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EXPLORING PERSISTENT DROUGHT SUSCEPTIBILITY: A PROGRESSIVE EXPLORATION OF DROUGHT VULNERABILITY IN LITERATURE

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Abstract
The present investigation explores the interconnectedness between human activities and the current dependencies of human life on the environment. The study delves into the various attributes of drought, including severity, duration, spatial extent, loss of life, economic repercussions, social implications, and the enduring effects as outlined in existing literature. It is highlighted that the socio-economic impacts of droughts can stem from natural conditions and human factors such as alterations in land use, water demand, and utilization. Frequent studies underscore the role of excessive water withdrawals in exacerbating the consequences of drought. Additionally, research indicates that diminished productivity in crops, rangelands, and forests leads to reduced water levels, heightened fire risk, increased livestock and wildlife fatalities, as well as harm to wildlife and fish habitats. The studies emphasize that the decline in crop productivity often translates to reduced income for farmers, elevated food prices, unemployment, and migration. A significant finding of the research is the association between global warming and drought, supported by mounting evidence. The investigation into drought estimation employs various satellite data and formulates diverse indices, representing a sequential progression in the literature dedicated to drought analysis.

Keywords: *Drought, Vulnerability, Environment, Climate, Hazards, Literature*, JEL Classification: Q510, Q540, Y30, Y50

Introduction
Drought, both a recurring and critical issue, stems from various natural and artificial causes, including low rainfall, global warming, improper water irrigation, and deficiencies in city water supply (Chitale M., 2012). To address these challenges, water distribution should be based on production value, fostering awareness about the economic value and efficient use of water. Crucial solutions such as rain harvesting, advanced technology adoption, water management, and pollution control have been proposed (Mane, 2010). Additionally, irregularities in nature, lack of irrigation, environmental changes, and government policies contribute to drought. Proposed measures include free electricity for farming, innovative seeds, tax exemptions, improved loan systems, and modern technology implementation. Agronomical and socio-economic factors play a crucial role in identifying and overcoming problems in drought-prone areas (Dracup et al., 1980). Drought assessment involves analyzing spatial and temporal water-related data, utilizing various quantitative methods and indices. Despite efforts, the perception of drought varies between crisis and a management issue. In India, a significant portion of the country is drought-prone, impacting agricultural areas, with about 16 percent of the country being drought-prone and 68 percent of the sown area affected by drought (Chitale M., 2012). The study emphasizes the importance of

understanding drought through comprehensive research, providing insights into its inevitability for all living beings on Earth.

Background

Drought may be attributed to the agricultural production pattern, particularly the prevalence of numerous sugar factories and extensive sugarcane cultivation, indicating an aggressive focus on sugarcane production. A recommendation emerges to diversify crops, opting for those with lower water requirements. Moreover, studies highlight the construction of numerous dams without effective rainy season management to fill them (Pawar P., 2009). In major developing countries, urban water supply schemes are prevalent, but many are outdated and inefficient, with a low success rate in cities and a significant percentage of dam water flowing into rivers. Effective water and energy management is crucial for both small and large-scale food production, employing science-based solutions to enhance efficiency and minimize pollution (Boron J.S., 2020). A comprehensive, stepwise approach is advocated to improve crop yield, providing subsidized access to fertilizers and enhancing crop seeds for rural farming households. Water use efficiency in rain-fed regions is critical, and it can be increased through soil management practices, crop residue management, and attention to soil nutrient status. The liberalization policy of 1991 in India led to increased industrialization, diverting a substantial amount of water resources from agriculture to industry (Kasabe M.G., 2021). The pollution from these industries directly affects rivers, impacting the water vaporization system and causing issues like irregularities in rainfall. Solutions such as rooftop rainwater harvesting, land-based harvesting, and the construction of small dams and lakes in villages are proposed to address these challenges.

Data & Methods

The modern approach to identifying drought risk areas involves utilizing Geographical Information System (GIS) and remote sensing technology, as highlighted by Prathumchai et al. (2001). GIS-based data processing is further employed to detect changes in vegetation conditions in response to drought by analyzing the Normalized Difference Vegetation Index (NDVI) between normal and drought years in each risk area. Lower NDVI values in high drought risk areas support the modified criteria of the Ministry of Science, Technology, and Environment (MOSTE). Shiva Prakash (2005) emphasizes the significant outcomes of drought severity mapping and management using GIS-based models. To identify drought severity, IRS LISS III satellite images are frequently used due to their regular availability and short time intervals, aiding researchers in predicting both rapid and slow events of droughts. Liu Sun et al. (2011) introduce a multi-index drought (MID) model that combines various drought indices to provide a more reliable assessment of agricultural drought conditions. The MID model proves superior in early drought risk detection, prediction, and accuracy assessment compared to single drought indices. Barua (2010) develops a Drought Assessment and Forecasting model using a Nonlinear Aggregated Drought Index (NADI), employing Artificial Neural Network (ANN) techniques for forecasting. The results show effective drought forecasts up to about 6 months ahead. Subramanyam (1964) introduces the aridity index (Ia) for drought classification, defined as the percentage ratio of annual water deficiency to annual water need or potential evapotranspiration.

Meteorological Drought Assessment

Meteorological drought is characterized by a significant deficit in precipitation from the normal levels over a specific area, a definition that can vary based on truncation levels and base periods to identify rainfall deficiency and drought periods. Palmer (1965) introduced a water balance technique, incorporating current and antecedent rainfall, evapotranspiration, and soil moisture in his index to assess drought severity in space and time. Instead of using normal precipitation, he introduced the concept of CAFEC precipitation. This method has been widely applied by many countries to identify drought periods and assess their intensity, including non-rainy months. George et al. (1973) utilized Palmer's methodology to delineate drought periods and intensity across various regions of India over a 71-year span. However, a limitation of this method is its lack of uniform applicability across all agro-climatic zones. Shewale (2001) pointed out that Palmer's method primarily represents agricultural drought in humid zones but signifies hydrological drought in semi-arid and arid zones. The Task Force on Drought Prone Area Programme (DPAP 1973) defined drought differently, classifying areas with less than 750 mm of annual rainfall as drought-prone and those receiving 750 mm to 800 mm as vulnerable to drought. McKee et al. (1993) introduced the Standardized Precipitation Index (SPI) to quantify precipitation deficits over different time spans and assessed the impact on various water supplies. The Meteorological Department of the Government of India defines a moderate drought-prone area when annual rainfall is less than 75% of the normal and severe drought when the deficiency exceeds 50%. The Irrigation Commission identifies an area as drought-prone if the irrigated area is less than 30% of the irrigable area. These diverse definitions highlight the complexity of assessing and managing drought across different regions and climatic conditions.

Hydrological Drought Assessment

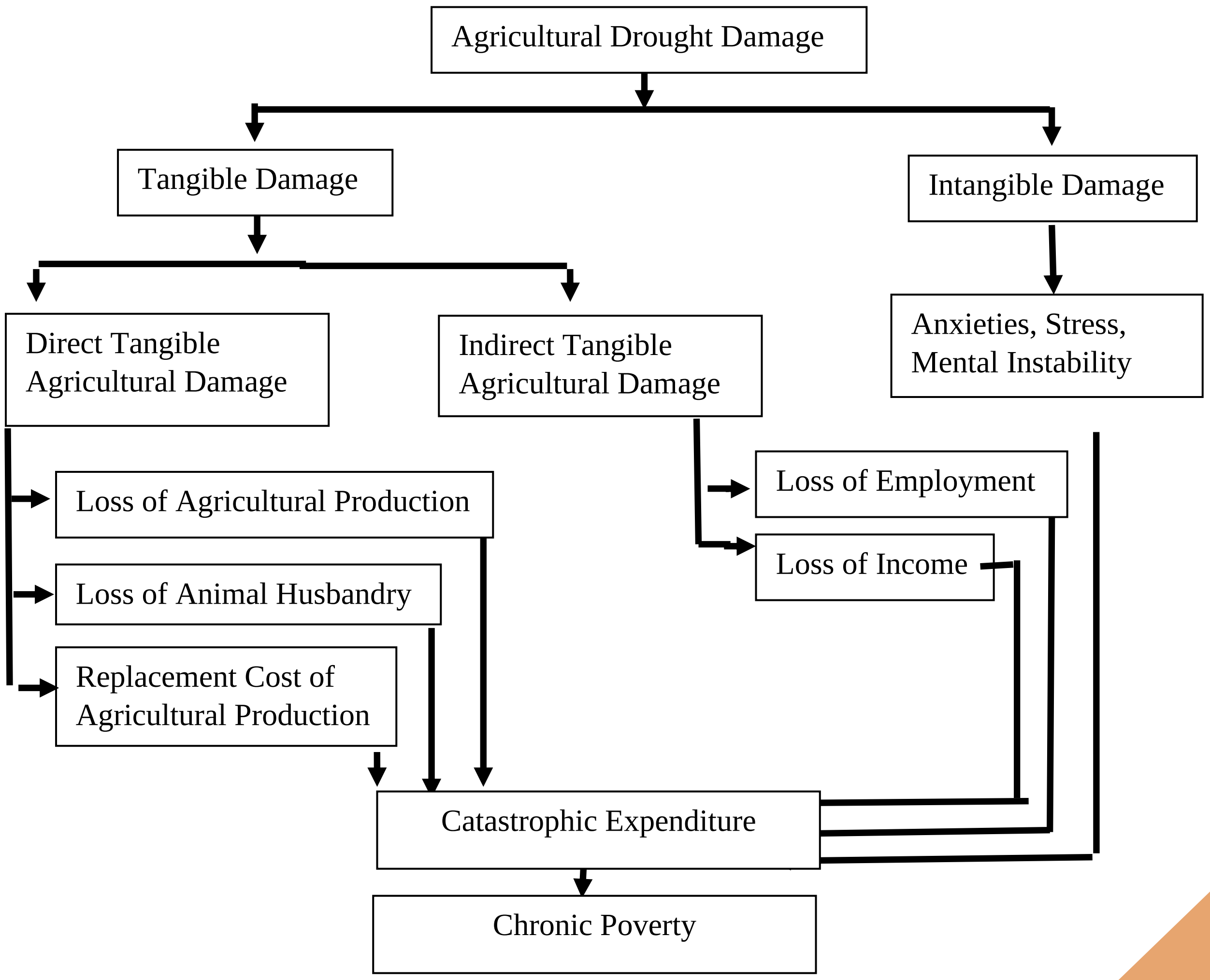
Hydrological drought assessment involves various methodologies to quantify and understand the impact of low stream flows on water availability. Chow (1964) utilized low stream flows as a metric for quantifying droughts, observing that the deviation of stream flow from normal is more pronounced during precipitation shortages compared to rainfall deviation. To effectively monitor droughts, Chow emphasized the need to specify low flow data in terms of flow magnitude (Chow, 1964). Mohan and Rangacharya (1991) adopted the theory developed by Herbst et al. (1966) to assess meteorological drought severity, applying it specifically to stream flow. Their method involved calculating the effective available water (Qe) for a particular month by combining the actual water availability (Q) with the excess or deficit of the previous month's available water from the long-term mean monthly available water. This approach incorporated a weighting factor (W) and provided insights into the frequency, onset, termination, and severity of hydrological drought on a watershed or river basin scale (Mohan & Rangacharya, 1991). In a different approach, Dracup et al. (1980) developed a method using the concept of long-term mean stream flow as the truncation level. This study employed three deterministic approaches based on different truncation levels to describe drought periods using stream flow data (Dracup et al., 1980). These methods contribute to the broader understanding of hydrological drought dynamics, offering insights into its frequency, severity, and temporal characteristics.

Agricultural Drought Assessment

Prajapati et al. (1977) employed stochastic analysis to quantify water deficiency during agricultural droughts. In contrast, Rama Prasad (1990) sought to measure water deficiency during agricultural droughts using soil moisture, specifically employing an Antecedent Precipitation Index (API) (Rama Prasad, 1990). Agricultural drought damage (ADD) is distinguished by a line between tangible and intangible damage. Tangible agricultural damage (TAD) is expressed in monetary values, while intangible agricultural damage (IAD) affects the physical or economic network system, which may or may not be expressed in monetary terms. Tangible agricultural damage is further categorized into direct and indirect tangible agricultural damage. Direct tangible agricultural damage (DTAD) includes loss of agricultural production, expansion of rainfed/unirrigated agricultural land, expansion of culturable wasteland, expansion of barren land, reduction in animal husbandry directly dependent on pastures, groundwater scarcity, and water-based poverty. Indirect tangible agricultural damage (ITAD) involves loss of employment, inadequate meals, increased poverty, heightened malnutrition, and economic loss. The quantification of agricultural drought damage is contingent upon various parameters, including temperature, precipitation, heat index, groundwater levels, evapotranspiration, chlorophyll index, water-holding capacity of soil, and irrigation. The primary objective of the study is to elucidate the relationship between agricultural drought damage and its exacerbating factors. The research questions are as follows: To what extent does a drought exert influence, leading to the loss of agricultural production, diminution in animal husbandry, increased purchase costs of crops due to drought damage, job loss, income reduction, inadequate meals, heightened poverty, escalated malnutrition, and amplified levels of anxiety, stress, and mental instability?

Result Analysis

The analysis of results suggests several solutions for water harvesting, including creating small holes in hilly and non-agricultural land. Some studies propose constructing drinking water dams in areas with maximum rainfall. It is recommended to divide drought-prone areas into smaller parts and implement various measures to mitigate the effects of drought. The study highlights significant inconsistencies in southwest monsoon patterns, affecting the socio-economic and environmental aspects of the country. Examining various drought management initiatives and experiences, the study describes critical areas of concern, along with necessary approaches, strategies, and technologies to combat drought-related adversities. Research on mapping agricultural drought in India utilized remote sensing and GIS with years of data. Landsat TM and ETM+ temporal images were assessed for high drought-prone areas. Brightness Temperature (BT) and Land Surface Temperature (LST) were estimated using Landsat-7 ETM+ and Landsat-5 TM satellite sensor data. These values were converted to Vegetation Conditions Index (VCI) and Temperature Conditions Index (TCI), aiding in vegetation health and agricultural drought estimation. Correlation and regression analysis were performed between Normalized Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), VCI, TCI, and Food Grain Anomaly. The study area was classified into moderate, mild, and no drought areas based on these indices. Multinomial logit models were employed to analyze the influences on decisions regarding coping strategies in response to climate extreme events. The study found that various socioeconomic and environmental factors impact coping strategies, with education of the household head, male gender of the household head, farm income, livestock ownership, access to extension services, farmer-to-farmer extension, temperature, ownership of radio, and better-quality housing positively influencing coping strategies (Deressa et al., 2010).



Drought Indices

(a) Percent of Normal: The percent of normal is a effective index for assessing drought on a regional or seasonal basis. It is straightforward to understand and provides varying indications of drought conditions based on location and season. This index is calculated by dividing actual precipitation by normal precipitation (typically a 30-year mean) and multiplying by 100. It can be calculated for different time scales, ranging from a single month to a group of months, depending on the specific drought season, or for an entire annual or water year. However, a major disadvantage is that mean precipitation may not align with median precipitation, as precipitation on monthly or seasonal scales does not always follow a normal distribution. The use of percent of normal precipitation is most suitable when the data is normally distributed, where the mean and median are considered the same.

(b) Palmer Drought Severity Index (PDSI): Developed by Palmer (1965), the PDSI is a soil moisture algorithm model that assesses drought using precipitation, temperature data, and local available water content. The index is based on the supply-demand concept of the water balance equation and takes into account precipitation deficits at specific locations.

(c) Standardized Precipitation Index (SPI): McKee et al. (1993) introduced the SPI to quantify precipitation deficits for various time scales, reflecting the impact of precipitation deficiency on water supply availability. SPI values are calculated for 3, 6, 12, 24, and 48-month scales to capture the temporal behavior of the impact. The calculation involves fitting a long-term precipitation record to a gamma distribution and transforming it into a normal distribution, ensuring a mean SPI of zero (Steinemann, 2003).

(d) Aridity Index (Ia): Subramanyam (1964) developed the Aridity Index (Ia) for drought classification, defined as the percentage ratio of annual water deficiency to annual water need or potential evapotranspiration. It is computed using the formula (Water deficit)/(Water need) = (Potential evapotranspiration - Actual evapotranspiration) / Potential evapotranspiration. The climate water balance procedure of Thornthwaite and Mather (1955) is used to calculate water deficit, and the values of the Aridity Index are used to compute the arithmetic mean and standard deviation over the calculation period.

$$Aridity\ Index\ (Ia)\ = \frac{Water\ deficit}{Water\ need}$$
$$= Potential\ evapotranspiration$$
$$-\ Actual\ evapotranspiration\ Potential\ evapotranspiration$$

(e) Deciles: Gibbs and Maher (1967) introduced "Deciles" to overcome weaknesses in the "percent of normal" approach. The distribution of occurrences over a long-term precipitation record is divided into tenths, each referred to as a decile. This categorization is used to classify rainfall amounts based on their occurrence frequency. The deciles are classified into five groups, and a long climatological record is required for accurate use of the decile system.

(f) Crop Moisture Index: In addition to the Palmer Drought Severity Index (PDSI), Palmer (1965) introduced the Crop Moisture Index (CMI), which utilizes a meteorological approach to monitor week-to-week crop conditions. Unlike the PDSI, which focuses on long-term meteorological wet and dry spells, the CMI is designed to evaluate short-term moisture conditions in major crop-producing regions. It is specifically tailored to assess short-term moisture conditions affecting developing crops, making it less suitable as a long-term drought-monitoring tool (Palmer, 1965).

(g) Aggregate Drought Index (ADI): Keyantash and Dracup (2004) developed the Aggregate Drought Index (ADI), a multivariate drought index that considers the overall quantity of water across meteorological, hydrological, and agricultural regimes of drought. The ADI is applied to regions with climatic uniformity, such as a National Climatic Data Center (NCDC) climate division. It employs Principal Component Analysis (PCA) of monthly hydrologic data to aggregate and assess water-related resources (Keyantash & Dracup, 2004).

(h) Water Availability and Water Stress Indices: The Water Availability Index (WAI) serves as a global measure of water available for socio-economic development and agricultural production. It estimates the accessible water diverted from the runoff cycle in a given country, region, or drainage basin, expressed as volume per person per year. Water stress can be calculated by comparing the volume of renewable water resources per capita at a national level. Critical values of the Water Stress Index (WSI) classify various ranges of water scarcity. Smakhtin and Hughes (2004) reviewed existing drought indices for their applicability in drought prediction and management, specifically in the context of South Asia. They developed a software package for automated estimation, display, and analysis of various drought indices. Due to the limited input data requirements of the Standardized Precipitation Index, they observed and used this index in Southwest Asia, citing its flexibility and simplicity in calculations as key reasons for its selection (Smakhtin & Hughes, 2004).

Drought Forecasting

Accurate forecasting of drought conditions is crucial for developing effective procedures and policies to mitigate the detrimental effects of droughts. A common approach is the use of statistical models for hydrologic drought forecasting based on time series methods. However, these models often assume linearity and stationarity, limiting their ability to capture non-stationarities and nonlinearities in hydrologic series (Grayman, 2005). Alternative models are required when forecasting hydrological droughts, especially when nonlinearity and non-stationarity play a significant role. Variability and uncertainty are important considerations in drought forecasting, yet they are often ignored in many studies. Grayman (2005) highlighted the importance of explicitly considering variability/uncertainty in hydrologic analysis, distinguishing between variability and uncertainty. According to Vose (2000), variability is the effect of change, while uncertainty is the level of ignorance about the parameters characterizing the physical system being modeled. Fuzzy set theory, introduced by Zadeh (1965), is well-suited for handling ambiguous and imprecise data in drought forecasting. Fuzzy rules derived from historical data provide consistency between the model and observed hydrologic behavior, offering explicit qualitative and quantitative insights into the physical system. Various studies have employed different methodologies for drought forecasting. Yevjevich (1967) used geometric probability distribution to investigate drought properties, defining drought as consecutive years with inadequate water resources. Saldariaga and Yevjevich (1970) used run theory to predict drought occurrence. Rao and Padmanaban (1984) employed stochastic models to forecast and simulate yearly and monthly Palmer's drought index. Yevjevich (1967) suggested the use of ARMA models for short and long-term drought prediction, applying them to stream flow and annual precipitation series. Other studies utilized ARMA models for various purposes, such as analyzing droughts over the Sahel area, forecasting precipitation and stream flows in South Africa (Dyer, 1977), and modeling winter rainfall in England and Wales (Rodda et al., 1978). Zekai and Sen (1980, 1989) developed a drought generating mechanism using extremes of random variables combined with the theory of runs. Beersma and Buishand (2007) used a time series model based on nearest-neighborhood sampling to develop a distribution of annual maximum precipitation deficit for six districts in the Netherlands. Moreira et al. (2008) employed log-linear models for drought category prediction using the Standardized Precipitation Index (SPI) for short-term prediction of drought severity classes. These methodologies contribute to our understanding of drought forecasting, emphasizing the importance of addressing nonlinearity, non-stationarity, variability, and uncertainty in developing effective forecasting models.

Drought Monitoring and Vulnerability Assessment

Vulnerability assessment is crucial to identify appropriate actions for reducing vulnerability before the damage caused by drought is realized. Wilhelmi and Wilhite (2002) emphasized the complexity of mapping vulnerability to drought due to the lack of a universal definition for drought. They proposed a spatial, GIS-based assessment of agricultural drought vulnerability in Nebraska, considering factors such as climate, soils, land use, and access to irrigation. The study developed a numerical weighting scheme to evaluate drought potential and concluded that non-irrigated cropland and rangeland on sandy soils in areas with a high probability of seasonal crop moisture deficiency were the most vulnerable to agricultural drought. Wu et al. (2002) employed a GIS-based agricultural drought vulnerability assessment model in China, focusing on factors like seasonal crop water deficiency, available soil water-holding capacity, and irrigation. The study revealed significant differentiation in agricultural drought vulnerability, both north–south and east–west, with various levels of vulnerability across the country. Kiumars et al. (2012) assessed drought vulnerability among wheat farmers in Western Iran, considering economic, socio-cultural, psychological, technical, and infrastructural factors. The study categorized vulnerability into very high, extremely high, and critical levels and found varying vulnerability across the study area. IMD's long-range forecasts and remote sensing data, validated with ground-based observations, were suggested for sustainable agriculture. Agromet parameters estimated through NADAMS project, Agro-meteorology of ICAR and IMD, and the Drought Prone Area Programme (DPAP) and Desert Development Programme (DDP) were considered essential for effective drought management. Sivakumar et al. (2011) highlighted the importance of national drought policies, emphasizing cooperation and coordination at all government levels. The study proposed a proactive, risk-based national drought policy to address repeated occurrences of droughts and their significant impacts on various socio-economic sectors. Dai et al. (2004) and Narisma et al. (2007) discussed changes in rainfall patterns in arid and semi-arid regions, attributing susceptibility to strong positive feedbacks between vegetation and climate interactions. The increasing fraction of land surface area classified as drought-prone was noted, and the socio-economic impacts of droughts, including reduced crop productivity, increased food prices, unemployment, and migration, were outlined. Ray Motha (2000) emphasized the importance of a national drought policy based on preparedness, planning, proactive mitigation, risk management, resource stewardship, environmental considerations, and public education. Adequate national observation networks and a drought information gateway accessible to the entire user community were deemed necessary. Zuqiang Zhang (2011) stressed the need for comprehensive stakeholder involvement, public participation, and efforts from non-governmental organizations and volunteers in drought management. Agriculture insurance services, charity, and capacity building for self-reliance were considered essential measures in drought risk management. Philippe Rougier and Gil Mahe (2010) used the Standardized Precipitation Index and Effective Drought Index to assess water stress and droughts in the Bani River (Niger basin, Mali). They discussed the importance of precipitation threshold parameters in studying drought events and addressing issues related to irrigation water management. Todisco et. al. (2009) made distinctions between potential and actual agricultural drought, differentiating between agricultural drought and agricultural aridity on inter-seasonal time scales. Janki Jiwan (2012) classified sustainable drought management into short-term and long-term strategies, including drought preparedness, prevention, and management of natural resources in a watershed framework. In summary, these studies emphasize the multifaceted nature of drought vulnerability assessment, considering various factors and proposing a range of strategies for effective drought monitoring and management. The importance of stakeholder involvement, national policies, and proactive measures is highlighted to enhance resilience and reduce the impacts of drought on different sectors of society.

The secondary effects of drought

The secondary effects of drought are multifaceted and often result from intricate interactions and transactions among various industries and sectors. These impacts can be categorized into downstream (forward), upstream (backward), and induced effects. Downstream effects occur when industries that rely on agricultural outputs, such as food processors and ethanol plants, face challenges due to reduced supplies from farmers experiencing crop losses. This can lead to elevated input costs or reduced production in downstream industries, affecting their consumers in turn. Conversely, upstream effects emerge when farmers decrease their demand for inputs like fertilizer, impacting upstream suppliers. The amalgamation of these upstream and downstream effects constitutes indirect effects. Income reduction resulting from drought can also lead to induced effects, prompting consumers to curtail spending and initiating a cascade of economic repercussions. The Input-Output (I-O) model is a widely used approach for estimating secondary effects arising from exogenous shifts like drought. This model relies on the interdependencies among industries and sectors within a specific economic region. The IMPLAN software package is commonly employed for conducting I-O analyses. However, I-O models have limitations, including assumptions of no input substitution, no price effects, and no resource constraints, which may lead to overestimations of secondary impacts. An alternative approach for gauging secondary effects is the Computable General Equilibrium (CGE) Model, which is considered an advanced extension of the I-O model. The CGE model offers increased sophistication and flexibility, overcoming many limitations of the I-O model. It accommodates input substitution, integrates price effects, and considers resource constraints. However, the implementation of the CGE model is more intricate, requiring a broader spectrum of data and a higher degree of sectoral aggregation (Shoven and Whalley 1992, Rose 1995).

Non-Market Drought Impacts

Drought impacts are traditionally categorized into economic, environmental, and social realms (Wilhite and Glantz 1985, Wilhite 1993). While previous sections explored the economic impacts across various sectors and industries, it's essential to recognize that environmental and social impacts can also have economic consequences. Any changes in human welfare resulting from these impacts should be considered part of the overall economic assessment of drought. For example, if drought adversely affects the habitat of endangered species, the well-being of individuals concerned about these species becomes a component of drought-induced losses. Similarly, if drought leads to health issues such as stress and anxiety among individuals, their diminished welfare should be factored into the economic evaluation of drought-induced losses. Economists and social scientists employ various methodologies to assess non-market values, with the most commonly used methods being travel cost, hedonic pricing, and contingent valuation (Freeman 1993, Wilson and Carpenter 1999, Champ et al. 2003). Despite the potential significance of non-market losses, they are often excluded from drought impact assessments and disaster loss calculations, which tend to focus exclusively on impacts measured by market values. As noted by Cochrane (2004), "Disaster losses are almost exclusively limited to impacts measured by market values," and "non-market losses are never estimated." Several factors contribute to the challenges in estimating non-market impacts, including the difficulty, expense, and time required for non-market evaluation methods, the need for researchers to possess a high level of economic knowledge and specialized expertise in data collection and modeling, and the inherent incommensurability or intangibility of some non-market impacts.

Conclusion

The effects of drought manifest slowly over a considerable period, and their impact can extend for several years after the drought period ends (Mishra et al., 2007). Drought is a creeping phenomenon, making the precise determination of its onset and end challenging. While the impacts of drought cut across various sectors, the majority of studies have focused on the agricultural sector or its subsectors for several reasons. Firstly, agricultural activities are highly sensitive to weather variability, making drought impacts on crops and pastures immediate and discernible. Secondly, data accessibility in the agricultural sector surpasses that of other sectors, with many studies adopting a 'with and without' approach to estimate drought losses. Historical average values, often available through the USDA's National Agricultural Statistics Service (NASS), serve as benchmarks for normalcy. Thirdly, monetary estimates of drought losses, crucial for federal disaster aid applications, have historically been predominantly available for agriculture. These estimates are pivotal for federal relief funding determinations. However, caution is necessary when using these estimates as they are often compiled within constrained timeframes, sometimes even before the drought concludes and impacts manifest entirely. In the United States, most empirical evaluations of drought impacts have occurred at the state level. For example, a study by Diersen et al. (2002) scrutinized the economic repercussions of the 2002 drought on South Dakota, estimating the initial total impacts in the billions. Subsequent reevaluation factored in improved market conditions and direct federal aid, highlighting the necessity of circumspection with estimates. Research beyond the agricultural sector is limited, with most studies concentrating on municipal water supply. Economic losses in this context have been estimated for sectors such as industry and commerce. Beyond water supply, studies have explored impacts on consumer welfare during droughts in locations like Seville, Spain. Impact assessments in sectors like horticulture, landscaping, tourism, and recreation are often qualitative or localized, showcasing the need for comprehensive evaluations across various domains to understand the multifaceted impacts of drought.

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