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Integrated approaches to understanding and reducing drought impact on food security across scales

Xiaogang He^{1,2}, Lyndon Estes³, Megan Konar⁴, Di Tian⁵, Daniela Anghileri⁶, Kathy Baylis⁷, Tom P Evans⁸ and Justin Sheffield^{1,6}

Understanding the cross-scale linkages between drought and food security is vital to developing tools to reduce drought impacts and support decision making. This study reviews how drought hazards transfer to food insecurity through changes in physical processes and socio-environmental systems across a wide range of spatial and temporal scales. We propose a multi-scale, integrated framework leveraging modeling advances (e.g. drought and crop monitoring, water-food-energy nexus, decision making) and increased data availability (e.g. satellite remote sensing, food trade) through the lens of the coupled human-natural system to support multidisciplinary approaches and avoid potential policy spillover effects. We discuss current scale-dependent challenges in tackling drought-induced food security whilst minimizing water use conflicts and environmental impacts.

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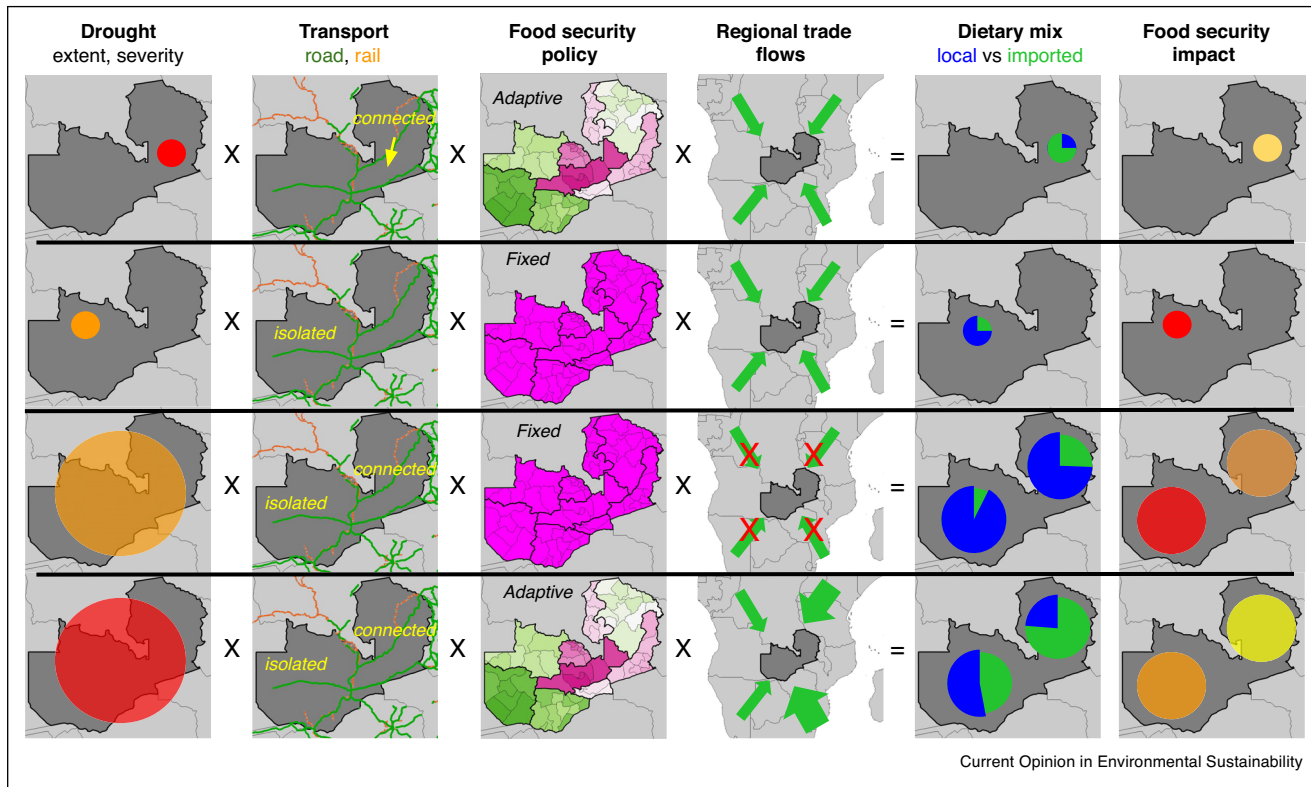
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Introduction

Recent decades have witnessed substantial strides in increasing global food production. Yet we still face challenges to feed 9.8 billion people by 2050, especially over drought-prone and dry areas of the developing world. For example, in sub-Saharan Africa, food crises are periodically triggered by droughts, and could be further exacerbated by other compounding factors (e.g. heat waves, floods, conflict). Over the last five decades, food production shocks (i.e. sudden losses) have become more frequent across all regions and all food sectors [2*]. Half of these shocks are caused by extreme weather [2*] with disproportionate effects on countries with low coping capacity, such as the ability of farmers to diversify food production or the ability of governments to import food or provide insurance. For instance, the 2017 Kenya drought led to a national emergency and left 2.5 million people facing food insecurity [3]. With more effective adaptation strategies and actions, the impact of elevated drought risk due to climate change [4,5] can be reduced and help facilitate progress towards hitting the second United Nations Sustainable Development Goal (SDG) (i.e. zero hunger). Synchronous challenges are emerging if multiple inter-related SDG goals are to be achieved simultaneously (e.g. SDG2 to ensure food security, SDG6 to ensure water security, SDG13 to foster resilience), as they interact across a range of spatial and temporal scales, leading to diverse trade-offs, synergies and even competing policy responses with impacts that are also scale-dependent [6**]. Understanding such cross-scale interactions is key for policymakers and stakeholders to develop adaptation policies that can effectively reduce the impacts of drought on agricultural production, and to increase societal resilience to future drought-induced emergencies, while still meeting competing demands and enhancing environmental sustainability.

Figure 1 conceptualizes a range of potential food security outcomes, for the example of Zambia, driven by cross-scale interactions of a range of plausible physical and socio-economic scenarios. The effect of drought (or other hazards) on individuals and communities depends on both the direct impact of the drought on local food production and the response of trade networks and institutions to drought occurrences (e.g. aid/relief organizations), which are reliant upon domestic infrastructure to move food resources. The impacts of droughts are also

Figure 1



Examples of food security scenarios, illustrating the interactions between droughts of different scale and impact (localized or national coverage; mild or severe), transportation access (isolated or connected), food security policies (fixed or adaptive subnationally), and regional trade (free trade, preferential trade or trade barriers), and their impacts on average household dietary mix (ratio of local to imported food) and overall food security.

shaped by existing policies and institutional factors, such as agricultural subsidy programmes. For example, the food security impact of a small but severe drought can be mitigated if the affected region is well connected to regional transport and food distribution networks, provided food transfer policies are flexible and adaptive enough, or regional trade flows are sufficient so that enough food can be transferred to the affected region to make up for local farmers' production losses (Figure 1, top row). On the other hand, a drought of the same extent but of less severity could lead to much larger food insecurity in a region that is relatively isolated (making it less likely that market forces can meet food shortfalls, even given substantial regional trade), particularly if food security policy is relatively inflexible and unable to concentrate and prioritize resources at a subnational scale (Figure 1, 2nd row). Other scenarios can play out based on other combinations of drivers and responses (Figure 1, rows 3 and 4).

Given scale-dependent drought-food security linkages in both the environmental and socio-economic realms, disciplinary approaches are unlikely to solve such 'wicked' problems. Instead, interdisciplinary approaches across

scales are needed to fully understand drought-linked food security outcomes, and the corresponding interventions that can minimize impacts. To this end, we review recent progress in drought risk and food security analysis, and modeling approaches from both the biophysical and socio-economic perspectives. We also discuss how to leverage emerging opportunities in modeling advances and rich datasets to develop scalable and integrated decision support frameworks that incorporate local knowledge and stakeholder involvement. These frameworks can be used to reduce drought impacts on food security and help address SDG targets.

How does drought impact food security?

In this review, we focus on three categories of food security: availability (i.e. crop production, stock, and trade), access (related to physical and economic factors such as food trade, income, market, price), and stability (adequate access to food), all of which are directly or indirectly affected by drought risk, either through biophysical processes (related to the hazard component) or socio-economic processes (related to vulnerability and exposure components). We do not address the utilization aspect (i.e. the appropriate use of the nutritional content

by the human body) of food security as this is generally less affected by drought, and we focus on crops rather than livestock.

Drought impacts on agricultural production

Drought is an extreme state of the hydrological cycle and reflects a situation with below average water availability conditions. Drought usually starts with precipitation deficit (called meteorological drought) and sometimes can be exacerbated by increased evapotranspiration due to high temperature, which can further propagate to the land surface and lead to reduced soil moisture (called agricultural drought) and streamflow (called hydrological drought). Water stress during drought slows down crop root growth, delays maturation and reduces agricultural productivity. Physically, this directly leads to reduced food availability especially for regions where livelihoods are highly dependent on rain-fed agriculture that are susceptible to droughts (e.g. sub-Saharan Africa). Globally, droughts caused 1820 million Mg loss of cereal (maize, rice, and wheat) production over the past four decades [7]. The extent to which various types of drought affect food security is highly linked to their spatio-temporal footprint. For instance, the timing and duration of droughts largely determine their impact on agriculture. Individual drought events with short-duration (several weeks) exert less pressure on agricultural and water management compared to multi-year prolonged droughts, whose effects can ripple across other sectors [2^{*}]. The timing of drought occurrence is important, as the sensitivity of crop yield to water stress differs with growth stage, which is related to the fundamental biophysical mechanisms of crop growth [8]. Given this, there is a need to assess drought impacts on agricultural productivity separately for specific growth stages, which is more meaningful for agricultural water management [9]. Statistical and process-based models are important tools for estimating drought impacts on crop yields [10^{*}], but these are inherently scale dependent, ranging from the farm level to global scale [7,11]. This highlights the need for multivariate probabilistic approaches [12,13] to simultaneously consider the joint distribution of the spatial and temporal footprint of drought. Such approaches can be combined with model-based large ensembles [14] for more robust quantification of agricultural risk, but should consider whether risk assessments are transferable across scales.

Drought is a risk multiplier to the interlinked food, energy and water (FEW) sectors, making agricultural sectors more vulnerable as the FEW sectors become more interconnected [15]. Globally, there is increasing competition between urban water provision and agriculture water demand [16^{**}]. Water allocated to domestic/industrial uses necessarily decreases water available for irrigation which can result in decreased yields in times of inadequate rainfall. The situation could become more

challenging if water is diverted for more profitable non-food sectors (e.g. irrigation for biofuel production or water for mining) [17]. Such trade-offs in terms of water allocation not only exist across sectors, but are also manifested through the spatial patterns of upstream-downstream relationships along the river network, with competing goals between, for example, upstream hydropower generation and downstream irrigation. Although hydropower is a non-consumptive water use (except for seepage and evaporation), hydropower reservoirs can alter the timing when water would naturally flow into the river system. This can sometimes interfere with downstream agriculture, especially when the crop growing season and high electricity demand periods do not coincide [18^{*}]. However, the extent to which there are trade-offs depends on the duration and spatial footprint of droughts, as well as whether there are cross-basin and large-scale water-transfer infrastructures.

Drought interactions with markets and trade

Besides the direct physical influence of drought on agriculture, drought also indirectly jeopardizes food security through its impact on socio-economic systems. The impact is scale-dependent, not only because the hazard component of drought risk varies across different spatio-temporal scales [19], but also because vulnerability and exposure vary across scales, and are influenced by infrastructure (e.g. reservoirs, roads) and policies (e.g. subsidies, trade policy). At the local scale, farmers whose production is affected by drought face the double-shock of both a loss of income along with potentially increasing food prices. Even urban consumers who are not directly linked to farming systems are affected by increased prices for food in urban markets. At the regional scale, spatially extensive droughts could destabilize regional food systems, and further increase the volatility of crop prices. Such regional impacts can ripple into the globally interconnected markets, exacerbating the vulnerability of countries whose economies strongly rely on international food trade [20].

Water is embodied in traded goods across spatial and temporal scales. Extensive research has focused on the global virtual water trade, or the water embodied in internationally traded commodities [21], with increasing interest in determining the source of the water (e.g. rainfall, surface supplies, or groundwater) [22^{**},23^{*}]. Recent research has examined virtual water transfers at smaller spatial scales, including domestic virtual water flows [24] and transfers to urban areas [25^{*}]. Food trade appears to exhibit the same structural properties across spatial scales [26^{*}], indicating that it likely also improves water use and food security at smaller scales of analysis, though research is still needed to better understand this. Most water footprint studies are at the annual temporal scale [27^{*}]. For example, research has examined unsustainable groundwater resources that are embodied in the

global trade system [22**]. However, to evaluate the buffering capacity of groundwater to supply chains during drought events, we require estimates at the subannual time scale [23*]. Future research should resolve virtual water trade flows in space and time to better understand the exposure of supply chains to both long-term water stress and shorter-term hazards (e.g. drought, flood). It is important to note that virtual water does not necessarily indicate if trade is leading to more or less water use. The critical question is how much water (sustainable and unsustainable) would be used in the absence of trade. To address this critical question, tools of causal inference are needed. Recent work has shown that trade decreases water use (on average) in agriculture [28*] and does not increase nutrient applications [29*]. At the subnational scale, causal inference methods have been used to show that the ability to transfer food leads to less famine in India [30*].

Drought and food policy

From the policy perspective, local, national and international policies could either alleviate or intensify the drought impact, and in some cases can lead to unintended consequences across scales. For example, recent work using causal inference finds that crop insurance policy has spillovers to water use [31**] because farmers tend to use more water than they would have in the absence of crop insurance. At the national level, decisions to prevent exports to mitigate drought impacts can harm domestic food security and agricultural markets, by increasing price volatility rather than the intended goal of price stabilization and reduction [32]. Internationally, global food trade can help mitigate the effect of local production shocks, by facilitating movement of food from other regions whose production was unaffected, but can also spread the effect of drought-related shocks across time and space [33]. These effects can be exacerbated by the imposition of export barriers, particularly by traditionally major exporters, such as were imposed by India, Thailand, Russia, Argentina and many others in the face of the 2008 food price increase. For example, Zambia enacts explicit export bans (prohibition of maize exports) as well as implicit bans (limits on export licenses) depending on national level maize production [34]. While successful at lowering price variability within the country, by restricting global supply, these policies exacerbated the global price increase for rice and wheat in particular [35,36]. Many developing countries also have stock-holding policies meant to mitigate production shocks. In Africa, stockholding has become increasingly popular among governments over the past two decades, and government marketing boards have become major players in African food markets [37]. Subsidized grain purchases are combined with often subsidized consumer sales to raise prices to farmers and lower them to consumers, with the goal of reducing price volatility. These programs are often large and expensive. India's combined stock-holding and food

subsidy program is the largest social safety net in the world, costing 6% of the government budget. Despite their popularity, it is unclear how well these policies work to stabilize price across space, within or across years [38]. Policies that impact crop prices or production supports (e.g. biofuel mandates, input supports) can promote expanded crop production, which may lead to greater investment into a single crop at the expense of crop diversity, or increased cultivation in agriculturally marginal lands [39,40]. Either result may increase the risk of failure due to drought.

Recent advances in integrated drought impact mitigation approaches

The multifaceted impact of drought and its cross-scale interactions between physical and socio-economic systems requires a portfolio of integrated approaches to mitigate its impacts on food security. In this section, we review recent advances in hydrological and crop modeling, satellite remote sensing, and machine learning that can be used to detect and anticipate drought impacts, as well as how to translate the scientific advances to support real-world decision making through nexus approaches within the coupled human-natural system.

Drought early warning and forecasting

Progress in the development of drought early warning and forecasting has been made in recent years due to advances in understanding predictability, land surface modeling, satellite-based measurement of key hydrological variables (e.g. precipitation, soil moisture), as well as advances in machine learning algorithms facilitated by the surge of big data of the Earth system. Techniques to monitor and forecast drought can be distinguished as process-based approaches, data-driven approaches and hybrid approaches. Process-based approaches are physically oriented, relying on large-scale meteorological forecasts from climate and weather models to drive hydrological models to obtain critical hydrological variables, which are used to calculate agricultural and hydrological drought indices [41–43]. This has been routinely adopted to develop regional and global scale drought monitoring system across different temporal scales, from short-term to seasonal [41,44**]. However, there remain challenges in translating the skill of large-scale, short-term hydrological forecasts to the local scale at long lead time (e.g. subseasonal, seasonal), which is more relevant for agricultural management and planning. This requires bias-correction and downscaling techniques [45] to pre-process large-scale meteorological input so that they have commensurate resolution with hyper-resolution hydrological models [46,47] and therefore drought impact assessment is locally relevant. More importantly, the predictability of the forecasts themselves need to be substantially improved through enhanced understanding of the underlying drought mechanisms [48]. This also applies to data driven approaches, which aim to develop

statistical relationships between drought characteristics (e.g. severity, spatial extent, duration) and environmental covariates (e.g. hydrological, meteorological, climatic variables). The wealth of environmental datasets from different sources (e.g. *in situ* observations, remote sensing, retrospective simulations, reanalysis products, climate projections, and even citizen-science observations) combined with advanced machine learning models (e.g. deep learning, [49^{••}]) and increased computational power (e.g. cloud computing, [50]) makes data-driven approaches increasingly attractive for drought monitoring and forecasting [51–53,54^{••}]. However, as drought is a dynamic process and its evolution (i.e. onset, persistence, and recovery) is space and time dependent [55], challenges exist in terms of how to select the most informative and scale-dependent predictors from the wealth of data. This can be guided through advances in physical understanding of drought mechanisms [48]. At the same time, data-driven approaches can provide insights for diagnosing the underlying mechanisms and therefore could identify new pathways for physical model improvement. Hybrid models [49^{••}] which harness advantages from both physically based and data-driven approaches show promise for future development and enhancement of regional [41,56] and smaller scale systems. For instance, the flexibility of machine learning in adapting to multi-resolution datasets can be used to replicate physical model parameterization schemes across different scales. It is also possible to use machine learning based emulators to fully or partially replace the computationally expensive physical model to accelerate the simulation process of drought monitoring and forecasting systems, especially when they are running operationally and at high resolution.

Crop monitoring and yield forecasting

To understand how drought impacts agriculture, it is essential to estimate and forecast crop yields at the scale of individual fields or agricultural landscapes over large extents (countries to regions), in order to understand how productivity impacts propagate across scales. There are three critical pieces of information that must be accurately measured, in sequence, to provide reliable, fine-scale information on crop productivity: Firstly, the location and extent of crop fields; secondly, the crop types growing within them; and finally, the yield response [57,58,59[•]]. Obtaining accurate estimates of each of these three elements remains a major challenge, particularly in regions dominated by smallholder farming systems, where agricultural census is often lacking or inaccurate, and the ability to accurately measure these properties with remote sensing is particularly challenging. Accurately mapping croplands at the characteristic scales of individual fields (1–2 ha) is arguably an unsolved problem, one that can propagate significant error into crop type and crop yield estimates [60,61,59[•]].

Despite such challenges, recent technological and methodological developments are helping to rapidly improve agricultural datasets. The emergence of small satellite fleets is providing imagery at the high spatial and temporal resolutions required to accurately map smallholder-dominated croplands [62^{••},61], while recent work using Sentinel and Landsat imagery have led to 20–30 m resolution, global to continental scale cropland maps [63,64]. Such efforts are facilitated by the increasing availability of cloud-based image processing, such as Google Earth Engine [65^{••}], which provides a free platform combining open image archives, large-scale computing, and advanced processing and classification algorithms. Advances in computer vision and machine learning are helping to improve agricultural mapping [64,61]. Alongside these algorithms, which typically require large training datasets, new crowdsourcing platforms allow large, distributed networks of human mappers to digitize labels by visually interpreting high resolution satellite imagery [66–68]. In addition, the Sen2Agri system provides an operationalizable method for creating annual maps of both cropland and crop types that has been demonstrated at national scales [69[•]]. However, this approach must be trained with large volumes of *in situ* crop type observations, which are often challenging to obtain, thus recent work demonstrating a training data-free crop type mapping approach appears promising, at least over more homogeneous cropping systems [70[•]].

Progress has also been made in field-scale yield estimation. Prominent among these is the Scalable Yield Mapper approach [71], which uses a mechanistic crop simulator to develop an empirical model of yields that uses remotely sensed predictors (e.g. vegetation indices, gridded weather variables), thereby foregoing the need for field data. This approach has been used to map between-field differences in yield and crop management practices (e.g. planting date) in smallholder-dominated systems, with errors comparable to those in field-collected yield data [72,73^{••}]. Most recently, it has been combined with automated crop type mapping [70[•]] to map maize yields over Kenya and Tanzania [74[•]]. The rise of new *in situ* sensing systems, novel SMS-based farmer survey methods [75] and autonomous aerial vehicles [76^{••}] will make it easier to calibrate and constrain crop simulations used by this method, by substantially increasing the amount of field data that can be collected on crop phenology and management.

Accurate crop yield forecasting plays an important role in risk management, trading, policy making, and decision making for improving food accessibility. A number of approaches have been developed for crop yield forecasting at regional, national, and international levels. Empirical approaches are based on deriving statistical relationships between crop yields and satellite vegetation indices [77], climate data and forecasts [10[•],78–80], or both

satellite and climate information [81]. Combining climate data and remote sensing based vegetation indices is a relatively new and promising approach. Process-based approaches with dynamic crop simulation models combined with climate forecasts are used as well [82]. These advances have been incorporated into land data assimilation systems, which take advantage of the improved skill of climate forecasts at subseasonal and seasonal lead times, and have been employed for crop growth monitoring and crop yield forecasting at global and regional scales [83]. Compared with empirical approaches, process-based approaches have large data requirements which could prevent their spatial generalization and application. In contrast, empirical approaches using statistical models provide a simple alternative for spatially explicit crop yield forecasts, but are generally limited to the range of variability they were developed for. Both empirical and process-based methods are transferable across different scales contingent upon the scale of the input data. Studies have also been conducted to investigate the linkages between large-scale climate variability and crop yields, providing the basis to develop climate-informed seasonal crop yield forecasting [84,85]. Benefitting from these advances, a few systems have been developed and are running operationally, such as the European Commission MARS Crop Yield Forecasting System (MCYFS) (<http://agri4cast.jrc.ec.europa.eu/>).

Decision support and risk reduction for water and agricultural management

Progress in understanding drought mechanisms and crop impacts combined with easy access to timely data and improved physical models have enabled the recent development of agricultural drought monitoring and forecasting systems [41,56]. These systems run operationally and disseminate data to a wider scientific community and stakeholders, and therefore are valuable decision support tools [86–89]. For instance, these systems can aid in the strategic planning of water and agricultural resources across scales (e.g. local, regional). With forecast information available at seasonal or even longer time scales, these systems can allow local government to establish coping strategies to ward off famine and allow the humanitarian community to develop more effective assistance. This has been demonstrated during the 2016/2017 East African drought, with the Famine Early Warning Systems Network (FEWS NET) contributing to enhanced drought resilience in Kenya and reduced mortality rate in Somalia compared to the 2010/2011 drought [56]. Of key importance is to make similar progress towards integrating cross-scale policies (e.g. national trade agreements, local subsidies) and food transfers (e.g. international and domestic food trade, food aid) into drought early warning systems through hierarchical and scalable network approaches. Recent implementation of risk-based frameworks [90,91] has demonstrated their value in enhancing resilience for both short-term (e.g. coping and recovery of

drought) and long-term horizons (e.g. anticipating trends and variability for future long-term planning such as infrastructure, water banking, etc.). It is extremely challenging for policy-makers to identify and implement strategies which address the complexities and deep uncertainty associated with climate and non-climate factors (e.g. society, land use, economy, etc.) that lead to drought impacts [92]. Generally speaking, there are two main approaches to deal with deep uncertainty from the decision making perspective [93]: Firstly, robust decision making approaches which look for strategies or interventions which guarantee a minimum performance against a wide range of possible future scenarios [94,95^{••}]; and finally, adaptive decision making approaches which periodically revise strategies and interventions to adapt to changes in the decision making context as future uncertainties unfold [96,97]. Recently developed end-to-end probabilistic risk assessment frameworks account for the full spectrum of risk (i.e. risk mitigation, risk forecast, and risk transfer instruments) [98]. This framework not only considers physical-loss risk due to lowered crop production caused by droughts, but also addresses how it translates to direct and indirect economic loss, which is more directly related to decision making. If applied in real contexts, such scientific advances have the potential to enable the exploration of constraints and tipping points of food security as well as the identification of probabilistic solutions that can be used for domestic food transfers to optimize food security across scales. However, research on the integration of such environmental and economic decision making into current drought monitoring and early forecasting systems is still in its infancy.

Coupled modeling and assessment of human and natural systems

Better understanding of drought risk and its translation to crop impacts is one aspect of supporting decision making. From the adaptation point of view, decision making can be more cost-effective if adaptation capacities associated with different levels of stakeholders (e.g. individual farmer, environmental agency) are jointly considered [99]. On one hand, this is important for more accurate estimation of agricultural water demand, especially over regions with irrigated agriculture, where farmers can adapt to droughts by changing their irrigation behaviors or through land use changes (e.g. changing crop types, fallowing land). Their decisions on agricultural management can be further aided if their perception on drought risk is better informed through seasonal forecasting [100]. The importance of such behavioral dynamics has been increasingly recognized by the physical modeling [101] and risk assessment communities [102], especially under the influence of climate change [103]. The recently developed human-climate model [104] enables the bi-directional coupling between human behaviors and the climate system, and represents a useful approach to understand the potential interaction of overlooked

behavioral dimensions and environmental consequences. Such large-scale conceptual models can be applied in the context of drought to evaluate the usefulness of potential policy interventions as well as to identify feasible adaptation pathways that can lead to sustainable agricultural development. However, challenges still exist in terms of how to downscale the spatial human dimensions from larger (e.g. global scale) to more relevant scales (e.g. basin scale), and how to better consider the dynamics of inter-connectedness across scales [105]. The scaling issue becomes even more vital as the increased pace of globalization is strengthening the inter-connectedness and tele-connectedness of coupled human–water systems [106]. More and more evidence has shown that even piecemeal behaviors/actions can add up to a much larger scale and trigger a cascade of effects [107,105]. This further highlights the necessity to extend current coupled frameworks [108,109] to larger scales from the bottom-up point of view, but using hierarchical model structures to reconcile the top-down approach with layers of different spatial and temporal resolutions, and appropriate complexities thereof. Agent-based modeling (ABM) has advantages to characterize such complexities (e.g. farmer–farmer, farmer–government, farmer–environment interactions), but is usually limited to small spatial scales and is highly reliant on the availability of empirical data (e.g. survey data) to characterize various agents' behaviors and their associated heterogeneity, as well as to validate model assumptions. Despite these challenges, coupled hydrological and ABM systems are useful to understand the relative importance of social and behavioral dimensions in agricultural decision making, compared to other factors (e.g. climate change). They also have the potential to promote behavioral changes and inform adaptation strategies to increase society's resilience to drought [110].

Representing water-food-energy connections through multi-scale nexus approaches

Progress towards reducing drought impacts on food security, and in general, towards achieving SDGs related to water, also needs consideration of the manifold interlinkages among water, food and energy [111,112^{**},113]. These interlinkages can be directly altered by climate shocks such as droughts [114], which themselves vary across different spatial and temporal scales. Of particular importance is the spatial dimension, recently highlighted by Liu *et al.* [115^{**}], who proposed a new integrated and metacoupling framework for investigation of nexuses in three different types: intracoupling (within a specific place), pericoupling (between adjacent places) and telecoupling (between distance places). This framework can be used to understand the linkages between drought and food security, and help identify potential intra-regional policy instruments [114] to facilitate decision making for different levels of stakeholders. Take the food trade in sub-Saharan Africa as an example. Although local food production is vulnerable to prolonged droughts (e.g.

Kenya), food shortage could be buffered by international food trade/aid. However, for the poorest of the population, food security can be negatively affected by the interaction of policies at different scales (e.g. local, domestic, international) [116], yet the spatial expression of these impacts is still unknown. Therefore, local to international food trade should be jointly considered for understanding and planning of the entire food system. This should also account for embedded virtual water, especially for countries (e.g. Pakistan) whose export of agricultural production is at the expense of environmental degradation (e.g. groundwater depletion) [22^{**}]. Furthermore, droughts can exacerbate competition for water resources between irrigation water supply and hydropower generation, usually through upstream–downstream relationships [117,118]. The fact that 54% of hydropower plants compete with irrigation water use at the global scale [18^{*}] indicates that we need to reconcile competing water demands among different upstream–downstream sectors, optimize water use to minimize conflicts and maximize synergies among multiple goals [112^{**},95^{**}]. The temporal scale of nexus approaches should also be considered for future planning, through scenario analysis based on explicit drought shocks [113] or through dynamic life cycle assessment methods [119].

Challenges, opportunities and future directions

Progress towards closing yield gaps in the face of drought risk, and ensuring food security requires a range of research and interventions, including improving the availability and use of methodological tools (either physically based or data driven or both) and datasets (e.g. satellite remote sensing, climate and hydrological model simulations, citizen-science observations) for monitoring and predicting food security. It is of critical importance to deliver data (e.g. forecasts of drought and crop yield) at the time scale that is relevant for decision making and can be used to support management practices. These datasets should also be long-term, consistent and continuous such that risk quantification is robust and accurate enough. It is also critical to develop policy instruments which could balance the temporal trade-offs between conflicted short-term (e.g. buffer droughts through groundwater pumping) and long-term objectives (e.g. maintain sustainability of depletable groundwater resources). A more challenging issue is how to factor in climate change information for long-term planning such that drought risk management is adaptive and proactive [120,121]. This requires different levels of adaptation strategies that are targeted for different time horizons. For example, incremental adaptation (e.g. farmers make moderate changes of existing irrigation behaviors) may be adequate for the short-term response to drought, but large-scale transformation options (e.g. fundamental changes of agricultural systems through innovation) may be needed for longer planning horizon [122]. A specific challenge is to avoid maladaptation, in

which short-term benefits may lead to worse situations in the long-term. This was reflected in the 2007–2009 California drought, where high agricultural and energy production were maintained through adaptation strategies that increase the vulnerability of other sectors in the long-term [123]. For instance, the increased purchase of natural gas to replace declining hydropower leads to more greenhouse gas emissions. Although high agricultural production was maintained during this drought, increased groundwater pumping over the Central Valley to cope with longer and more severe droughts for future generations is unsustainable.

From the spatial perspective, we face challenges in terms of how to vertically integrate data, models, and decision making processes in a consistent way. The context and location specific challenges in drought-induced food insecurity require tailoring models and the representation of agricultural management (e.g. irrigation) to local, more policy-relevant scales, with a view to delivering effective climate/hydrologic services for food security. On one hand, we are benefiting from the wealth of data-based predictive information which can be used to understand drought risk and to reduce its agricultural impact. But on the other hand, this information is derived from different sources and is usually spatially and temporally down-scaled/upscaled based on different assumptions, and therefore may lead to data inconsistencies. This highlights the need to merge information to reduce uncertainty. Given the increased availability of geospatial data emerging from various sources, a promising avenue is to combine machine learning with these data, but guided by physical modeling [49^{••}], so that more interpretable information can be extracted and integrated across disciplines and scales. This will aid the development of nested models, which have flexible resolutions and complexities to consider multiple levels of spatial heterogeneity (e.g. local details, cross-scale interactions).

Conflict of interest

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