Earth observation for drought risk financing in pastoral systems of sub-Saharan Africa

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As climate-related crises increase globally, climate risk financing is becoming an integral part of financial protection and resilience building strategies of African countries. Drought-induced crises result in devastating human impacts and high costs for vulnerable countries, threatening longer-term investments and development efforts. While earth observation (EO) has been widely used for drought early warning, new opportunities emerge from integrating EO data and methods into index-based drought risk financing (IBDRF) instruments. Such instruments aim at supporting an effective and timely response during drought shocks and improving the resilience of small-holder farmers and livestock keepers. This review documents the current status, and discusses future prospects and potential challenges for EO utilization in IBDRF applications in sub-Saharan Africa. We focus on pastoral systems, which are hotspots in terms of vulnerability to climate and environmental change, food insecurity, poverty, and conflicts. In these systems, EO-based IBDRF interventions are rapidly scaling up as part of national and international risk management strategies.

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Introduction

Crisis risk financing refers to mechanisms that aim at reducing adverse socio-economic or ecological impacts of potential crises [1•]. This can include paying to prevent and reduce the risk, or to prepare for and respond to a shock. Climate risk financing (CRF) targets climate-related shocks (e.g. drought, floods and heat waves) and is becoming an integral part of climate risk management frameworks as key components of financial protection strategic planning for low and middle income countries [2]. Multiple CRF approaches exist, including market-based instruments (e.g. insurance schemes, catastrophic bonds and swaps), contingent financing (e.g. credit), or budgetary tools (i.e. dedicated reserve funds or contingency budgets). These approaches are all designed to increase financial resilience to climate-related crises, linking the response actions to pre-defined mechanisms for timely release of financial resources. In this way, they aim at ensuring rapid and cost-effective preparation, assistance, recovery or reconstruction efforts.

Droughts, defined as periods with water deficit relative to normal conditions, are one of the most disrupting natural disasters, each year affecting millions of people worldwide with devastating impacts [3,4]. Severe droughts cause massive disruptions to national economies and dramatic impacts on the livelihood and food security of small-holder farmers and livestock keepers. Standard responses to drought in African countries, such as humanitarian support in the form of cash or food transfers, are important instruments to support drought-affected vulnerable populations. However, these responses have proven to be often too slow, cost-ineffective, and to foster dependency rather than resilience, especially when not integrated into holistic risk management strategies [2].

Among the different CRF instruments, index-based approaches have gained considerable traction over the last two decades, particularly for targeting drought shock impacts on African small-holder farming systems. Index-based drought risk financing (IBDRF) uses trigger mechanisms that rely on a transparent and objectively measured indicator of drought (i.e. the index). The underlying index must be highly correlated with drought-related economic losses to be useful in tracking, and, therefore, transferring, the risk. Payouts are made when the index values fall below a pre-defined threshold, normally derived from historic index realizations. When compared to *ex-post* loss verification (e.g. traditional insurance), IBDRF limits information asymmetry issues, such as adverse selection and moral hazards,[3] reduces transaction and verification costs, and

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[3] This terminology originates from insurance literature: adverse selection occurs when potential policyholders make decisions based on information about their risk exposure that is not available to the insurance provider. Moral hazard occurs when the policyholders engage in activities that increase their exposure to risk, leaving the insurer exposed to higher risk than had been assessed for premium rate determination.

enables more effective and timely distribution of payouts. However, these advantages come at the cost of the inherently imperfect correlation between index and actual loss, also known as basis risk [5].

Pastoral production systems dominate the African drylands, cover about 43% of Africa's land mass, and are the main livelihood for about 268 million people in these areas [6]. Drought is a distinctive feature and over millenia the pastoral livelihood developed to deal with this [7]. However, particularly in SSA, the combination of increasing rainfall variability [8] and other pressures (e.g. changes in land use and tenure, population growth, rangeland degradation [9]) is weakening the resilience of pastoral communities and the effectiveness of traditional drought coping mechanisms (e.g. mobility, restocking). Severe droughts can lead to catastrophic herd losses in pastoral regions, and as such cause food insecurity and poverty trap dynamics, and dramatically reduce national GDPs of SSA countries [5]. Consequently, the development and implementation of drought risk management strategies for pastoral regions, including IBDRF initiatives, is a key component of the policy agendas of development institutions and national governments.

The scarcity and poor quality of ground data and national statistics in SSA pastoral regions [10] has made in most cases Earth observation (EO) by satellites the only viable option for designing IBDRF instruments for large-scale implementation. The growing availability and increased quality of long-term EO datasets of rainfall products and vegetation indices [11•] have been instrumental in designing indices that are thought to reliably represent drought risks. Furthermore, the close interlinkage between rangeland condition and impacts on productive assets (i.e. livestock) and livelihoods has facilitated the design of financial triggering mechanisms that link impact to payouts. Therefore, datasets obtained through multitemporal satellite imagery are currently a key component of IBDRF initiatives in pastoral regions.

However, whilst the scientific literature on drought monitoring is vast, only a few studies reviewed the contribution of EO to insurance [12,13•], and currently no overview exists of the IBDRF initiatives, challenges, and prospects in sub-Saharan Africa.

Evolution of IBDRF in pastoral Africa
During the last decade IBDRF initiatives in African pastoral drylands have gained significant momentum, also thanks to large international initiatives such as the InsuResilience Investment Fund [14] and the Global Index-Insurance Facility (GIIF). While for several years IBDRF schemes have largely remained at the pilot level, constrained by the limited demand for retail micro-insurance products [15,16], these schemes are now gradually covering larger areas, given their growing integration in country-wide social protection and drought risk management programs. This caused a significant increase in volume of financial transactions and a growing participation of international re-insurance companies, which facilitates risk transfer toward international financial markets, and promotes larger investments by governments and international organizations.

Table 1 summarizes operational IBDRF initiatives in SSA.. These initiatives, initially launched as retail micro-level index-insurance schemes (IBLI), more recently have expanded their scope and modality of implementation, including fully subsidized insurance programs targeting vulnerable pastoralists (KLIP, SIIPE), sovereign-level insurance schemes (ARC), and scalability mechanisms of shock responsive safety nets programs (HSNP, NUSAF). At the same time, IBRDF product design evolved from indices designed to assess an observed loss (i.e. the IBLI livestock mortality scheme), thus triggering when drought is already impacting pastoralist assets, to indices designed to identify deteriorating forage condition, thus triggering at the earlier drought stages, with the aim of supporting pastoralists to protect their assets (i.e. livestock or livelihood) or countries implementing early response actions.

While fully operational initiatives in pastoral areas are concentrated largely in East Africa and, to a lesser extent, in the Sahel, several insurance providers and organizations are launching similar IBDRF solutions on a retail basis across SSA, including in Niger, Zambia and South Africa. In addition, feasibility studies are being conducted in Somalia, Senegal, Burkina Faso, and Mali. Thus lessons gathered from early implementation efforts are of key relevance for sustainable scaling of IBDRF in SSA.

EO-based index design in operational IBDRF schemes
Similar to most drought early warning systems [e.g. Refs. 17•,18,19], existing IBDRF schemes for pastoral systems predominantly use vegetation indices or rainfall estimates (RFE) as input (Table 1). These EO products should meet the fundamental operational requirements for IBDRF, which include 1) full transparency and accessibility of the source data, 2) availability of historical records for financial risk modelling and pricing of ideally 20 years or more, 3) near real-time availability, and 4) an expected remaining lifetime of at least a few years. Satellite-derived RFE can provide a direct indication of meteorological drought, which largely determines water availability in rangelands. While availability of drinking water is important for livestock health, monitoring this for large areas is cumbersome, given that much water for livestock comes from wells or small water bodies that cannot easily be monitored with EO data. RFEs are instead typically used in IBDRF to estimate the available water for vegetation, for example using simple water-balance models.

Table 1

Summary of operational IBDRF programs targeting pastoral drylands, ordered chronologically with insurance programs listed first and non-insurance programs at the bottom

Program[a]	Years	Scope	Satellite[b] sensor/indicator	Index[c]	Area	Households (nr)
IBLI	2010–2015	Retail micro-insurance for drought related livestock mortality	AVHRR NDVI	Livestock mortality	Marsabit (Kenya), Borana (Ethiopia)	5983
IBLI	2015 – present	Retail micro-insurance for asset protection	MODIS NDVI	z-score seasonal NDVI	Northern Kenya and Borana (Ethiopia)	7000
KLIP	2015 – present	Subsidized insurance for asset protection	MODIS NDVI	z-score seasonal NDVI	Northern and Eastern Kenya	18 000
SIIPE	2017- present	Subsidized insurance for asset protection	MODIS NDVI	z-score seasonal NDVI	Somali region (Ethiopia)	5000
ARC	2017- present	Sovereign level insurance	RFE – multiple datasets	WRSI (RFE based)	East Africa and Sahel	N/a[d]
ARC	2019- present	Sovereign level insurance	MODIS NDVI	z-score NDVI or VCI	East Africa and Sahel	N/a[d]
HSNP	2015- present	Social protection scalability mechamism	MODIS NDVI	VCI running average	Northern Kenya	>100 000
NUSAF	2017- present	Social protection scalability mechanism	MODIS NDVI	NDVI percent anomaly	Karamoja (Uganda)	25 000

[a] IBLI = Index-based Livestock Insurance, KLIP = Kenyan Livestock Insurance Program, SIIPE = Satellite Index-Insurance for Pastoralists in Ethiopia, ARC = African Risk Capacity, HSNP = Hunger Safety Net Program, NUSAF = Northern Uganda Social Action Fund.
[b] AVHRR = Advanced Very High Resolution Radiometer. MODIS = Moderate Resolution Imaging Spectroradiometer, NDVI = Normalized Difference Vegetation Index, RFE = Rainfall Estimates (using satellite data).
[c] Z-score is sometimes referred to as standard score, WRSI = Water Requirement Satisfaction Index, VCI = Vegetation Condition Index.
[d] As ARC is a sovereign-level insurance scheme, the recipient of the payout is the country and the number of households covered will depend on the country's contingency plans. ARC is offering insurance cover for rangelands in the entire Sahel and Horn of Africa and plans to offer it also in Central and Southern Africa. The NDVI product has been launched in Chad, Niger, Mali, Mauritania, and Kenya.

The water requirement satisfaction index (WRSI) used by ARC is such a model; it estimates evapotranspiration demands of vegetation and compares this with a simple 'bucket' model of the soil that gets filled with rainfall [20,21]. Two main drawbacks exist when using rainfall-based indices for large-scale pastoral IBDRF: 1) despite the growing availability of gridded rainfall products, the quality, accessibility, and density of rainfall station data in pastoral SSA is generally low [22,23], resulting in unknown or poor accuracies in these areas [24]; 2) the link between rainfall and the vegetation's water availability is complex, and depends on vegetation characteristics, soil, and rainfall distribution [25,26], which cannot be characterized sufficiently with 10-daily rainfall sums [27].

For extensive pastoral systems, forage availability is a key determinant of livestock health, as alternative feed resources are largely unavailable or inaccessible. To overcome drawbacks of RFEs, optical sensors onboard satellites can be used to measure the vegetation's reflectance. Dense healthy vegetation reflects much in near infrared (NIR), and little in red wavelengths, and spectral vegetation indices, like the normalized difference

vegetation index (NDVI), use this to monitor vegetation condition. For drought monitoring, NDVI images from coarse-resolution satellites (250 m and up) are generally used, because 1) long time series exist to describe long-term variability in forage conditions, 2) their daily data collections allow for more cloud-free observations to describe vegetation changes throughout the season, and 3) documented evidence exists for a strong relationship between rangeland biomass and NDVI [28,29]. Required pre-processing steps to effectively use NDVI for anomaly analysis include temporal compositing [transforming daily to, e.g. 10-day data, keeping the best-quality observation for each pixel; 30], and smoothing to further reduce atmospheric effects [31].

To transform NDVI or alternative drought indices into a useful index for pastoral IBDRF schemes, three steps are required:

1) Spatial aggregation; geographic units are normally larger than grid cells, both for operational reasons and to reflect that herds move. Aggregation within units generally incorporates a mask of where rangelands occur.

2) Temporal aggregation; most schemes aim to assess seasonal forage scarcity, requiring expert or EO-derived [32] knowledge on rainfall/vegetation seasonality.

3) Normalization to compare the current index value against historic index realizations in past years. Multiple options exist, such as for example z-scoring (subtract mean and divide by standard deviation), linear scaling between minimum and maximum historic values [i.e. the vegetation condition index, or VCI; 33], or percentile calculation.

The term 'index design' in IBDRF refers to: a) the choice of input data, b) the precise methods for performing the above-mentioned three steps, c) the sequencing of these steps, and d) the testing of the resulting index against drought-related loss estimates. Eventually, the choice for a design will at least partly depend on the IBDRF instrument's purpose, satisfaction of stakeholders on historic and current index readings, and (scientific) background of the 'designers'. Given that droughts normally affect large regions and are simultaneously characterized by reduced precipitation and vegetation growth, it is well possible that alternative designs provide similar index outcomes during main drought events.

Opportunities and challenges for EO contribution to IBDRF

Recent targeted research efforts for EO support to innovative design of IBRDF solutions, made in the framework of the programs listed in Table 1, helped to remove critical barriers for scaling IBDRF initiatives in pastoral drylands. Here, we discuss four emerging trends in IBDRF where the demand for innovative solutions from EO research is strong. While we argue that the quality of IBDRF product design differs and that EO-aided solutions can play an important role to improve operational programs, we also emphasize that each solution is context-specific and needs to consider the trade-off between a) timing and accuracy of the assessment, b) cost-effectiveness of the response action, and c) the complexity of the interaction between drought shocks and the socio-ecological pastoral systems (Figure 1) with the goal of mitigating impacts and speeding-up recovery in the short term, while building long-term social and environmental resilience.

Emerging EO data products for IBDRF

EO data products used for IBDRF index design in pastoral areas have evolved over time in response to stakeholder feedbacks and with emerging technologies. For example, the ARC product for extensive rangelands has recently transitioned from WRSI to NDVI (Table 1), meeting the demand of key stakeholders. However, besides vegetation index (e.g. NDVI) products that provide a direct measure of forage status, drought characteristics can be obtained, for example, from EO-derived

precipitation [35], soil moisture [36,37], or evapotranspiration [38] products [for reviews on EO drought monitoring options see also Refs. 11•,39]. A variety of these products have already been proposed and in some cases integrated into drought index-insurance pilot projects for crops in Africa, for example, through data service provision by commercial EO companies [e.g. Refs. 40–43]. These efforts provide promising alternative drought indices for innovative IBDRF design by addressing multiple phases of drought progression and thus merit further analysis.

IBDRF design could also take advantage of the continuous stream of free 10−30 m resolution EO data that are provided by satellites such as Sentinel-1, Sentinel-2, and Landsat-8. Given their high observation frequency, timely fine-scale estimates of seasonality and forage conditions can be provided [44], even if cloud cover remains a concern for short vegetation seasons [45]. Arguably pastoral IBDRF may not require fine-scale data because droughts generally affect large areas, but where drought impacts differ due to greater landscape variability (e.g. in agro-pastoral systems) they could prove beneficial. As historical archives of 10−30 m resolution data are building, and tools to analyze resulting large data amounts become commonplace [46], finer-scale drought analysis will likely find its way into IBDRF.

Remote sensing advances for improved product design

The spatial component of basis risk (i.e. impacts are not equally distributed within a geographic insurance unit) is a recurrent issue for IBDRF products in pastoral areas, as administrative units cannot fully reflect the agro-ecological variability and herd mobility patterns. This type of basis risk has been reported for some insurance units in Kenya and Ethiopia, especially at the fringe between agro-pastoral and extensive pastoral systems. To deal with this issue, administrative units could be replaced by more meaningful ecological units, for example, defined based on similar temporal behavior of NDVI [47]. In addition, high resolution EO data can help to improve rangeland mapping and characterization [48], allowing to better spatially focus coarser-resolution drought indices on the areas within insurance units that matter most for forage production.

Payout timing and temporal aggregation is another critical component of product design. Triggering early action for expected adverse events can make disaster response more cost-effective [49•,61]. Because drought is a slow-onset shock, indicators can be designed that detect early stages of the drought progression [11•]. EO has supported the anticipation of the response by effectively characterizing between-year variability of forage conditions earlier in the season through shortening temporal aggregation windows, with the aim of designing asset protection insurance products [49•,62,63]. This has been a fundamental

Figure 1

Current Opinion in Environmental Sustainability
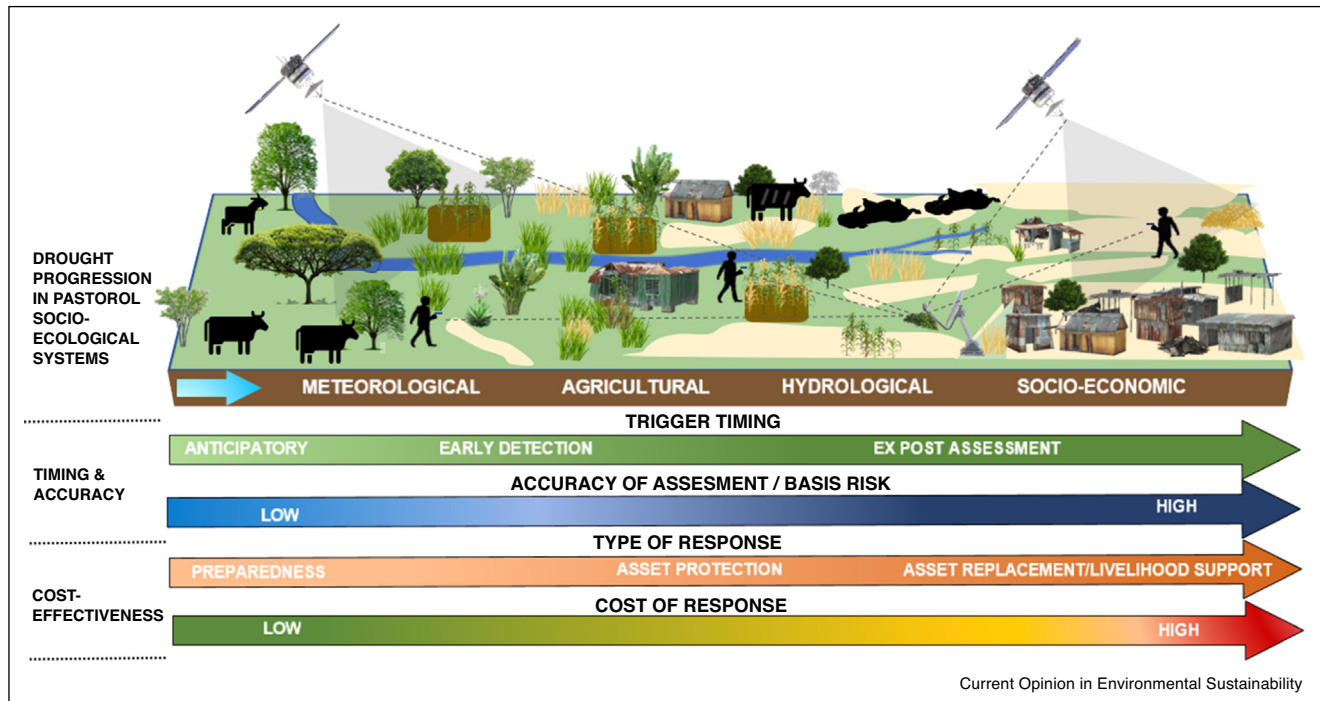
Ground and satellite EO applications can contribute to monitor drought progression and its ecological and socio-economic impacts to support context-specific design of IBDRF instruments. The upper part of the Figure illustrates the progression of drought impacts following Mishra and Singh [34]. While drought evolves from meteorological to socio-economic, IBRDF design needs to consider trade-offs to maximize the social-ecological benefits, while accounting for economic costs to ascertain long-term sustainability of the instruments. For example, an EO-based index designed with an early trigger is expected to be more accurate in detecting meteorological or agricultural drought, but might be less effective in assessing socio-economic impacts. This source of basis risk may (or may not) be counterbalanced by the savings in economic costs associated with asset protection and early response. These assumptions are context-specific and product quality assessment is thus fundamental to evaluate trade-offs.

step for the IBLI and KLIP programs to increase the uptake and gain political support toward geographic scaling. However, indices that allow for early triggering must also be backed by efficient payout delivery mechanisms to avoid negative impacts on program sustainability.

More recently, forecasting approaches based on time series analysis and machine learning techniques have been developed to predict time-integrated (seasonal) NDVI anomalies from lagged NDVI, rainfall, and climate indices [64–68]. While research on drought forecasting models is gaining momentum, particularly for early warning systems (e.g. HSNP, Table 1), the implementation of forecasts into IBDRF instruments is challenging given the forecasts' large uncertainty at local scales and longer time lags [69]. Using forecasts as a triggering index could thus increase basis risk and lead to operational implementation challenges (e.g. in case of false alarm and unneeded response) [61,70]. Moreover, deciding on thresholds for response triggering could be complex because this relates not only to the level of the impact, but also to its probability. A different challenge emerges when forecasts are not directly used but could nonetheless affect IBDRF instruments such as insurance.

For example, since insurance premiums are based on historical realizations of the index, reasonably accurate forecasts made before insurance sales [possibly through indigenous indicators: 71] could lead to adverse selection if prospective purchasers have information about expected payouts that the product's pricing does not account for [e.g. Ref. 15]. Overall, while anticipatory risk financing based on forecasts is a promising innovation in IBDRF, its operational implementation would require a careful assessment of associated risks and effective harmonization with other IBDRF instruments.

Quality assurance of IBDRF

Basis risk remains a critical concern for the quality and sustainability of IBDRF schemes. For operational initiatives a few recent studies compared results from multiple index designs [41,47,49•,50]. Notwithstanding, these studies highlighted that evaluation of the resulting indices remains complex given the scarcity of and/or difficulty to collect good-quality *in-situ* data on drought outcomes. While EO product development and improved index design have potential to reduce basis risk, ultimately it remains an empirical question whether this potential is

realized. This question goes beyond the traditional accuracy assessment approaches in the EO domain (e.g. an evaluation if soil moisture is accurately represented in a soil moisture product), as it should encompass also the socio-economic value of the proposed solution [49•], and be formalized through quality metrics, minimum standards and robust assessment frameworks [1•,51]. The overarching goal should be to design rigorous quantitative metrics and approaches to assess and compare the utility of IBDRF interventions.

A main challenge is collecting and analyzing relevant reference data on drought outcomes, given the limited formal data sets [52]. Potential data sources include multi-year forage biomass measurements [53], drought recall exercises [52], and repetitive household surveys on drought outcomes such as livestock mortality [49•] or child nutrition [54]. Given the cost-intensive and labor-intensive nature of collecting such data, ground-based EO approaches can provide a useful addition. A good example is the repetitive observation of the same vegetation, either by permanent cameras [55,56], or through crowdsourcing platforms [57]. For crops, this has already led to the idea and implementation of 'picture-based-insurance' whereby farmers repeatedly collect pictures of their fields for verification of insurance claims [58]. This idea could be extended to rangeland and livestock conditions, possibly taking advantage of computer-vision based automation of body scoring techniques [59,60]. Increased efforts in reference data collection are urgently needed to answer the empirical question and provide quality insurance products.

Socio-economic and environmental impact evaluation

With the geographic expansion and growing number of households covered, the need for impact evaluation of IBDRF initiatives has increased. Traditionally impact evaluation of drought crises on small-holder farmers and livestock keepers largely focused on socio-economic factors through mixed qualitative-quantitative household-level surveys [72]. However, the high costs and complexity of such surveys have prevented a systematic integration of impact assessment studies in IBDRF initiatives, so that only few robust assessments are available in pastoral regions [e.g. Ref. 73•]. In addition, environmental impacts have been poorly considered so far, while scaling IBDRF interventions to a large number of households might have relevant ecological impacts. For example, reduced herd losses may result in increased grazing pressure on rangelands [74•,75], although empirical studies suggest on the contrary that insured pastoralists keep smaller herds because they reduce their use of livestock as precautionary savings [76].

EO approaches for rangeland health monitoring are well established [e.g. Ref. 77]. However, only few studies, focused on land restoration, have integrated these approaches into impact assessment of large programs in drylands [78,79]. Recent literature also showed potential

for assessing food security and household wealth [80,81•,82], but pointed out that satellite EO capacity to directly monitor socio-economic indicators of household wellbeing and rapid land use dynamics during drought events (e.g. land accessibility, land tenure changes, migration) is limited. Impact evaluation could be improved by combining satellite EO information with *in-situ* collected environmental and social-economic data [83], which are increasingly available via mobile and crowdsourcing platforms also in rural Africa [e.g. Refs. 84•,85,86]. This can be supported by advances in machine learning algorithms, allowing to extract patterns and understand spatial connections from diverse data sources [87]. Data driven approaches should be, however, used with caution and framed within a robust set of causal hypotheses, taking into account the cross-scale interactions between physical and socio-economic factors [81•].

Conclusions

IBDRF initiatives are scaling up as part of the policy agendas of SSA countries and development organizations on resilience building, poverty reduction, and sustainable development. EO plays a key role in sustaining this trend in pastoral drylands, with the potential of significant societal and policy impact in the region. Innovations from ground and satellite EO technologies could contribute to design more accurate, cost-effective, and harmonized drought risk financing programs, as well as to assess their effectiveness during shocks and their longer-term impacts. However, this can only be achieved if the EO community does not limit its role to providing technological solutions and services, but rather becomes an integral part of the interdisciplinary framework to address drought risk management in complex socio-ecological systems, understanding synergies and trade-offs between research, operational implementation, and policy formulation.

Conflict of interest statement

Nothing declared.

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