecological interactions between drought, land degradation and population exposed to desertification, land degradation and drought. We discuss how improvements in Earth observation data sets and algorithms will allow UNCCD land-based progress sub-indicators (changes in primary productivity, land cover, soil organic carbon, drought, and population exposure) to be computed at enhanced spatial resolutions.

KEYWORDS

desertification, earth observation data, land degradation and drought, land degradation neutrality, socio-ecological systems, sustainable development goal, UNCCD

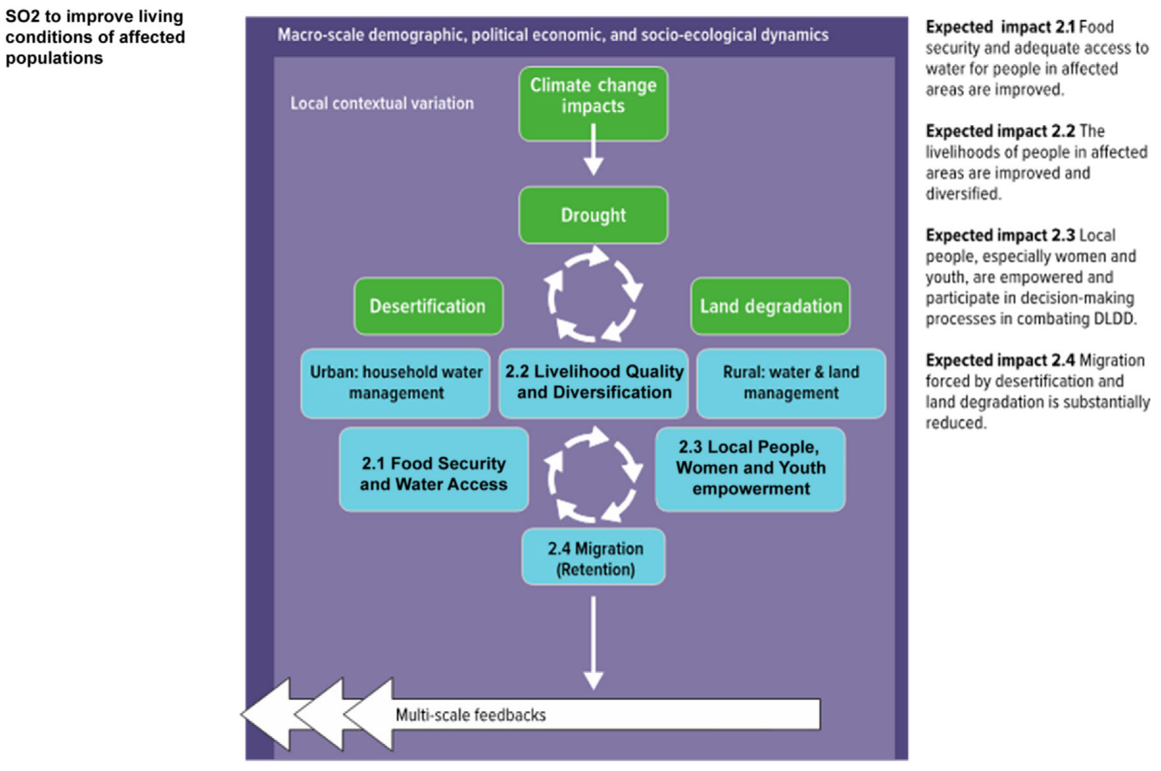

FIGURE 1 Community (blue) and ecosystem (green) vulnerability and resilience to desertification, land degradation and drought (DLDD) as presented in UN Convention to Combat Desertification's (UNCCD) SO 2 (to improve the living conditions of affected populations) that details the interactions among climate change impacts and aspects of community resilience (food security, livelihoods, migration(Source: UNCCD2017 ICCD/COP(13)/CST/7) [Colour figure can be viewed at wileyonlinelibrary.com]

1 | INTRODUCTION

Land degradation—the reduction or loss of the productive potential of land—is a global challenge currently experienced on roughly 20% of the Earth's vegetated surface by over 1.3 billion people with significant economic ramifications (Cherlet et al., 2018). Land degradation reduces agricultural productivity and increases the vulnerability of those areas already at risk of impacts from climate variability and change. Multiple international processes have highlighted land degradation as a key development challenge in the coming decades, underscoring that sparse reliable information and cost-effective and standardized methods for data collection and analysis hamper the creation of policies to address the challenge (Daldegan et al., 2020). Achieving Sustainable Development Goal (SDG) target 15.3: "By 2030, combat desertification, restore degraded land … including land affected by … drought and flood, and strive to achieve a land degradation-neutral world". is the First Strategic Objective of the UN Convention to Combat Desertification's (UNCCD) Strategic Framework (UNCCD, 2017 ICCD/COP(13)/CST/7). To meet these challenges and, specifically to achieve SDG 15.3, Strategic Objective 2 (SO 2) of the UNCCD, we look to the Strategic Framework for 2018–2030 (Decision 7/COP.13), which aims *to improve the living conditions of affected populations*. This document sets out the priority to support country Parties to effectively monitor changes in desertification, land degradation and drought (DLDD), and the human dimensions and feedbacks associated with those changes, including livelihoods, food security and water access, land management, empowerment, and migration (Figure 1). To date, the UNCCD leads the charge in creating a spatially explicit framework for monitoring and reporting on land degradation neutrality (LDN) goals that countries can also integrate into their land planning policies. However, integrating socio-economic vulnerability and resilience measures with climate change science remains a significant challenge, especially given the data-rich databases for climate typically far exceed the spatial and temporal coverage of socio-economic data. In part for these reasons, the UNCCD has yet to integrate biophysical indicators of drought impacts and mitigation into their DLDD monitoring framework. Similarly, UN frameworks for mitigating and monitoring adaptation and resilience to DLDD have yet to fully identify and integrate socio-economic indicators towards achieving the 2030 SDGs.

Addressing LDN and the human dimensions of DLDD globally to achieve SDG target 15.3 by 2030 is anchored in a rich literature on socio-ecological systems (SESs) and coupled natural-human systems recognizing the necessity of an SES approach to researching systems dynamics and pursuing these integrations in operational ways (Chen, 2015; Fischer et al., 2015; Gibson et al., 2000; Stringer et al., 2018). Development interventions recognize the need to work collaboratively and across scales and disciplinary divides in SESs (Bodin, 2017; Chambers, 1981), yet many global and regional initiatives aimed at understanding, quantifying, and creating actionable decisions in complex SESs still encounter challenges with methodological and collaborative engagement (McGreavy et al., 2015; Stringer & Dougill, 2013; Wilson et al., 2010). Research on SESs has emerged from the understanding that multiscale and multidirectional feedbacks operate among the components of complex systems that include both humans and the resource base they depend on, as illustrated in Figure 1 (Nassl & Löffler, 2015). Practitioners and policymakers are increasingly recognizing that it is at the intersection between humans and environment that ecosystem processes, such as the ones impacted by DLDD, become ecosystem services and ecosystem components become natural resources, shaping management directions and people's livelihoods (Pricope et al., 2020). SES research is highly interdisciplinary and requires scientists, scholars, and practitioners to address the dynamic intersection of social and ecological scales. Hence, there is ample opportunity for innovation and cross-sectoral collaboration through adopting frameworks that account for the constraints and challenges these various scales and participant inputs place on implementing metrics for monitoring these systems.

To build on the rich tradition of SES research in the human dimensions of global change literature and align to UNCCD's Strategic Objectives (SO) 1, 2 and 3, we present an integrative socio-ecological framework to simplify and operationalize setting targets, monitoring and reporting on progress towards achieving LDN globally, at individual national scales. The proposed framework demonstrates how freely available global geospatial data sets can be leveraged through an open-source platform, Trends.Earth (Conservation International, 2018), and supported by country-specific land management information. We present globally available data sets and improvements in Earth Observation (EO) data sets and algorithms to compute UNCCD land-based progress sub-indicators (changes in primary productivity, land cover and soil organic carbon) as well as drought indicators at enhanced spatial resolutions. Then, we discuss a suite of data sets and a conceptual framework approach that can be used to understand the socio-ecological interactions among drought, land degradation and population exposed to DLDD. Finally, we provide global results to demonstrate how the integration of EO-based DLDD metrics and human population components can be operationalized in an open-source computational platform and further contextualized with a suite of candidate socio-economic data sets.

2 | BACKGROUND

The UNCCD, custodian agency of the SDG 15.3, defines LDN as "…a state whereby the amount and quality of land resources, necessary to support ecosystem functions and services and enhance food security, remains stable or increases within specified temporal and spatial scales and ecosystems." (UNCCD, 2019 ICCD/COP(14)/CST/7). To monitor progress towards SDG 15.3 1, 2 and 3, the UNCCD created a Strategic Framework that encompasses three SOs:

1. *Strategic Objective 1 (SO 1)*: To improve the condition of affected ecosystems, combat desertification/land degradation, promote sustainable land management and contribute to land degradation neutrality
2. *Strategic Objective 2 (SO 2)*: To improve the living conditions of affected populations
3. *Strategic Objective 3 (SO 3)*: To mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems.

LDN is relevant to all three Strategic Objectives, and therefore to SDG 15.3 overall. Typically, specific indicators are used to estimate the progress towards each SDG; in the case of SDG target 15.3 the progress towards a land degradation neutral world is being assessed by indicator 15.3.1 "...proportion of land that is degraded over total land area." UNCCD SO 2 and 3 and their respective progress indicators are highly relevant for DLDD monitoring and combatting, as well as assessing progress towards achieving LDN. However, they are not acknowledged indicators of SDG target 15.3. The LDN scientific conceptual framework states that universally applicable and interpretable metrics are required for monitoring efforts towards LDN (Cowie et al., 2018). Building upon this scientific framework, UNCCD published the SDG 15.3.1 Good Practice Guidance (Sims et al., 2021) recommending that a set of at least three sub-indicators should be integrated to assess land condition from local to global scales: changes in land productivity, in land cover, and in soil carbon stocks. Daldegan et al. (2020) present more statistically refined approaches and increasingly higher spatial and temporal resolution data sets that can be leveraged in the open-source platform, Trends.Earth, to monitor progress on land degradation towards SDG 15.3.1. However, drought monitoring and its effects on land degradation have not been fully integrated into SDG 15.3.1 reporting and a clear conceptual framework on how the three strategic objectives with bearing on SDG 15.3 can be combined into an overarching monitoring metric remains largely lacking.

Drought impacts increasingly larger numbers of people, livelihoods, ecosystems, and economies worldwide (IPCC, 2014). Given the complex relationship between drought and land degradation, when the latter is exacerbated by drought, it can expose already vulnerable populations to deleterious livelihood, environmental, socioeconomic, and health risks and decrease population and community resilience. Drought is a complex phenomenon, and impacts on crop and livestock production, and livelihoods depend on a variety of factors that change over different time scales. For example, a significant reduction in water availability that results in cascading effects on people's livelihoods and economic sectors can be quickly triggered by the absence of rain soon after a crop is planted and exacerbated by reduction in soil water holding capacity associated with long-term land degradation. 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 (IPCC, 2014; UNISRD, 2015). Moreover, the stresses on populations and ecosystems caused by drought are often compounded by other, often related, events including heatwaves, wildfires, sand/dust storms, or floods, thus further complicating detecting, measuring and reporting the presence and effects of drought on people and ecosystems.

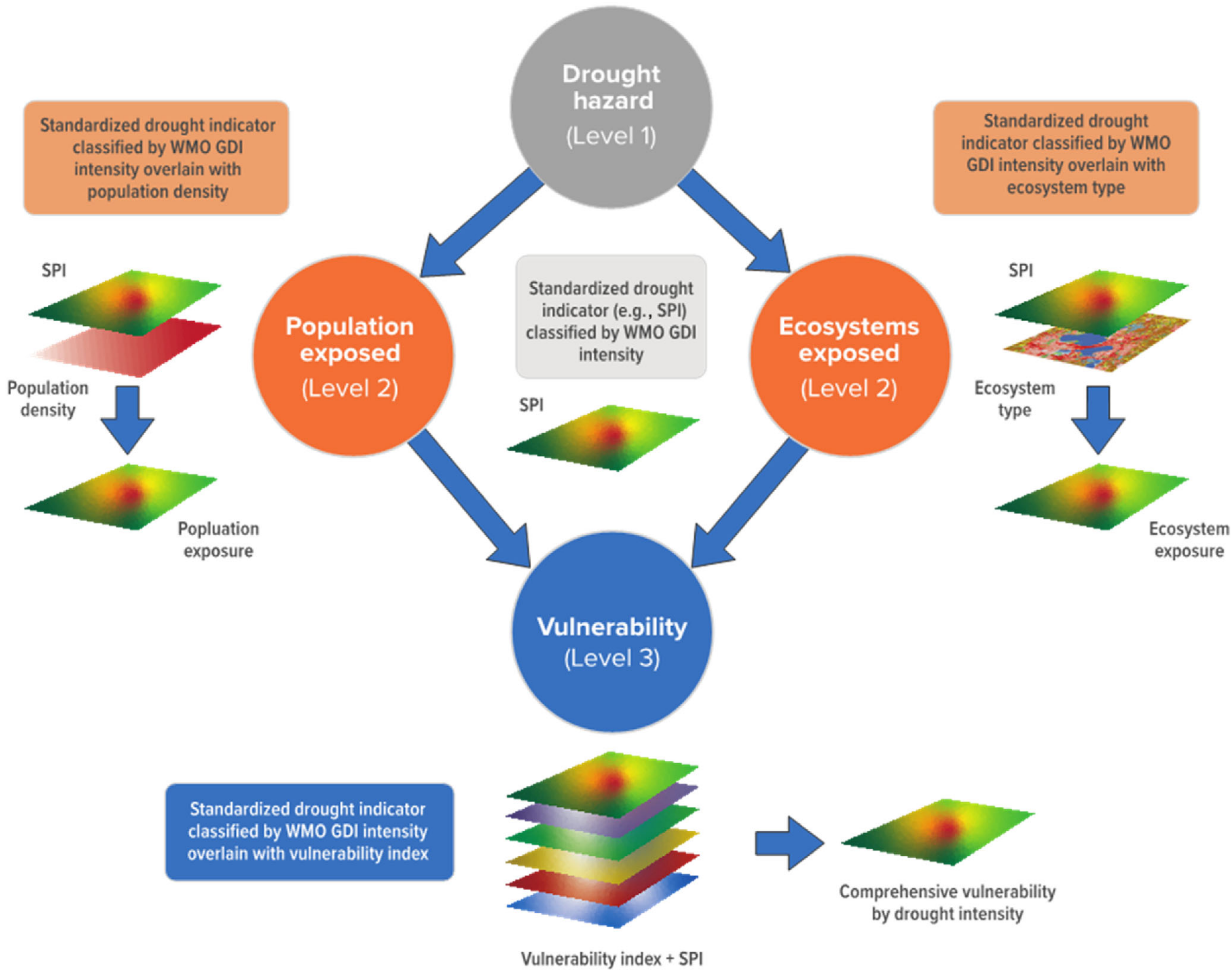

FIGURE 2 Integrated vulnerability index showing the existing UN Convention to Combat Desertification's (UNCCD) drought monitoring framework (UNCCD, 2019) operationalized using global, freely available data sets and indicators to measure hazard, exposure and vulnerability of populations and ecosystems to desertification, land degradation and drought (DLDD) (Source: Pricope et al., 2021). [Colour figure can be viewed at wileyonlinelibrary.com]

In order to address the nexus among land degradation, drought and population vulnerability and support the integration of the three UNCCD's Strategic Objectives we build on the UNCCD three-tiered drought monitoring framework (UNCCD, 2019). The UNCCD framework is originally based on the World Meteorological Organization (WMO) Global Multi-Hazard Alert System rooted in the Risk = Hazard × Exposure × Vulnerability model. In this paper, we build on these frameworks and introduce an integrative conceptual framework aimed at providing improved methods and tools for assessing DLDD and understanding the socio-economic conditions of vulnerable communities in affected areas through the integration of free and open platforms to support country level implementation and reporting on SDG 15.3 (Figure 2). In the methods section, we discuss global coverage, freely-available data sets that can be used to operationalize this framework focused on computing a comprehensive vulnerability metric as a function of hazard and exposure (Figure 2).

The integrated vulnerability index proposed here 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 (IPCC, 2014). The exposure component pertaining to human populations is given by population density, modified by gender classes (where the gender-disaggregated data is readily available) and/or rural versus urban populations, while the 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 from freely available geospatial data sets (Lopez-Carr et al., 2021; Pricope et al., 2021).

TABLE 1 Summary of proposed data sets in support of monitoring Sustainable Development Goal (SDG) 15.3.1 sub-indicators land productivity, land cover trends and carbon stocks

Sub-indicator	Name	Source	Spatial resolution	Temporal coverage	Temporal frequency	Extent
Land productivity	NASA/USGS MODIS Terra MOD13Q1 v006 NDVI	NASA-USGS	250 m	February 18, 2000–Present	16-Day Composite	Global
	NASA AHVRR GIMMS 3g.v0 NDVI	NASA-GIMMS	8 km	July, 1981–December, 2015	Monthly	Global
Land cover	ESA CCI land cover	ESA CCI land cover	300 m	1992–2018	Annually	Global
Carbon stocks	SOILGRIDS	ISRIC	250 m	2010	NA	Global

Following an in-depth review of the state-of-art global climate data sets used to better understand how drought impacts land degradation (and vice versa), including indicators on droughts occurrence, severity and impacts using global climate data sets to understand rainfall, soil moisture and temperature changes (Pricope et al., 2021), we surmised that it is feasible to implement a series of drought-related data sets and indicators into Trends.Earth to operationalize the integrated vulnerability framework that can be utilized to monitor the effects of DLDD on both global populations and ecosystems (Figure 2). There is a plethora of indices that can be used to operationalize drought monitoring, including the standardized precipitation index (SPI), standardized precipitation and evaporation index, or the standardized soil moisture index (Hayes et al., 2011). An index of anomalies (for instance, the number of months below an SPI threshold) or using a combination of precipitation and temperature calculated at the annual scale) is another approach utilized to highlight long-term trends (IOM/UNCCD, 2019). The additional inclusion of a soil moisture-based drought index within a global drought monitoring tool provides an opportunity for countries to replace or augment an SPI-based only 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 (Pricope et al., 2021).

In addition, to begin to develop an understanding of how to evaluate Strategic Objective 2, we similarly conducted an exhaustive literature and documentation review to identify global socioeconomic data sets that meet the criteria for monitoring the condition of affected populations, as put forth in Lopez-Carr et al. (2021). Specifically, socio-economic data sets that are freely available, have global (or nearly global) spatial coverage, provide subnational observations, and permit gender disaggregation are prioritized. Vulnerability is generally considered a function of human exposure to a stressor effect (also termed sensitivity or potential impact) and the recovery potential to that stressor (also termed resilience or the capacity to cope with or adapt to slow or fast-onset changes). In the context of DLDD, the vulnerability of human beings and their livelihoods is integral to improving the living conditions of affected populations. Livelihoods are intimately linked to DLDD and can have positive and/or negative consequences on DLDD and this is especially the case with migration where a move may have net positive impacts in one location and potentially net negative outcomes in the other location (or vice versa).

3 | MATERIALS AND METHODS

In order to demonstrate the SES integration framework presented above, first we present the land degradation, drought and socio-economic data sets and indicators to be used for monitoring SDG 15.3.1 and briefly discuss their applicability to global monitoring efforts towards achieving LDN. Second, we analyze spatially explicit population data to understand how vulnerable populations are affected by land degradation, drought and poverty, providing a conceptual framework to effectively integrate global drought and socio-economic data sets to better monitor DLDD in the world's most susceptible regions.

3.1 | Monitoring SDG indicator 15.3.1: The proportion of land degraded over the total land area

We used Trends.Earth to derive geospatial data representing each sub-indicator and to integrate them into the final SDG 15.3.1 Indicator (Table 1).Trends.Earth is a user-friendly geospatial analytical tool that leverages Earth observation data to monitor land degradation at sub-national to global scale. Spatial analyses are performed applying a standardized framework of indicators for a user-defined area of interest, with options for adjusting the period of analysis and various spatially explicit input data sets (i.e., default global or custom finer spatial resolution). Spatial resolution of global default integrated EO data inputs range from 250 m to 1 km and the outputs are maps of each of the three SDG 15.3.1 sub-indicators. The results of three sub-indicators are then combined into a single SDG 15.3.1 indicator, which defines area as degraded, stable, or improved. Trends.Earth results are packaged as maps and summary tables that tabulate total land area within each category and its results could be applied in support to reporting to the UNCCD.

Trends in land productivity were assessed at the pixel level over 16 years along changes in land cover classes and in soil organic carbon

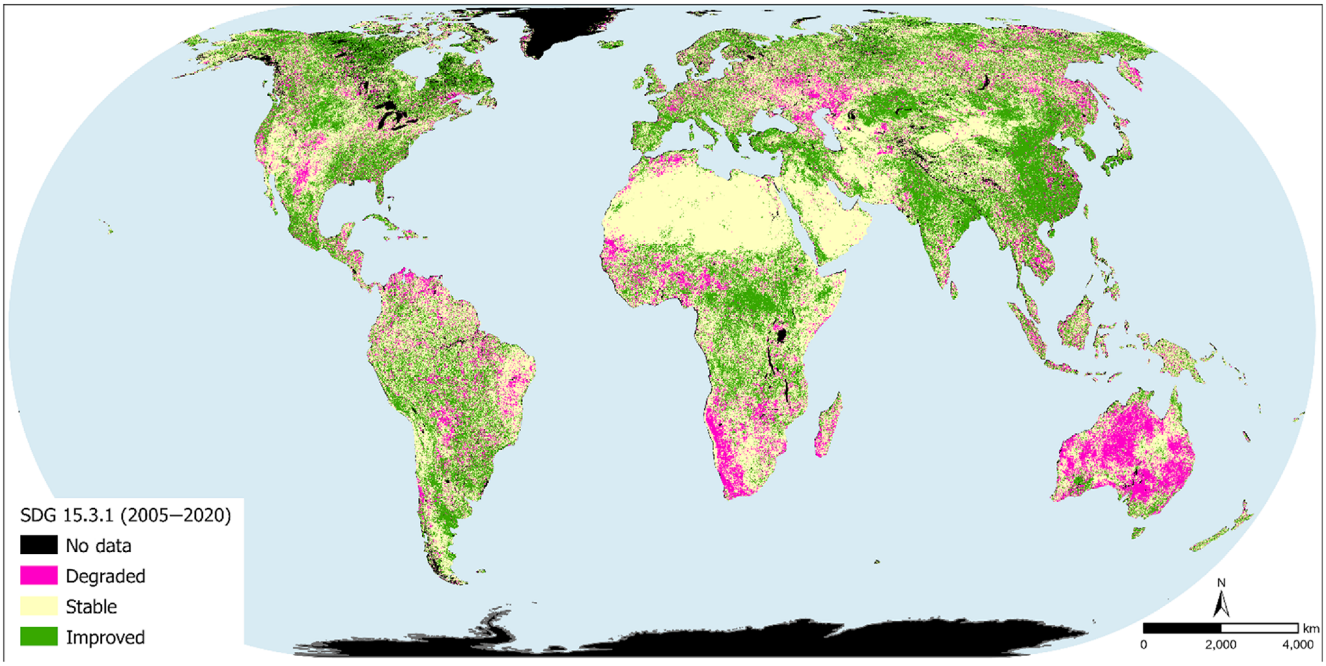

FIGURE 3 Global assessment of Sustainable Development Goal (SDG) 15.3.1 indicator for land degradation trends showing areas of decline, improvement or no trend (stable condition) for the 2005–2020 period (Source: authors) [Colour figure can be viewed at wileyonlinelibrary.com]

stocks, producing a final map identifying degraded lands for the entire globe (Figure 3). Following the LDN scientific framework, we applied the 'one-out-all-out' principle, whereby in the case any of the sub-indicators point to decreasing conditions for a given land unit, the final indicator result would indicate it as degraded (Cowie et al., 2018; Sims et al., 2021). Land productivity was assessed based on MODIS Normalized Difference Vegetation Index (NDVI: Tucker, 1979) annual integrals for a 15-year period starting in 2005. Second, we performed a change detection analysis of the European Space Agency (ESA) CCI land cover data set (https://www.esa-landcover-cci.org/) that allowed us to map transitions on the physical cover of the Earth's surface that took place between initial and terminal years. Third, changes in soil organic carbon stocks were estimated by applying an annual step analysis of land cover transitions and corresponding carbon conversion coefficients to the global gridded soil database (SoilGrids: Hengl et al., 2017), as shown in Table 1 (ISRIC SoilGrids: https://soilgrids.org/)".

3.2 | Monitoring UNCCD SO 3: To mitigate, adapt to, and manage the effects of drought in order to enhance the resilience of vulnerable populations and ecosystems

Based on an exhaustive literature and climate data set review, Table 2 includes a summary of global or near-global, freely available EO climate data sets that can be leveraged to monitor simple drought based on precipitation, temperature and soil moisture in support of SO 3. We present a subset of possible candidate data sets that can be utilized globally or at country scales so that potential users can make the most informed decisions, based on their needs and intended monitoring and planning outcomes (see Pricope et al., 2021 for a detailed description of each data set, including pros and cons). The Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) data set provides the highest spatial and temporal resolution precipitation data globally available over the last 35+ years (Funk et al., 2015), while a range of products are available from NASA, NOAA or other groups that can be used to monitor changes in temperatures and soil moisture.

Currently, the data sets implemented in the Trends.Earth platform are CHIRPS and the Global Precipitation Climatology Center (GPCC), and we used the GPCC data (given it is currently the recommended data set to be used by the UNCCD) to calculate drought indicators using SPI for the entire globe. A 30-year standard climatological period from 1981 to 2010 at monthly temporal resolution was used as reference when calculating the SPI (which is based on a 12-month lag) as recommended by the World Meteorological Organization (WMO, 2017) and the UNCCD GPG for SO 3 (Barker et al., 2021), and we derived the max drought per year by finding the lowest of the four December SPI values for each year in the period (2016–2019). This data then gets temporally aggregated into drought intensity classes based on SPI into four categories: mild drought (−1 to 0), moderate drought (−1.5 to −1), severe drought (−2 to −1.5) and extreme drought (less than −2). As the intensity classes become increasingly extreme, the likelihood of those values occurring (and the time spent in that category) decreases (Barker et al., 2021).

Second, to support the level two reporting for SO 3 (population and ecosystems exposed), we conducted a similarly exhaustive literature review of ecosystem and human population data sets that met

TABLE 2 Coverage and spatiotemporal resolutions of selected major gridded precipitation, temperature, and soil moisture products

Data set	Source	Spatial resolution	Spectral resolution	Temporal coverage	Spatial coverage
Precipitation					
CHIRPS 2.0	CHG UCSB	0.050 × 0.050 (~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	2.50 × 2.50 (~278 km at the Equator)	1979–present	Monthly, pentad	90 N–90 S
GCPC v 2.3 monthly	NASA GSFC	2.50 × 2.50 (~278 km at the Equator)	1979–present	Monthly	90 N–90 S
PERSIANN-CDR	NOAA CDR Program/NOAA NCEI	0.250 × 0.250 (~278 km at the Equator)	1983–present	1-hourly, 3-hourly, 6-hourly, daily	60 N–60 S
Temperature					
BETP gridded land	Berkeley Earth Group	10 × 10 (~111 km at the Equator)	1753–present	Daily, monthly	Global
CHIRTS-daily	CHG UCSB	0.050 × 0.050 (~5.5 km at the Equator)	1981–present	Daily	60° S–70° N
CRUTEM4	CRU, Hadley Center	50 × 50° (~555 km at the Equator)	1850–present	Monthly	Global
CPC Global Daily	NOAA	0.50 × 0.50 (~55.5 km at the Equator)	1979–present	Daily	Global
GISTEMP Land v4	NASA	20 × 20 (~222 km at the Equator)	1880–present	Monthly, Seasonally, Annually	Global
NOAA GlobalTemp V5	NOAA	50 × 50 (~555 km at the Equator)	1880–present	Monthly	Global
Soil moisture					
ERA5	ECMWF	0.28° × 0.28° (~31.1 km at the Equator)	1979–present	Hourly	Global
ESA CCI v05.2	ESA	0.25° × 0.25° (~27.8 km at the Equator)	1980–2019	Daily	Global
MERRA-2	NASA	0.5° × 0.625° (~55.5 km × 58.75 km at the Equator	1980–present	Hourly	Global
NASA-USDA global soil moisture data	NASA-USDA	0.25° × 0.25° (~27.8 km at the Equator)	2010–present	3-daily	Global

criteria for inclusion into a global vulnerability index framework (see Pricope et al., 2020 for a discussion of each individual data set's characteristics) (Table 3). If desired to be computed for monitoring and reporting purposes, ecosystem exposure can be determined as the percent area affected by drought or land degradation using, for instance, the CIESIN Anthropogenic Biomes data set (Ellis et al., 2010) or one of the globally available settlement layers (Table 3). In this paper, we report the population exposed to DLDD using the 100-m resolution WorldPop population count data for 2020 (Lloyd et al., 2019), subsequently resampled to 1.2-km resolution to facilitate a cloud-based, global computation of the metric and reported by drought intensity classes for the total population and by gender disaggregation based on the UNCCD GPG (Barker et al., 2021).

In order to compute SO 3 Level 2, a composite drought vulnerability index, we assess drought risk for the period 2000–2018 as a function of the three independent determinants (Levels 1 and 2 in Figure 2): hazard, exposure and vulnerability using the Carrão et al. (2016) methodology. Drought vulnerability is computed as the composite of factors of social, economic and infrastructural indicators, collected at both the national and subnational levels by the World Bank, Worldwide Governance Indicators, Organization for Economic Co-operation and Development, Food and Agriculture Organization, and Global Roads Open Access Data set. Based on these data sets, the resulting vulnerability index uses fifteen indicators to assess economic, social, and infrastructural factors that contribute to vulnerability and is computed as an arithmetic combination of the fifteen input indicators (after normalizing each to range from zero to one, and to account for the expected direction of their relationship with vulnerability, Figure 4) (Carrão et al., 2016).

3.3 | Monitoring UNCCD SO 2: To improve the living conditions of (DLDD) affected populations

Socio-economic data sets from WorldPop, Integrated Public Use Microdata Series (IPUMS)-International, World Bank's Living Standards

TABLE 3 Global gridded data sets for monitoring ecosystem exposure to drought and human drought exposure based on population: Summary characteristics

Data set	Source	Spatial resolution	Temporal coverage	Temporal resolution	Spatial coverage	Source for national level population totals	Gender disaggregation
Ecosystem exposure							
Anthropogenic Biomes v 1	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 5 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 × 30 m, 250 × 250 m, 1 × 1 km	1975, 1990, 2000, 2015	Irregular	Global	N/A	NO
Global Human Settlement Layer	European Commission JRC	1 × 1 km	2015	Irregular	Global	N/A	NO

Note: Settlement layers are included as a modifier for human exposure, which can be disaggregated by urban/rural populations.

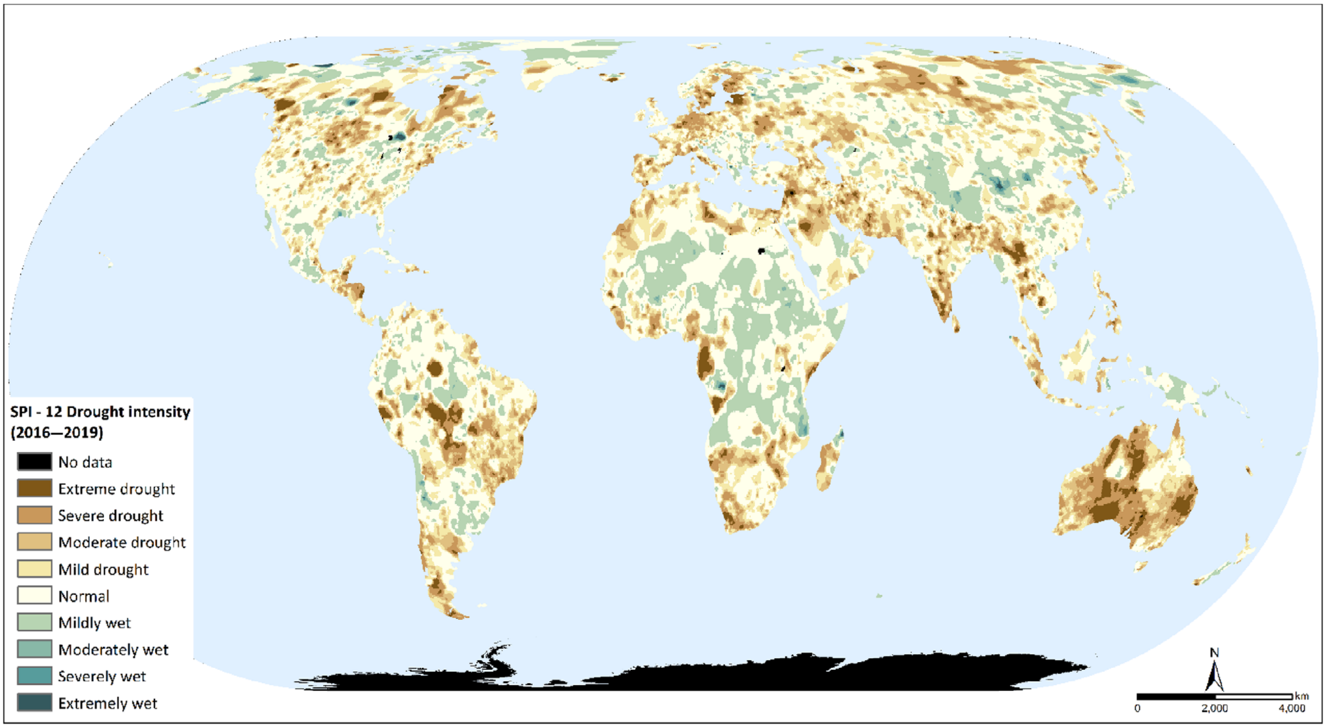

FIGURE 4 Composite drought vulnerability index (Strategic Objective [SO] 3 Level 3 composite indicator) computed using the Carrão et al. (2016) framework for 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

Measurement Study, and the Demographic and Health Surveys (DHS) form the basis of selected data that meets global monitoring and reporting criteria for UNCCD SO 2 globally (Table 4). These data sets can be leveraged at different spatial and temporal scales and integrated for country-specific applications. For instance, to support human exposure and livelihoods monitoring, priority data sets include WorldPop's gridded 100 m global estimation of population estimates (already incorporated into Trends.Earth) and DHS data. In addition, DHS data, where available, are a rich source of data on water access, health outcomes, and gender empowerment. The Famine and Early Warning Systems Network and the National Aeronautics and Space Administration (NASA) provide additional and potentially useful food security data. WorldPop Migration Flows and IPUMS-International provide sources of migration data with several caveats. With respect to monitoring land and water resources and sustainable management, Intact Forested Landscapes (IFL), NASA Trends in GRACE (for Gravity Recovery and Climate Experiment), and Copernicus and ESA land cover data provide useful complementary data sets (Lopez-Carr et al., 2021). In this paper, we do not explicitly tackle the integration of these socio-economic data sets into the DLDD monitoring framework but do leverage the WorldPop multipurpose data set to map patterns in the human populations affected by DLDD at the global scale.

4 | RESULTS AND DISCUSSION

Using the data sets and approaches presented above and applied to a global analysis of DLDD, we show a preliminary global assessment of the trends in SDG 15.3.1 and UNCCD's Strategic Objectives, particularly in regards to trends in land degradation, drought intensity, population exposed to drought, and a composite index of drought vulnerability, building on the levels one (hazards), two (population exposed) and three (vulnerability) of the UNCCD drought monitoring framework presented in Figure 2 and operationalized with a subset of the data sets presented in the methods section above.

4.1 | Global assessment of SDG indicator 15.3.1: The proportion of land degraded over the total land area

When considering trends in SDG 15.3.1 for a 16-year period over the last two decades (2005–2020), we observe that the world has experienced improvements in land condition, with special attention to Asia, central Africa, and the Americas. On the other hand, we also note broad clusters of decreased land condition spread all over Australia, over southwest and central-west Africa, along with relatively smaller but still extensive areas of persistent land degradation over southwest United States and eastern Russia. Moreover, marginal areas of sustained land degradation extend along coastal, highly populated regions of Madagascar, northern Venezuela and Colombia, Paraguay, north Africa, and regions bordering the Black and Caspian Seas. These patterns have remained somewhat consistent through the 16-year period analyzed here.

Until very recently, global geospatial data for land productivity and land cover were only available at relatively coarse spatial resolution (~250 m). However, recent and on-going efforts for downscaling

TABLE 4 Biophysical and socioeconomic data sets for monitoring SO 2

Data set	Source	Spatial resolution	Temporal coverage	Temporal resolution	Spatial coverage	Gender disaggregation
Multipurpose data sets						
Demographic and Health Surveys	The DHS Program	National, sub-national (provincial)	1984–2020	Annual	Quasi-global	Yes
WorldPop Population Counts (unconstrained)	WorldPop	30-arc seconds and 3-arc seconds (~1 km and 100 m at the Equator)	2000–2020	Annual	Global	Yes
WorldPop Population Density (unconstrained)	WorldPop	30-arc seconds (~1 km at the Equator	2000–2020	Annual	Global	Yes
Food security and water access (SO-2.1)						
Food Insecurity Hotspots Data Set v1	NASA SEDAC/CIESIN	250 m × 250 m	2009–2019	Annual	Regional	No
Food Security Classifications	FEWS NET	Sub-national (districts)	2009–present	3-monthly	Regional	No
Land and water management						
Global Land Cover v3.0	Copernicus Global Land Service	100 m × 100 m	2015–2019	Annual	Global	No
ESA CCI-LC (MRLC Maps v207)	European Space Agency	300 m × 300 m	1992–2018	Annual	Global	No
Intact Forested Landscapes (IFL)	IFL Mapping Team	Sub-national	2000, 2013, 2016	Irregular	Global	No
Trends in Global Freshwater Availability from the Gravity Recovery and Climate Experiment (GRACE)	NASA SEDAC/CIESIN	0.5° × 0.5° (~ 55 km at the Equator)	2000–2016	Annual, monthly	Global	No
Livelihoods (SO-2.2)						
Multidimensional Poverty Index (MPI)	OPHI (Derived from harmonized DHS and MICS data)	Household, sub-national	2010–2020	Annual	Quasi-global	Yes
Local people, women's, and youth empowerment (SO-2.3)						
Modeled Surfaces: Women's literacy ED_ LITR_W_LIT	The DHS Program	5 km × 5 km	2013–2018	Irregular	38 countries	NA (women focused indicator)
Landmark	Landmark	National, sub-national	2018	Monthly to annual	Global with gaps	No
Migration (SO-2.4)						
Migration Global Variables (Person)	IPUMS-International	National, sub-national	1960–2018 (depending on variable and country)	Annual	Select nations	Yes
WorldPop Internal Migration Flows	WorldPop	Sub-national	2005–2010	N/A	LMIC	No

Note: DHS and WorldPop data are considered multi-purpose due to inclusion of variables relating to water access and women's empowerment in addition to demographic and socio-economic variables (DHS) or due to being gender/age disaggregable (WorldPop).

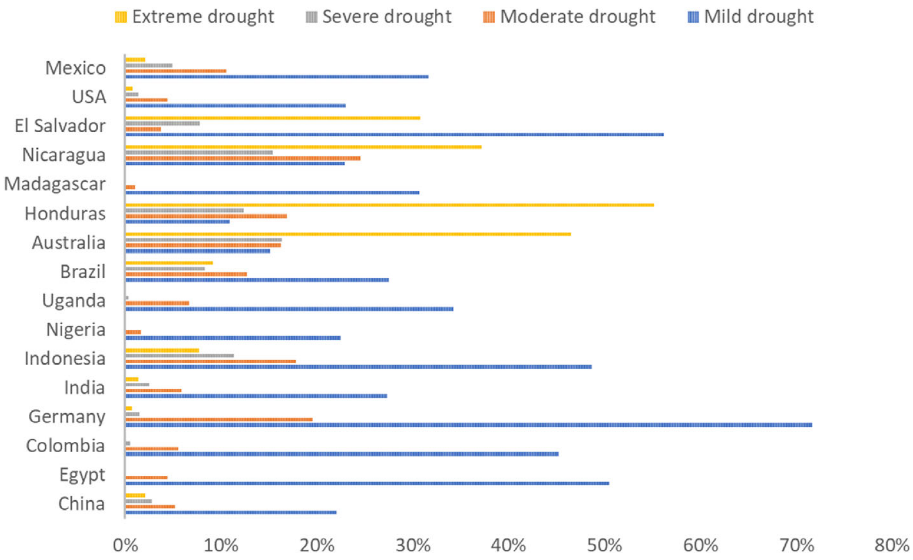

FIGURE 5 Global distribution of drought intensity classes (Strategic Objective [SO] 3 Level 1) based on the standardized precipitation index (SPI) computed from GPCC data for 2016–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

these data to a finer spatial resolution have successfully developed layers at a 10-m resolution. For instance, the ESA WorldCover project published a land cover map for the entire globe for 2020 (Zanaga et al., 2021), and Conservation International is currently developing land productivity layers for 2018–2020 (Daldegan et al., 2021), both derived from the SENTINEL family of sensors at 10-m spatial resolution. Although not yet covering a time-series long enough to allow application of these products for monitoring LDN, these recent developments have proven the great potential for bringing the socio-ecological monitoring and reporting framework presented here to an unprecedented fine detail in the near future. More spatially refined analyses coupled with field or expert knowledge verification (Teich et al., 2019) would both contribute to lowering uncertainty estimates that continue to linger in both research and practice as underscored by Safriel (2007) early on in the land degradation discourse.

4.2 | Global assessment UNCCD SO 3: To mitigate, adapt to, and manage the effects of drought in order to enhance the resilience of vulnerable populations and UNCCD SOs 2–3: To improve the living conditions of (DLDD) affected populations

We also show how the multi-level monitoring and reporting framework proposed in Figure 2 can be used to assess UNCCD SO 3 in a sequential manner by creating indices of hazard, exposure and combined vulnerability. Using global EO climate data sets, we computed yearly drought intensity classes using the GPCC data set in Trends. Earth and show areas of extreme to mild drought, normal conditions and areas that have been experiencing mild to extremely wet conditions in any given year or time period (Figure 5). Of course, the metric of interest for monitoring DLDD is drought intensity, which is computed using an SPI approach (Hayes et al., 2011). For the most recent temporal period of data availability from GPCC, regions in Australia, western and South Africa, central-west Africa, the Baltic states, southern China and India emerge as having experienced severe to extremely severe drought exposure for the 2016–2019 period (Figure 5). Other areas that were significantly impacted by drought during the same time period in northwestern Brazil, central Russia and Canada are areas of low population compared to the regions highlighted above. Even though in this paper we do not perform a spatial overlap analysis between areas identified as degraded using the land productivity sub-indicator for SGD15.3.1 and the drought intensity classes that form the basis of identifying Level 1 (hazard) for SO 3 as per Aukema et al. (2017), we immediately observe areas of spatial overlap among land degradation and drought that merit further investigation towards more effective integration. These areas of overlap concentrate in western Australia, southwest and west-central Africa, northeastern Brazil, as well as the North American southwest and east-central European regions.

Similar to efforts to enhance the spatial and temporal resolutions and computational efficacy for metrics of land degradation (SDG 15.3.1), current efforts are being implemented by Conservation International to enhance the spatial and temporal resolution of calculating drought indices using CHIRPS precipitation data and other drought indicators as outlined in Table 2. These efforts are supported by a rich literature showing that satellite-based precipitation data support monitoring different types of drought with global societal implications (Blauhut et al., 2016; Lai et al., 2019; Zhao & Gao, 2019).

Even though computed globally at coarse spatial resolutions, drought intensity indices can be utilized by respective countries as quantitative measures at yearly or composite time periods, as needed for reporting, monitoring, and planning when preparedness plans or drought mitigation activities need to be put into practice (Figure 6). For instance, using similar global-scale, cloud-computed metrics of degradation applied to Argentina, Teich et al. (2019) demonstrate that when validated with participatory expert knowledge, assessments based on global EO data and cloud computing using an existing framework such as Trends.Earth provide valuable management information at regional to local scales. Furthermore, these EO-based trajectories

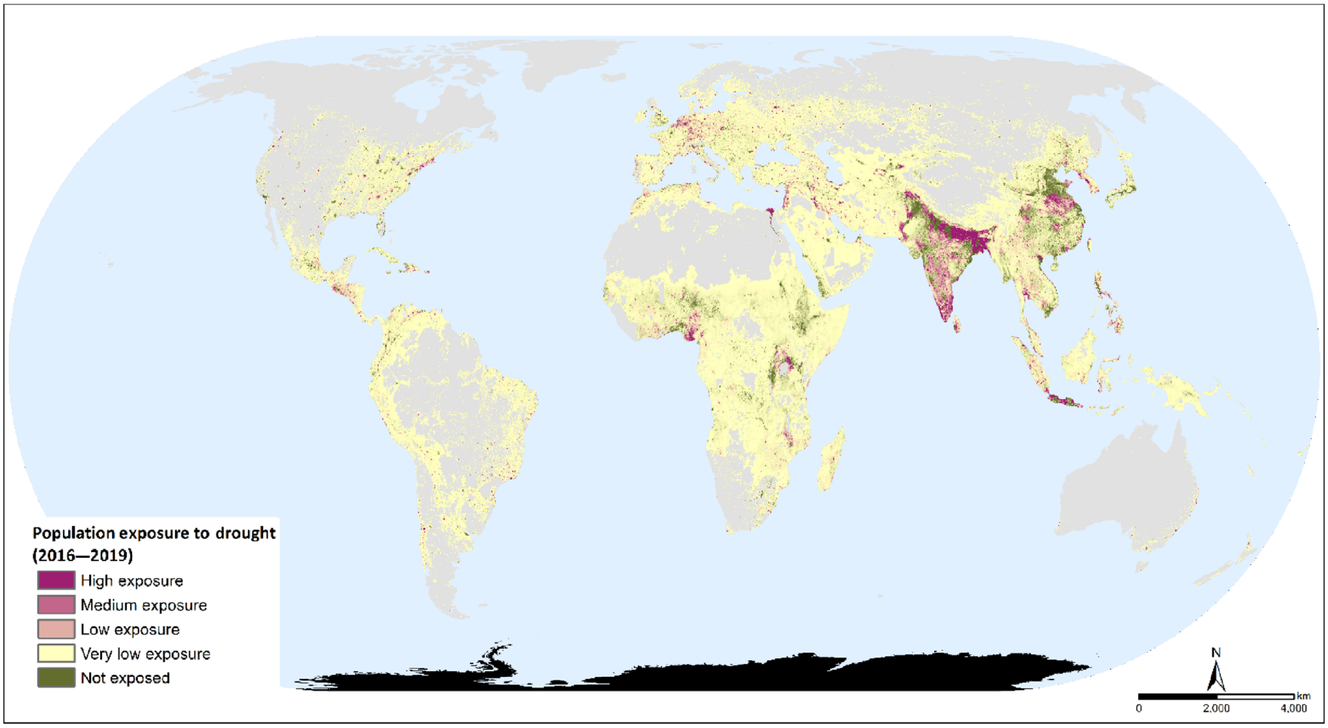

FIGURE 6 Drought intensity (mild, moderate, severe and extreme) distribution by percent of the total area by country for countries most affected by drought in 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

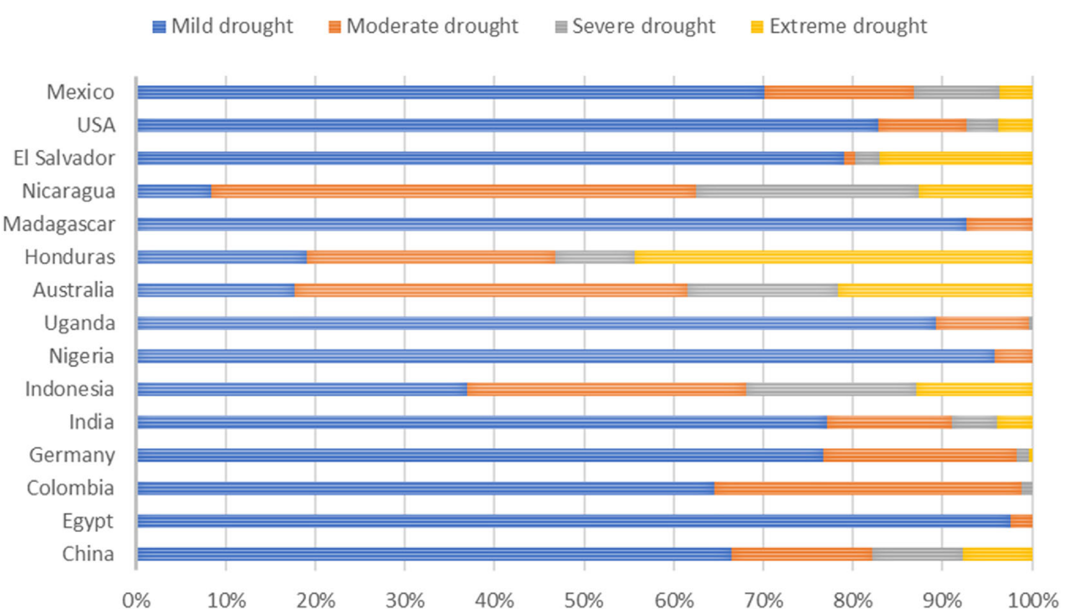

FIGURE 7 Population exposed to drought for the period 2016–2019 (Strategic Objective [SO] 3 Level 2) computed using WorldPop population count data and resampled to 1.2-km resolution [Colour figure can be viewed at wileyonlinelibrary.com]

can be integrated with land management practices (such as the World Overview of Conservation Approaches and Technologies Sustainable Land Management database) to initiate actionable practices aimed at achieving land degradation neutrality (Gonzalez-Roglich et al., 2019). Using these quantitative metrics (Figure 6), baseline drought conditions can be established for respective countries and a determination of drought intensity by class (mild, moderate, severe, and extreme, as defined in the UNCCD GPG document) can be made at different temporal averages. For the time period presented in Figure 5 (2016–2019), countries such as Honduras, Australia, Nicaragua, and El Salvador stand out as having been affected by extreme drought to significant extents (between 30% and 60% of the country area), while

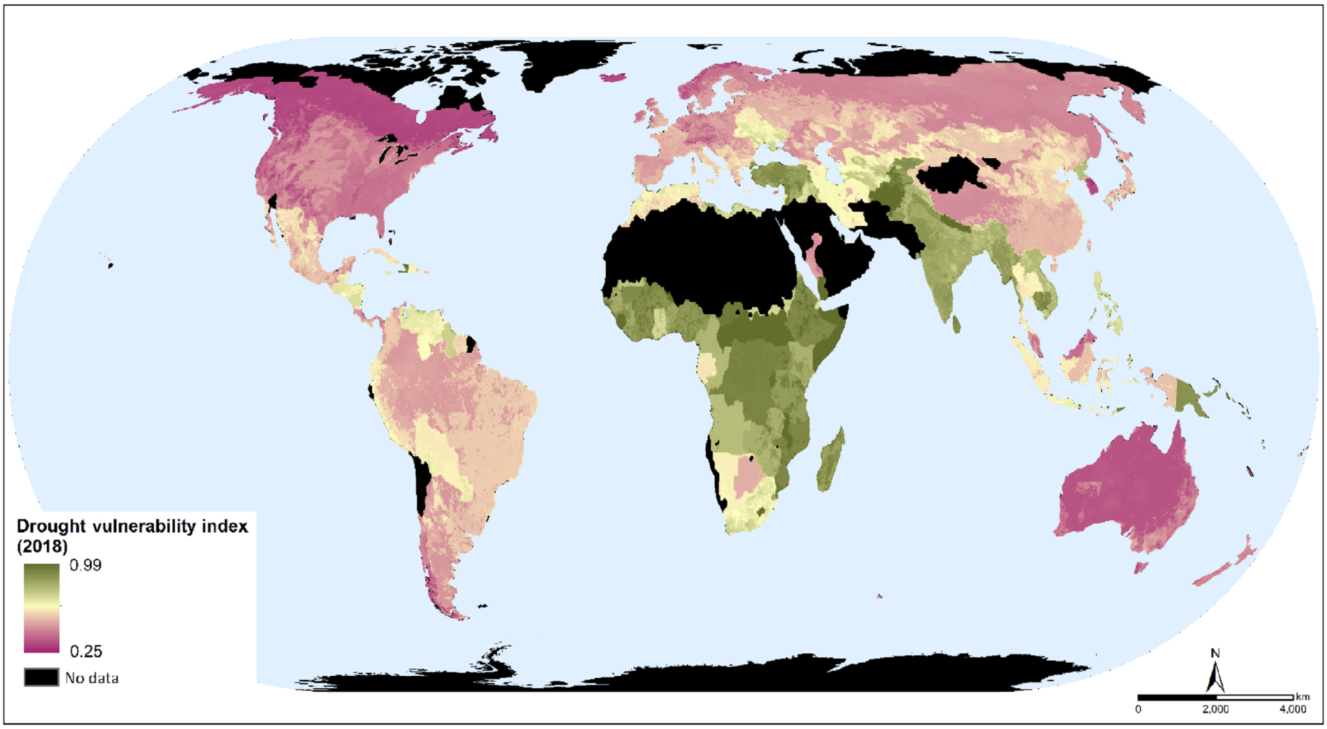

FIGURE 8 Population exposed to different drought intensity classes (mild, moderate, severe and extreme) in 2019 as a percent of total drought affected populations of most affected countries based on WorldPop population estimates [Colour figure can be viewed at wileyonlinelibrary.com]

countries such as Germany, El Salvador, Egypt and Indonesia were affected by mild droughts in over 50% of their area for the same time period. Similar estimates can be computed at different temporal and spatial scales at country or sub-country levels as necessary for planning, monitoring and reporting (Data S1).

When computing SO 3 Level 2 indicator, human population exposed to drought, using temporally coincident population count data to the drought intensity data, we highlight regions of the world with high population densities that spatially overlap with areas that are experiencing drought impacts (Figure 7). Regions that stand out as having experienced drought impacts on their human populations include, with very high exposure, the Indian subcontinent (as well as Nepal and Bhutan), Australia and very densely populated areas in Southeast Asia. These regions are primarily characterized by smallholder, rainfed agriculture and, as such, are disproportionately at high risk from DLDD (Mainali & Pricope, 2018; Neeti et al., 2021). Similar regions of high population exposure to drought during the 2016–2019 period include the Lake Victoria basin of eastern Africa, a region highlighted by prior work as highly vulnerable to the combined effects of drought, degradation, and high population exposures (López-Carr et al., 2014; Pricope et al., 2013). The same region in south-central West Africa, centered upon the Niger Delta, Cote d'Ivoire, southern Burkina Fasso, and parts of Senegal shows significant numbers of people as potentially impacted by drought, as do regions throughout east-central Europe, northeastern Brazil, Central America, and the central plains of North America (Figure 7).

Similarly to drought impacts, we can quantitatively assess drought impacts by total population of any given country (or at sub-country levels if desired) at different temporal aggregations and determine not only the total population impacted (Figure 8), but also how drought affects populations by gender (Data S1). As shown below, the human populations of Nicaragua, Honduras, Australia and Indonesia were affected by moderate to extreme drought at rates exceeding 60% which poses major health, planning and adaptation risks at country levels and internationally.

Finally, to address SO 3 Level 3 indicator for a composite index of vulnerability, we relied on the implementation of the Carrao et al. (2016) framework for computing vulnerability as a function of 15 indicators to assess economic, social, and infrastructural factors that contribute to vulnerability (Figure 2 and Tables 3 and 4). Given the reliance on national data sets with low to no granularity at subnational scales, the results in Figure 7 provide an incipient assessment of composite drought vulnerability for 2018 and highlights countries of high to low vulnerability, as mediated by higher or lower socioeconomic buffering capacities and adaptation potential (Cruz et al., 2021). As expected, the Indian subcontinent, Southeast Asia, central Europe, and sub-Saharan Africa stand out as regions that are currently experiencing high DLDD vulnerability. Future work is focused on creating finer-grained assessments of DLDD vulnerability using spatially explicit subnational data sets wherever possible (Table 4, also see Giuliani et al., 2020) and validating them with in-country participatory, expert, and community knowledge (Teich et al., 2019) as well as by contextualizing geospatial analyses with sustainable land management practices (Liniger et al., 2019). In doing so, this manuscript contributes to the exploration of conceptual ways to reconcile the complexity of measuring land degradation with global and country-level needs for methods that are simplified and operationalized in line with UNCCD reporting requirements.

The integration of EO data sets with population and socio-economic data sets to study human-environment interactions and monitor progress towards improving the conditions of populations affected by DLDD still lags behind other areas of research, largely due to spatio-temporal scale mismatches between EO and socio-economic data sets (Carrão et al., 2016; Pricope et al., 2021). However, recent cloud-based computational algorithm improvements (Daldegan et al., 2021; Huntington et al., 2017) at ever increasing spatial and temporal resolutions will help fill this gap as socio-economic and population data sets themselves become increasingly spatialized and more granular (Lloyd et al., 2019; Lopez-Carr et al., 2021). Results obtained using the approach presented here can subsequently supplemented by expert knowledge elicited via stakeholder engagement processes with groups ranging from government officials to end-users of data in the field and thus verified and validated for use in respective countries.

5 | CONCLUSIONS

In responding to a call to address DLDD mapping and LDN SDG targets, we present an exhaustive list of free, globally available and geospatially-explicit socio-economic and EO data sets that can be integrated into metrics to assess progress towards a land degradation-neutral world consistent with the 2030 Agenda for Sustainable Development. Improving the process of integrating socio-economic data with climate change science is necessary for optimal monitoring and evaluation of international objectives such as the SDGs. Ultimately, the accurate monitoring and reporting of integrated socio-economic, EO, and biophysical outcomes in response to land degradation is essential to improve the livelihoods of those most affected and to build resilience to safeguard against the most extreme effects of climate change, drought and land degradation. However, as our analysis of convergence between DLDD, populations affected, and vulnerability demonstrates, in the absence of policy and on-the-ground interventions to reverse the directionality of these trends, albeit at coarse global scales, the regions of the world that stand out as most impacted will continue to struggle to achieve SDGs aimed at reducing land degradation and improving the living conditions of affected populations. Future research and policy could fruitfully focus on improving monitoring and evaluation tools especially for these most vulnerable populations.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest in performing the work reported here.

DATA AVAILABILITY STATEMENT

The data and analyses presented in this manuscript can be openly accessed and computer on the open-access platform Trends.Earth (Conservation International).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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