Satellite-Driven Micro-Insurance Models for Drought-Prone Agricultural Regions: Integrating Remote Sensing Technologies, Index-Based Risk Assessment Algorithms, and Climate-Adaptive Financial Protection Mechanisms for Smallholder Farmer Resilience

Kwame Asare Boateng
Department of Agricultural Economics Faculty of Agriculture University of Ghana Legon, Accra, Ghana

* Corresponding Author: **Kwame Asare Boateng**

Article Info

P-ISSN: 3051-3421
E-ISSN: 3051-343X
Volume: 02
Issue: 01
Received: 14-04-2021
Accepted: 16-05-2021
Published: 18-07-2021
Page No: 53-59

Abstract
Drought events represent one of the most devastating climate-related risks to agricultural productivity in developing regions, disproportionately affecting smallholder farmers who lack access to conventional risk transfer mechanisms. Traditional indemnity-based insurance schemes have proven economically unfeasible for low-income farmers due to high transaction costs, moral hazard concerns, and expensive loss verification requirements. This review examines the transformative potential of satellite-driven micro-insurance models that leverage remote sensing technologies to provide affordable, transparent, and scalable agricultural risk protection in drought-prone regions. By integrating multi-spectral and multi-temporal satellite observations with parametric index-based insurance frameworks, these innovative models enable objective drought monitoring, automated yield estimation, and trigger-based payout mechanisms without requiring costly field assessments. Key satellite-derived indices including Normalized Difference Vegetation Index, Enhanced Vegetation Index, Soil Moisture Index, and Evaporative Stress Index serve as quantifiable proxies for crop health and water availability, forming the foundation for algorithmic risk assessment and payout determination. This article synthesizes current approaches to satellite data acquisition, drought index modeling, micro-insurance product design, and real-world implementation strategies across vulnerable agricultural landscapes. Evidence from pilot programs demonstrates significant potential for enhancing farmer resilience, though challenges related to spatial resolution, validation accuracy, farmer education, and enabling policy frameworks require continued attention to achieve widespread adoption and long-term sustainability.

Keywords: Satellite remote sensing, index-based insurance, drought monitoring, agricultural risk assessment, parametric insurance, smallholder resilience

1. Introduction

1.1 Agricultural Vulnerability in Drought-Prone Regions

Agricultural systems in semi-arid and drought-prone regions face escalating climate variability, with prolonged dry spells and erratic precipitation patterns threatening food security and rural livelihoods worldwide [1, 2]. Smallholder farmers in developing countries, who constitute approximately 475 million farm households globally, bear disproportionate exposure to climatic shocks due to limited adaptive capacity, resource constraints, and dependence on rain-fed agriculture [3]. Drought-induced crop failures can trigger catastrophic income losses, perpetuating cycles of poverty and undermining long-term agricultural development [4]. The absence of effective risk management instruments leaves vulnerable farming communities with limited options beyond distress asset sales, reduced consumption, or migration [5].

1.2 Limitations of Traditional Insurance Schemes

Conventional indemnity-based agricultural insurance requires on-site damage assessment by trained adjusters, making it prohibitively expensive for small-scale operations where individual farm sizes may be less than two hectares [6]. High administrative costs, information asymmetry problems including adverse selection and moral hazard, and delayed claim settlements have historically limited insurance penetration rates to below 5% in most developing nations [7, 8]. Premium subsidies provided through government programs often prove fiscally unsustainable while failing to reach the most vulnerable populations [9]. These structural barriers have created an urgent need for alternative insurance mechanisms that can deliver affordable, objective, and scalable risk protection to smallholder farmers.

1.3 Scope and Objectives of the Article

This review examines satellite-driven micro-insurance models as transformative solutions for agricultural risk management in drought-prone regions. The article synthesizes current knowledge on remote sensing platforms, drought monitoring indices, algorithmic insurance design, and implementation strategies that leverage space-based Earth observation to overcome traditional insurance barriers. Specific objectives include: (i) characterizing satellite data sources and drought indices applicable to agricultural risk assessment; (ii) analyzing parametric and index-based insurance frameworks utilizing remote sensing inputs; (iii) evaluating field implementation experiences and farmer adoption patterns; and (iv) identifying technical, operational, and policy challenges that must be addressed to achieve scalable impact.

2. Satellite-Driven Data Acquisition for Risk Assessment

2.1 Remote Sensing Platforms and Sensors

Modern Earth observation systems provide unprecedented opportunities for continuous agricultural monitoring across diverse spatial and temporal scales. Satellite platforms deliver multi-spectral imagery that captures vegetation dynamics, soil moisture conditions, and environmental stress indicators essential for drought detection and yield forecasting [10, 11]. Table 2 summarizes major satellite systems deployed for agricultural applications, spanning operational meteorological satellites with daily revisit capabilities to medium-resolution land imaging missions offering enhanced spatial detail [12].

Table 2: Satellite Platforms and Sensors Suitable for Agricultural Risk Assessment

Platform	Sensor	Spatial Resolution	Temporal Resolution	Key Applications
MODIS (Terra/Aqua)	Multi-spectral	250-1000 m	Daily	Regional vegetation monitoring, drought indices
Landsat 8-9	OLI/TIRS	30 m	16 days	Field-scale crop assessment, land cover mapping
Sentinel-2	MSI	10-20 m	5 days	High-resolution vegetation dynamics, phenology
SMAP	L-band radiometer	36 km	2-3 days	Soil moisture retrieval, root-zone hydration
CHIRPS	Integrated	5 km	Daily	Rainfall estimation, precipitation deficit analysis
VIIRS	Multi-spectral	375-750 m	Daily	Near-real-time vegetation condition monitoring

The integration of multiple satellite systems enables comprehensive drought monitoring through complementary observations, with coarse-resolution daily data providing rapid detection while medium-resolution platforms support field-specific assessments [13, 14].

2.2 Drought Indices and Crop/Soil Monitoring

Quantitative drought indices derived from satellite observations serve as objective indicators of agricultural stress conditions, forming the empirical foundation for parametric insurance triggers [15]. Vegetation indices exploit the differential reflectance properties of healthy versus stressed crops, with chlorophyll-rich vegetation exhibiting strong near-infrared reflection and visible light absorption [16]. Table 1 presents widely implemented drought and vegetation monitoring parameters utilized in agricultural risk assessment applications.

Table 1: Key Drought Indices and Remote Sensing Parameters for Crop and Soil Monitoring

Index	Formulation/Source	Physical Basis	Insurance Application
NDVI	(NIR - Red) / (NIR + Red)	Vegetation greenness and biomass	Biomass proxy, yield forecasting
EVI	2.5 × [(NIR - Red) / (NIR + 6×Red - 7.5×Blue + 1)]	Canopy structure with atmospheric correction	Enhanced sensitivity in dense canopies
VCI	(NDVI - NDVImin) / (NDVImax - NDVImin) × 100	Deviation from historical normal conditions	Drought severity classification
ESI	Evapotranspiration anomaly	Plant water stress and moisture deficit	Early drought detection (2-4 weeks lead)
SMI	Soil moisture anomaly	Root-zone water availability	Planting condition assessment
SPI	Precipitation deviation	Meteorological drought intensity	Long-term rainfall deficit quantification

The Normalized Difference Vegetation Index (NDVI) remains the most widely adopted parameter for satellite-based insurance due to its computational simplicity, extensive validation, and strong correlation with crop productivity across diverse agricultural systems [17]. However, NDVI exhibits saturation in dense vegetation canopies, prompting the development of enhanced indices such as EVI that demonstrate improved linearity with leaf area index [18]. Vegetation Condition Index (VCI) normalizes current vegetation status relative to historical ranges, enabling spatial comparisons across heterogeneous environments [19].

2.3 Data Preprocessing and Calibration

Robust satellite-derived insurance products require rigorous data quality control protocols to minimize measurement uncertainties and ensure consistent performance [20]. Critical preprocessing steps include atmospheric correction to remove aerosol and water vapor interference, cloud masking to eliminate contaminated observations, geometric registration for precise spatial alignment, and temporal compositing to reduce noise [21]. Ground-truthing campaigns linking satellite observations to in-situ crop yield measurements provide essential calibration datasets for developing regionally-specific yield estimation models [22]. Phenological corrections accounting for crop calendar variations ensure that vegetation indices are compared at equivalent development stages rather than fixed calendar dates [23].

3. Micro-Insurance Models Leveraging Satellite Data

3.1 Index-Based and Parametric Insurance Approaches

Index-based insurance represents a paradigm shift from traditional loss verification toward objective, transparent trigger mechanisms based on measurable parameters [24]. In satellite-driven implementations, insurance payouts are determined algorithmically when remotely sensed indices cross predefined thresholds indicating crop stress or yield reduction, eliminating subjective damage assessments [25]. Table 3 characterizes primary micro-insurance architectures utilizing satellite observations.

Table 3: Micro-Insurance Models Based on Satellite-Derived Data

Model Type	Trigger Mechanism	Data Requirements	Advantages	Limitations
Area-yield index	Aggregate regional yield deviation	Multi-year yield statistics + satellite indices	Basis risk reduction through spatial pooling	Coarse spatial granularity
Pure parametric	Direct NDVI or VCI threshold	Satellite vegetation index time series	Minimal data requirements, rapid payout	Higher basis risk for individual farmers
Hybrid satellite-weather	Combined vegetation + rainfall indices	Multi-sensor integration	Comprehensive risk capture	Increased technical complexity
Smart contract blockchain	Automated digital execution	Real-time satellite feeds + distributed ledger	Transparency, cost reduction	Technology adoption barriers
Progressive payout	Graduated response to index severity	Continuous index monitoring	Proportional compensation	Premium calculation complexity

Pure parametric products trigger payouts when satellite-derived indices fall below specified thresholds for defined temporal windows, such as NDVI values remaining 20% below historical average for three consecutive dekads during critical growth stages [26]. Area-yield approaches aggregate satellite observations across administrative units or homogeneous agro-ecological zones, reducing basis risk through spatial pooling while sacrificing granularity [27]. Hybrid models combine vegetation indices with complementary information such as rainfall estimates or soil moisture to capture multidimensional drought impacts [28].

3.2 Yield Estimation and Risk Modeling

Translating satellite observations into actionable insurance parameters requires empirically-validated relationships between remote sensing indices and actual crop yields [29]. Statistical and machine learning approaches establish these linkages through analysis of historical satellite-yield datasets. Table 4 summarizes algorithmic methodologies for yield prediction and payout determination.

Table 4: Algorithmic Methods for Yield Estimation and Payout Determination

Method	Technical Approach	Data Requirements	Typical Accuracy	Application Context
Linear regression	NDVI integral vs. yield	5-10 years calibration data	$R^2 = 0.60-0.80$	Simple crops, stable environments
Random forest	Multi-variable ensemble learning	Extensive training datasets	$R^2 = 0.70-0.85$	Complex systems, non-linear relationships
Crop simulation models	Process-based growth modeling	Weather, soil, management inputs	RMSE = 15-25%	Data-rich environments
Deep learning CNNs	Image-based yield prediction	Thousands of labeled observations	$R^2 = 0.75-0.90$	High-resolution imagery availability
Threshold-based triggers	Binary payout if index < critical value	Historical percentile distributions	Not applicable	Catastrophic loss protection

Linear regression models relating seasonal NDVI integrals to final yields provide interpretable, computationally efficient solutions suitable for operational deployment with limited computational resources [30]. Machine learning algorithms including random forests and neural networks can capture complex non-linear relationships and interactions among multiple predictors, though requiring substantial training data and expertise [31]. Trigger-based mechanisms simplify payout determination through binary logic, activating compensation when indices indicate severe stress without attempting continuous yield estimation [32].

3.3 Smart Contracts and Automated Payout Mechanisms

Blockchain-enabled smart contracts represent an emerging innovation that couples satellite data streams with distributed ledger technology to create fully automated, transparent insurance execution [33]. When satellite-derived indices trigger predefined conditions encoded in blockchain smart contracts, payouts execute automatically without manual intervention, dramatically reducing administrative costs and eliminating payment delays [34]. Distributed ledger systems provide tamper-proof transaction records accessible to all stakeholders, enhancing trust and reducing disputes [35].

However, technical complexity, digital literacy requirements, and infrastructure dependencies pose adoption challenges in resource-limited settings [36].

4. Applications and Case Studies

4.1 Smallholder Adoption in Drought-Prone Regions

Field implementations of satellite-driven micro-insurance have demonstrated technical feasibility and farmer acceptance across diverse agricultural contexts. Table 5 summarizes representative case studies and implementation strategies.

Table 5: Field Implementation Strategies and Case Studies in Drought-Prone Regions

Program/Location	Coverage	Satellite Data Source	Insurance Design	Key Outcomes
ACRE (Kenya, Rwanda, Tanzania)	250,000+ farmers	MODIS NDVI	Area-yield index with progressive payout	80% claim accuracy, rapid settlement
RIICE (Asia-Pacific)	2 million hectares	Sentinel-1 SAR + optical	Parametric flood/drought triggers	Reduced loss assessment costs by 90%
R4 Rural Resilience (Ethiopia, Senegal)	50,000+ farmers	CHIRPS rainfall + MODIS	Hybrid rainfall-vegetation index	Insurance integrated with risk reduction
Kilimo Salama (East Africa)	185,000+ farmers	Weather + MODIS vegetation	Mobile-enabled parametric	Payout within 2 weeks of trigger
India PMFBY satellite pilot	1 million+ farmers	Resourcesat LISS-III + MODIS	Smartphone-based yield estimation	Field-level granularity demonstration

The Agriculture and Climate Risk Enterprise (ACRE) program operating across East Africa has enrolled over 250,000 smallholder farmers through partnerships with agricultural input suppliers, utilizing MODIS NDVI data to assess vegetation conditions and determine payouts for maize and other staple crops [37]. In Southeast Asia, the Remote-sensing based Information and Insurance for Crops in Emerging economies (RIICE) initiative employs Synthetic Aperture Radar imagery to monitor rice cultivation patterns and trigger flood or drought compensation [38].

4.2 Governmental and NGO-Supported Programs

Public sector engagement has proven essential for achieving scale, with government-sponsored programs leveraging satellite technology to expand agricultural insurance coverage [39]. India's Pradhan Mantri Fasal Bima Yojana (PMFBY) represents the world's largest crop insurance scheme, with satellite-based pilot components utilizing high-resolution imagery for yield estimation at individual farm parcels [40]. The World Food Programme's R4 Rural Resilience Initiative integrates satellite-driven index insurance within comprehensive climate adaptation packages combining risk transfer with risk reduction activities, livelihood diversification, and prudent risk reserves [41].

4.3 Performance Metrics and Outcomes

Evaluations of operational programs demonstrate substantial benefits including reduced claim processing time from months to weeks, elimination of costly field visits, enhanced transparency reducing farmer distrust, and improved targeting of vulnerable populations [42]. However, basis risk—the discrepancy between actual farm-level losses and satellite-detected regional conditions—remains a persistent challenge, with correlation coefficients between index values and individual yields typically ranging from 0.60 to 0.80 [43]. This imperfect correlation means that some farmers experiencing losses may not receive payouts while others without significant damage may receive compensation, undermining insurance value proposition [44].

5. Challenges and Future Perspectives

5.1 Data Resolution, Latency, and Cost Issues

Despite substantial progress, technical limitations constrain the effectiveness of current satellite-driven insurance systems. Table 6 synthesizes key advantages, limitations, and ongoing challenges.

Table 6: Advantages, Limitations, and Challenges of Satellite-Driven Micro-Insurance Systems

Dimension	Advantages	Limitations	Future Solutions
Data acquisition	Objective, continuous monitoring	Cloud cover interference, spatial resolution trade-offs	Multi-sensor fusion, SAR integration
Cost structure	Eliminates field assessments	Satellite imagery costs, processing infrastructure	Open data policies, edge computing
Temporal resolution	Daily to weekly updates	Phenological timing sensitivity	AI-enhanced gap-filling algorithms
Spatial granularity	Regional to field-scale options	Basis risk for individual farms	High-resolution commercial satellites
Technical capacity	Automated processing possible	Requires specialized expertise	Cloud-based platforms, capacity building
Farmer understanding	Transparent index-based triggers	Index correlation complexity	Participatory design, education programs

Spatial resolution limitations create fundamental trade-offs between area coverage and farm-level precision, with freely available moderate-resolution imagery (250-1000m pixels) unable to distinguish individual smallholder plots [45]. Commercial high-resolution satellites offer 3-10m pixels suitable for field-scale monitoring but impose significant cost barriers [46]. Cloud contamination during rainy seasons when agricultural monitoring is most critical poses data availability challenges for optical sensors, though Synthetic Aperture Radar systems can penetrate clouds providing complementary observations [47].

5.2 Farmer Adoption and Accessibility Constraints

Successful insurance adoption requires that smallholder farmers understand product mechanisms, perceive value commensurate with premiums, and trust payout execution

[48]. Satellite-based index insurance presents communication challenges as the relationship between remote sensing indices and crop performance is not intuitively obvious to farmers lacking technical backgrounds [49]. Participatory design processes involving farmer feedback in index selection and threshold determination can enhance understanding and acceptance [50]. Bundling insurance with agricultural credit, inputs, or extension services creates value-added packages that incentivize adoption while reducing transaction costs [51].

5.3 Scalability, Policy Frameworks, and Climate Adaptation Integration

Achieving widespread impact requires enabling policy environments including regulatory frameworks for index-based products, public investment in satellite data infrastructure, premium subsidies or microfinance linkages making insurance affordable, and integration with broader climate adaptation strategies [52]. Governments can accelerate adoption through procurement of satellite imagery as a public good, subsidization of initial premium costs, and mandates linking agricultural credit to insurance coverage [53]. Figure 1 illustrates the comprehensive workflow from satellite data acquisition through risk assessment modeling to automated payout execution.

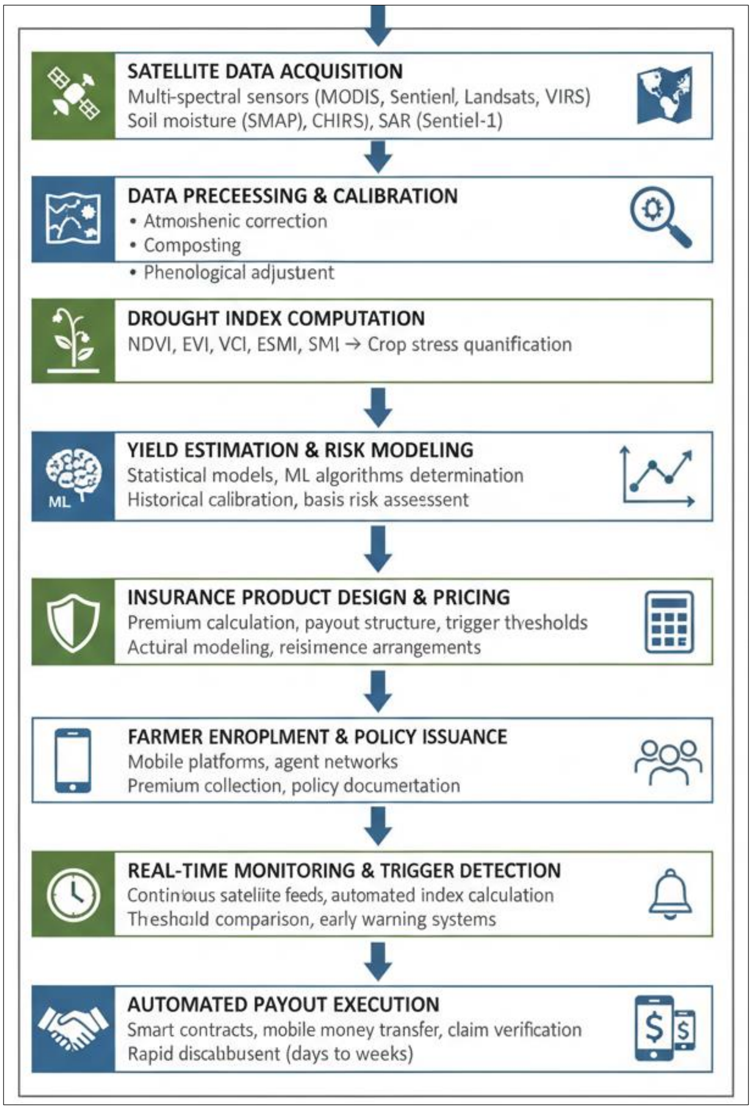

Fig 1: Satellite-Driven Workflow for Micro-Insurance Modeling: From Remote Sensing Data Acquisition to Risk-Based Payout

Satellite-driven insurance must function as one component within integrated climate risk management portfolios that include drought-resistant crop varieties, water harvesting infrastructure, diversified livelihoods, and social safety nets [54]. Forward-looking innovations including machine learning-enhanced yield predictions, blockchain-automated claim processing, and parametric coverage for multiple perils (drought, flood, pest outbreaks) hold promise for next-generation systems [55].

6. Conclusion

Satellite-driven micro-insurance models represent a transformative innovation addressing longstanding barriers to agricultural risk protection in drought-prone regions. By leveraging objective remote sensing observations to eliminate costly field assessments and enable rapid, transparent payout mechanisms, these systems provide scalable pathways for extending financial protection to millions of vulnerable smallholder farmers. The convergence of advancing satellite technologies, declining data costs, expanding mobile connectivity, and supportive policy frameworks creates unprecedented opportunities for mainstreaming parametric agricultural insurance. However, realizing this potential requires continued investment in data infrastructure, rigorous validation of satellite-yield relationships, innovative product designs that minimize basis risk, participatory approaches ensuring farmer understanding and trust, and integration within comprehensive climate adaptation strategies. As Earth observation capabilities continue to improve through higher spatial and temporal resolution sensors, artificial intelligence-enhanced analytics, and increasingly affordable data access, satellite-driven insurance systems are poised to become essential instruments for building climate resilience and food security in the world's most vulnerable agricultural landscapes.

7. References

1. Lobell DB, Schlenker W, Costa-Roberts J. Climate trends and global crop production since 1980. Science. 2011;333(6042):616-620.
2. Intergovernmental Panel on Climate Change. Climate Change 2021: The Physical Science Basis. Cambridge: Cambridge University Press; 2021.
3. Lowder SK, Skoet J, Raney T. The number, size, and distribution of farms, smallholder farms, and family farms worldwide. World Development. 2016;87:16-29.
4. Lesk C, Rowhani P, Ramankutty N. Influence of extreme weather disasters on global crop production. Nature. 2016;529(7584):84-87.
5. Carter MR, Little PD, Mogues T, Negatu W. Poverty traps and natural disasters in Ethiopia and Honduras. World Development. 2007;35(5):835-856.
6. Miranda MJ, Farrin K. Index insurance for developing countries. Applied Economic Perspectives and Policy. 2012;34(3):391-427.
7. Hazell P, Anderson J, Balzer N, Hastrup Clemmensen A, Hess U, Rispoli F. Potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods. Rome: International Fund for Agricultural Development and World Food Programme; 2010.
8. Jensen ND, Barrett CB, Mude AG. Index insurance quality and basis risk: Evidence from northern Kenya. American Journal of Agricultural Economics. 2016;98(5):1450-1469.
9. Mahul O, Stutley CJ. Government support to agricultural insurance: Challenges and options for developing countries. Washington DC: World Bank Publications; 2010.
10. Atzberger C. Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. Remote Sensing. 2013;5(2):949-981.
11. Fritz S, See L, Baerwolff G, McCallum I, Schill C, Perger C, *et al*. Mapping global cropland and field size. Global Change Biology. 2015;21(5):1980-1992.
12. Anderson MC, Hain C, Wardlow B, Pimstein A, Mecikalski JR, Kustas WP. Evaluation of drought indices based on thermal remote sensing of evapotranspiration over the continental United States. Journal of Climate. 2011;24(8):2025-2044.
13. Bolton DK, Friedl MA. Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. Agricultural and Forest Meteorology. 2013;173:74-84.
14. Kogan FN. Application of vegetation index and brightness temperature for drought detection. Advances in Space Research. 1995;15(11):91-100.
15. Vrieling A, Meroni M, Darvishzadeh R, Skidmore AK, Wang T, Zurita-Milla R, *et al*. Vegetation phenology from Sentinel-2 and field cameras for a Dutch barrier island. Remote Sensing of Environment. 2018;215:517-529.
16. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment. 2002;83(1-2):195-213.
17. Johnson DM. An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States. Remote Sensing of Environment. 2014;141:116-128.
18. Matsushita B, Yang W, Chen J, Onda Y, Qiu G. Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: A case study in high-density cypress forest. Sensors. 2007;7(11):2636-2651.
19. Kogan F, Stark R, Gitelson A, Jargalsaikhan L, Dugrajav C, Tsooj S. Derivation of pasture biomass in Mongolia from AVHRR-based vegetation health indices. International Journal of Remote Sensing. 2004;25(14):2889-2896.
20. Chantarat S, Mude AG, Barrett CB, Carter MR. Designing index-based livestock insurance for managing asset risk in northern Kenya. Journal of Risk and Insurance. 2013;80(1):205-237.
21. Vermote EF, Kotchenova SY. Atmospheric correction for the monitoring of land surfaces. Journal of Geophysical Research: Atmospheres. 2008;113(D23):D23S90.
22. Becker-Reshef I, Vermote E, Lindeman M, Justice C. A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. Remote Sensing of Environment. 2010;114(6):1312-1323.
23. White MA, Thornton PE, Running SW. A continental phenology model for monitoring vegetation responses to interannual climatic variability. Global Biogeochemical Cycles. 1997;11(2):217-234.
24. Carter MR, Cheng L, Sarris A. Where and how index insurance can boost the adoption of improved agricultural technologies. Journal of Development Economics. 2016;118:59-71.
25. Conradt S, Finger R, Bokusheva R. Tailored to the extremes: Quantile regression for index-based insurance contract design. Agricultural Economics. 2015;46(4):537-547.
26. Vogel E, Donat MG, Alexander LV, Meinshausen M, Ray DK, Karoly D, *et al*. The effects of climate extremes on global agricultural yields. Environmental Research Letters. 2019;14(5):054010.
27. Norton M, Holthaus E, Madajewicz M, Osgood D, Peterson N, Gebremichael M, *et al*. Evidence of demand for index insurance: Experimental games and commercial farming in Kenya. Environmental and Resource Economics. 2014;57(1):33-47.
28. Sibiko KW, Veettil PC, Qaim M. Small farmers' preferences for weather index insurance: Insights from Kenya. Agriculture & Food Security. 2018;7:53.

29. Lobell DB, Thau D, Seifert C, Engle E, Little B. A scalable satellite-based crop yield mapper. Remote Sensing of Environment. 2015;164:324-333.
30. Mkhabela MS, Bullock P, Raj S, Wang S, Yang Y. Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. Agricultural and Forest Meteorology. 2011;151(3):385-393.
31. Wang Y, Zhang Z, Feng L, Du Q, Runge T. Combining multi-source data and machine learning approaches to predict winter wheat yield in the conterminous United States. Remote Sensing. 2020;12(8):1232.
32. Flatnes JE, Carter MR. A little skin in the game: Reducing moral hazard in joint liability lending through a mandatory savings requirement. Journal of Economic Behavior & Organization. 2019;164:163-186.
33. Benincasa M, Guttormsen AG. Insurance against a nonmeasurable risk and the implications for sustainable agriculture. Environmental Development and Economics. 2020;25(5):501-522.
34. Sharma V. An overview of the field of organizational justice: Its origins, conceptualization and scope. In: Gilliland SW, Steiner DD, Skarlicki DP, editors. Theoretical and Cultural Perspectives on Organizational Justice. Greenwich: Information Age Publishing; 2001. p. 3-23.
35. Gupta D, Rani S, Ahmed SH, Verma S, Ijaz MF, Shafi J. Edge caching based on collaborative filtering for heterogeneous ICN-IoT applications. Sensors. 2021;21(16):5491.
36. Sharma A, Jain A, Gupta P, Chowdary V. Machine learning applications for precision agriculture: A comprehensive review. IEEE Access. 2021;9:4843-4873.
37. Binswanger-Mkhize HP. Is there too much hype about index-based agricultural insurance? Journal of Development Studies. 2012;48(2):187-200.
38. Holzman ME, Rivas R, Piccolo MC. Estimating soil moisture and the relationship with crop yield using surface temperature and vegetation index. International Journal of Applied Earth Observation and Geoinformation. 2014;28:181-192.
39. Rao KPC, Ndegwa WG, Kizito K, Oyoo A. Climate variability and change: Farmer perceptions and understanding of intra-seasonal variability in rainfall and associated risk in semi-arid Kenya. Experimental Agriculture. 2011;47(2):267-291.
40. Nair AS, Indu J. Enhancing the utility of satellite-based crop insurance: An application of RIICE in flood-prone regions. Remote Sensing Applications: Society and Environment. 2020;19:100358.
41. Hill RV, Robles M, Ceballos F. Demand for a simple weather insurance product in India: Theory and evidence. American Journal of Agricultural Economics. 2016;98(4):1250-1270.
42. Jensen N, Barrett C. Agricultural index insurance for development. Applied Economic Perspectives and Policy. 2017;39(2):199-219.
43. Karlan D, Osei R, Osei-Akoto I, Udry C. Agricultural decisions after relaxing credit and risk constraints. Quarterly Journal of Economics. 2014;129(2):597-652.