INDONESIAN JOURNAL OF INNOVATION AND APPLIED SCIENCES (IJIAS)
Journal Homepage: https://ojs.literacyinstitute.org/index.php/ijias
E-ISSN: 2775-4162

Volume 6	Issue 2	June (2026)	DOI: 10.47540/ijias.v6i2.2818	Page: 214 – 224

SIKAVALTA: A responsive webGIS-based calculator for prescriptive economic valuation of agricultural land losses caused by pests and hydrometeorological disasters in East Luwu

Rusmala[1], Abdullah Syukur[1], Fahrul Basir[2], Arsita Eka Oktaviani[1], Ichwan Muis[1], Andi Jumardi[1]
[1]Informatics Engineering, Universitas Cokroaminoto Palopo, Indonesia
[2]Mathematics Education, Universitas Cokroaminoto Palopo, Indonesia
Corresponding Author: Rusmala; Email: rusmala@uncp.ac.id

ARTICLE INFO

Keywords: Agriculture, Geospatial, Prescriptive, Valuation, WebGIS.

Received : 15 April 2026
Revised : 04 June 2026
Accepted : 30 June 2026

ABSTRACT

East Luwu Regency is a strategic food-producing area that increasingly faces a double exposure to crop-pest infestations and hydrometeorological disasters such as flooding. Until now, the assessment of post-disaster economic losses in the region has leaned on manual recapitulation, a method that is slow, prone to human error, and unable to capture the spatial variability between land parcels. The resulting delay holds up the disbursement of government relief and rice-farming insurance claims, which weakens the capital resilience of smallholders. This study develops SIKAVALTA, a responsive web-based geographic information system that converts physical crop damage from biotic and abiotic hazards into a monetary value expressed in Rupiah. The system was built through a Research and Development approach using the JITU method, namely Data Netting, Formula Interpretation, Web Technology, and Validity Testing. The prototype integrates on-map land digitization, automatic geodesic area computation, a deterministic valuation engine for rice and oil-palm commodities, and report export in document and spreadsheet formats. Black-Box testing confirmed that every feature operated as intended, and the user-acceptance evaluation cleared the minimum feasibility threshold. SIKAVALTA therefore shows a prescriptive spatial valuation capability that sets it apart from conventional descriptive mapping systems.

INTRODUCTION

East Luwu Regency in South Sulawesi has long been counted among Indonesia's regional food baskets, with most of its productive land given over to lowland rice and oil palm. Smallholders farm the greater part of that land, and worldwide such farms still produce roughly a third of the food supply, which makes their exposure to shocks a matter of food security rather than private misfortune (Ricciardi et al., 2018). That strength is also a vulnerability. The regency spreads across low river plains, and this leaves it open to two pressures at once: outbreaks of crop pests (grouped in Indonesian regulation as *organisme pengganggu tumbuhan*, OPT) and hydrometeorological hazards, chiefly flooding and the spells of extreme rainfall that recur along the rivers.

Pest pressure no longer acts on its own; a warming climate has begun to sharpen it. Global assessments put the yearly toll of pests and pathogens on the major food crops at a fifth to a third of attainable output (Savary et al., 2019), and those losses fall hardest on food-deficit regions with fast-growing populations (Ristaino et al., 2021). Warming accelerates insect reproduction, widens the geographic range of pests, and lengthens their active season, so projected losses for the main cereals climb steeply under a 2 °C scenario (Ma et al., 2025; Skendzic et al., 2021). Reviews confirm that research linking climate change to crop pests and diseases has expanded quickly over the past decade (Liu et al., 2023; H. Wang et al., 2024), and across Asia, the mix of heat, erratic rainfall, storms, and emerging pests is already reshaping the risk profile of rice systems (Habib-ur-Rahman et al., 2022; Malhi et al., 2021; Raza et al., 2019).

Hydrometeorological extremes open a second front. Flood inundation and rainfall anomalies depress rice yields and destabilise tropical food production, while drought erodes vegetation condition across whole districts (Badehian et al., 2025; Chandel, 2025; Le Page & Zribi, 2019). Farmers in East Africa and South Asia already name these climate risks as their dominant production concern (Abebaw, 2025; Aryal et al., 2021). For the smallholder, each event carries a monetary weight: foregone revenue plus the planting capital already sunk into the field, yet that weight is rarely quantified quickly enough to act on (Mueller et al., 2024).

For decision-makers at the sub-district level, the difficulty is rarely a lack of awareness. What is missing is an instrument that can turn physical damage on the ground into a defensible economic figure, and do so quickly. Assessment today still rests on manual record-keeping and paper-based recapitulation. This way of working carries high data latency, invites copying errors, and flattens out the real differences between one parcel and the next. Loss reports therefore arrive late, government relief and farm-insurance claims stall, and the capital resilience of smallholders weakens.

Digital agriculture offers part of the answer. Precision farming, machine learning, and the Internet of Things have a solid record of sharpening monitoring and on-farm decisions (Benos et al., 2021; Erickson & Fausti, 2021; Javaid et al., 2023; Khanna et al., 2024). Connected sensing and cloud platforms now stream field data in near real time (Assimakopoulos et al., 2024; Dhanaraju et al., 2022; Maraveas et al., 2022; Rehman et al., 2022; Snieg et al., 2025; Thilakarathne et al., 2023), and remote sensing paired with machine learning supports crop-condition and damage assessment at scale (Olson & Anderson, 2021; Ouhami et al., 2021; Teucher et al., 2022; J. Wang et al., 2024).

Geospatial technology ought to be the bridge between a damaged field and its cost, but most agricultural GIS stops at descriptive mapping: it shows where things are without computing what the damage is worth (Daud et al., 2024). WebGIS dashboards have guided management and land-suitability decisions in precision farming (Jurisic et al., 2022; Youssef et al., 2024; Panda et al., 2025; Shokr et al., 2023), and web-geoprocessing services now deliver soil-moisture and vegetation data straight to the browser(Feizizadeh et al., 2022; Mullapudi et al., 2023; Zhang, et al., 2022a; Zhang, et al., 2022b). Even so, a per-parcel financial figure is seldom treated as a core output. The loss-estimation tools that do exist tend to be statistical calculators detached from spatial context (Mueller et al., 2024), so their estimates ignore how much each parcel covers and where it sits. Meanwhile, the financial instruments meant to cushion farmers' index and bundled crop insurance depend on exactly this kind of timely, spatially grounded loss figure to trigger fair payouts (Aina et al., 2024; Akpan & Zikos, 2023; Amarnath et al., 2023; Madaki et al., 2023; Mthethwa et al., 2022). The gap, then, is the absence of a single interface that joins spatial reasoning to economic computation.

This study answers that gap with SIKAVALTA (*Sistem Kalkulator Valuasi Lahan Tani*), a responsive WebGIS that converts the physical impact of pests and hydrometeorological disasters into a Rupiah loss figure directly on the map. The system was developed through the JITU framework, Data Netting, Formula Interpretation, Web Technology, and Validity Testing, aimed at Technology Readiness Level 3, a proof of concept. Its contribution is twofold. Methodologically, JITU ties mathematics, informatics, and evaluation into a single problem-solving thread. As a product, the valuation is prescriptive rather than merely descriptive: it does not just map an affected field, it gives that field a measurable monetary value, parcel by parcel.

Two questions guide the work. First, how can a mathematical valuation model be constructed that integrates biotic and abiotic damage variables with reasonable precision? Second, how can that model be digitalised into a responsive web system fit for extension officers and policymakers working in the field?

METHODS

Research Design

The study followed a Research and Development (R&D) approach in a limited-development mode, meaning the product was built and tested at a restricted scale suited to a proof-of-concept target at Technology Readiness Level 3. Development was organised by the JITU model, a four-stage simplification of the Waterfall process: Data Netting, Formula Interpretation, Web Technology, and Validity Testing, chosen because it keeps a small interdisciplinary team moving from field data to a testable web product along one traceable line (Panda et al., 2025). Figure 1 sets out the four stages and their main activities.

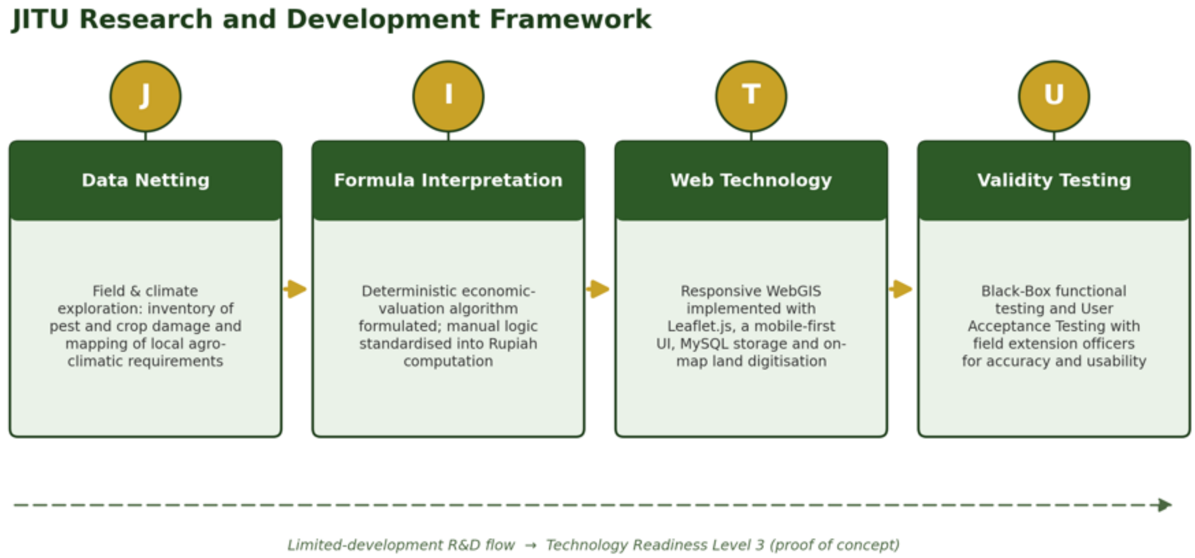

Figure 1. Research and development workflow based on the JITU method

The product itself is a three-tier WebGIS. The presentation tier is a responsive, mobile-first web interface (HTML, CSS, JavaScript) whose interactive map runs on Leaflet.js 1.9.4 with the Leaflet-Draw and GeometryUtil plugins and two base maps, OpenStreetMap and Esri World Imagery. The application tier holds the land-digitisation module, the economic-valuation engine, and the reporting and export module. The data tier stores GeoJSON spatial files together with a MySQL attribute database under XAMPP. Figure 2 shows how the three tiers exchange control and data.

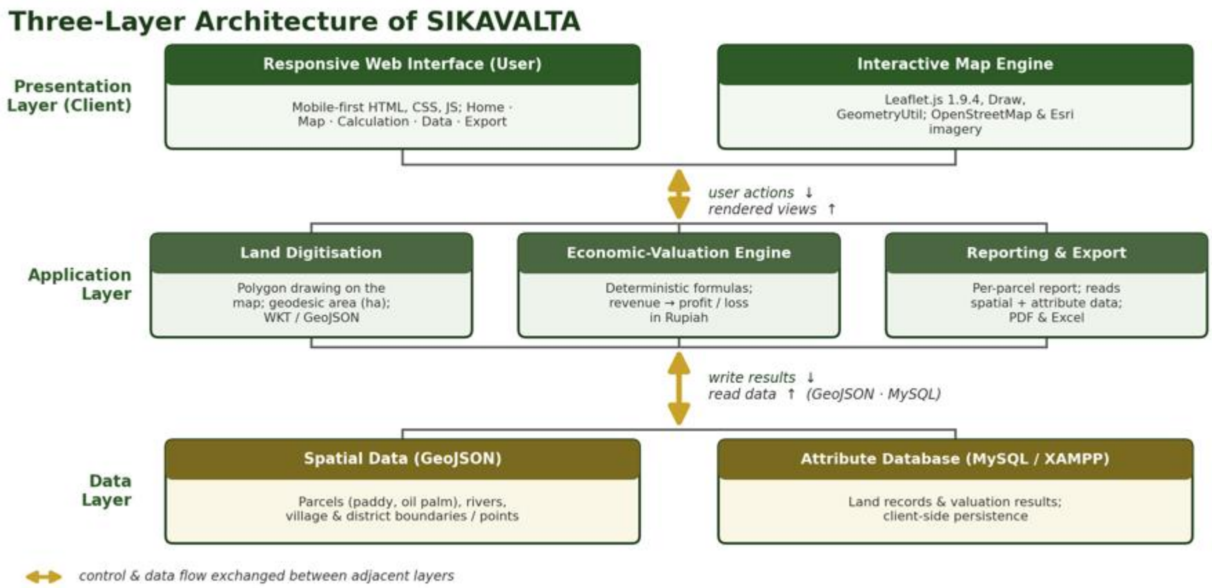

Figure 2. Three-layer system architecture of SIKAVALTA

Informant Selection

Informants were chosen purposively rather than at random because both the system's requirements and its later evaluation depended on people who actually manage agricultural land and disaster response in the study area. Three groups took part: agricultural extension officers, farming partners who cultivate rice and oil palm, and local administrative stakeholders in Mangkutana District, East Luwu. Mangkutana served as the test-bed because its eleven villages, centred near 2.4885° S and 120.8130° E on flood-prone lowland, represent the land typology and the twin commodities that dominate the regency. The same informants informed two moments of the work: the mapping of user needs during Data Netting, and the User Acceptance Test that judged the finished prototype.

Data Collection

Data collection combined field exploration with spatial and documentary work, in line with recent practice for in-situ digital data capture in agriculture (Feizizadeh et al., 2022; Teucher et al., 2022). Field exploration produced an inventory of pest types, records of crop damage, and the local agro-climatic parameters that frame the valuation. Two data families were then assembled. Spatial data were collected as GeoJSON layers — paddy and oil-palm parcels, rivers, and village and district boundaries through on-map digitisation and the capture of parcel coordinates, mirroring the browser-served geospatial data model now common in web GIS (Zhang et al., 2022a). Attribute data, commodity, planting age, productivity, price, and production cost were gathered by observation and documentation and stored in the MySQL database. Together, these supplied every input the valuation model needs.

Data Analysis

Analysis proceeded on two levels. The economic analysis applied a set of deterministic formulas that translate a digitised parcel area into a monetary value; the formulas differ by growth phase and by whether a parcel is productive or disaster-affected, and they are collected in Table 1. The system analysis then verified the software: Black-Box functional testing checked that every feature digitisation, geodesic area computation, valuation, and report export returned the expected output without error, and a User Acceptance Test scored usefulness and ease of use against a minimum feasibility threshold of 75 percent. Pairing a deterministic engine with structured functional and user testing follows the logic of the loss calculators and decision-support tools reported elsewhere (Jurisic et al., 2022; Mueller et al., 2024).

Table 1. Deterministic economic-valuation formulas implemented in SIKAVALTA

Component	Formula	Description
Gross revenue (mature crop)	$NE = L \times Y \times P$	L = land area (ha); Y = productivity (ton/ha); P = commodity price (Rp/ton)
Gross revenue (young crop)	$NE = L \times K \times Hb$	K = seed requirement (kg or seedling/ha); Hb = seed price (Rp/unit)
Net profit	$Profit = NE - (LC + FC + SC)$	LC = labour cost; FC = fertilizer cost; SC = seed cost
Economic loss	$Loss = NE + (LC + FC + SC)$	Foregone revenue plus sunk production cost on a damaged parcel

RESULTS AND DISCUSSION

Findings

The development produced a working prototype, reachable online as a proof of concept. Its main outcomes are set out below as six findings, each tied to the evidence in the figures and tables; the analysis that follows reads those findings against the wider literature.

Finding 1: A three-panel operational interface. SIKAVALTA opens from a plain landing page (Home, About, Contact, and an admin entry) into a map workspace arranged as three panels: navigation and layer control on the left, a map canvas in the centre, and the Calculation, Data, and Export tabs on the right (Figure 3).

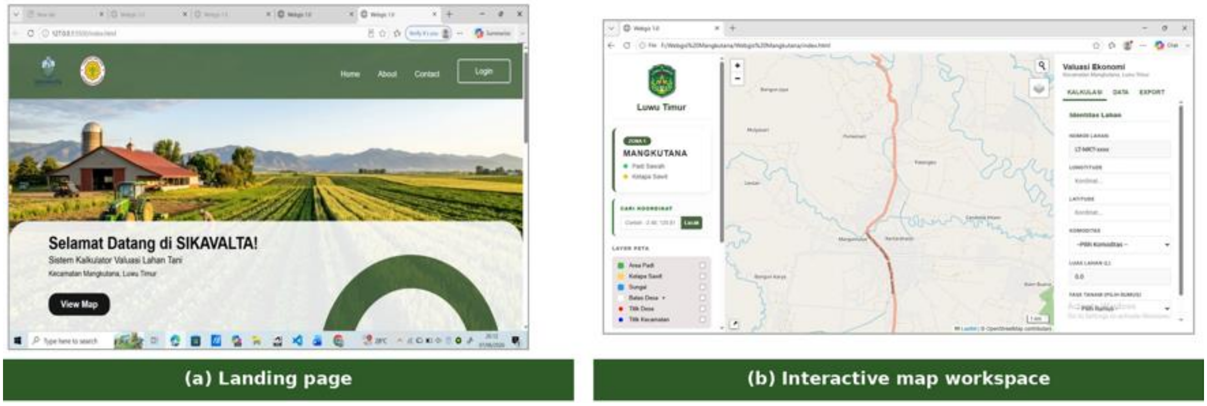

Figure 3. Main interface of SIKAVALTA: (a) landing page and (b) interactive map workspace with the layer legend

Finding 2: Automatic geodesic area from on-map digitisation. When a user closes a polygon over either base map, the system computes the parcel area in hectares through the GeometryUtil geodesic function and fills in the area, the centroid coordinates, and a parcel identifier on its own; each geometry is also stored as Well-Known Text for exchange with the database (Figure 4).

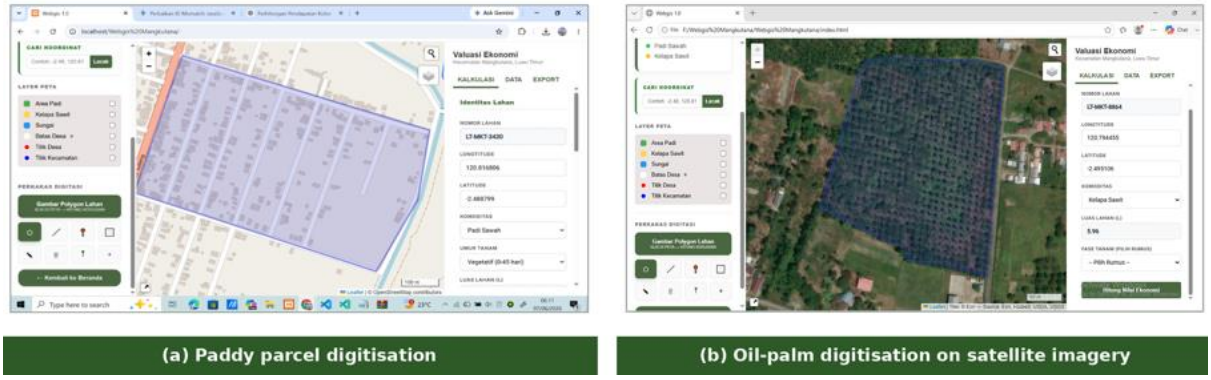

Figure 4. On-map land digitization with automatic geodesic area computation for (a) a paddy parcel and (b) an oil-palm parcel

Finding 3: On-the-fly gross-revenue valuation. After the user selects the commodity and growth phase and enters productivity and price, the engine returns gross revenue in Rupiah at once, applying the deterministic formulas of Table 1 (Figure 5).

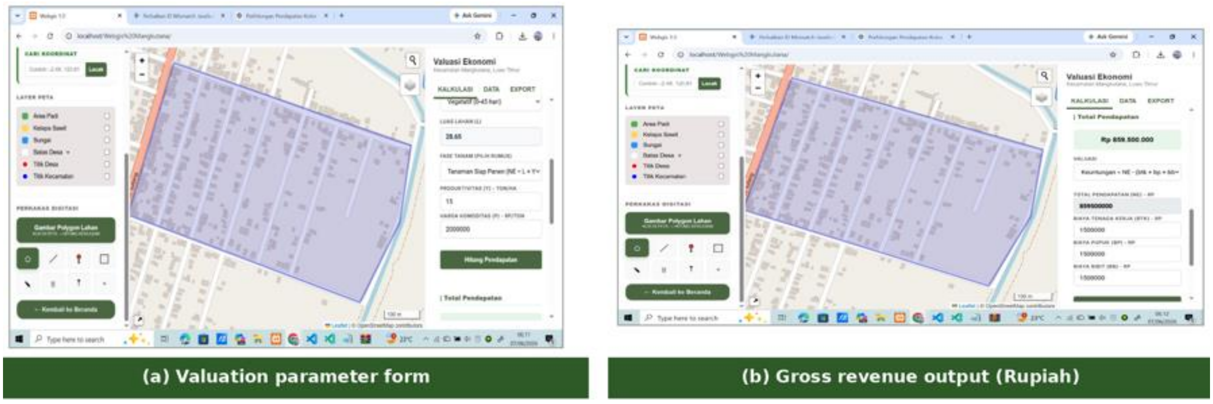

Figure 5. Economic-valuation engine: (a) parameter input form and (b) the resulting gross revenue in Rupiah

Finding 4: Paired profit and loss schemes. The same engine reports either a surplus (cost subtracted from revenue) or a disaster loss (cost added to revenue and flagged in red), so a single parcel can be read as profit or as loss according to its condition (Figure 6). Two worked parcels confirm the arithmetic: a 28.65-hectare paddy parcel returns a gross revenue of Rp 859,500,000 and a net profit of Rp 855,000,000, while a 27.64-hectare oil-palm parcel, flagged as affected, returns a loss of Rp 833,700,000 (Table 2).

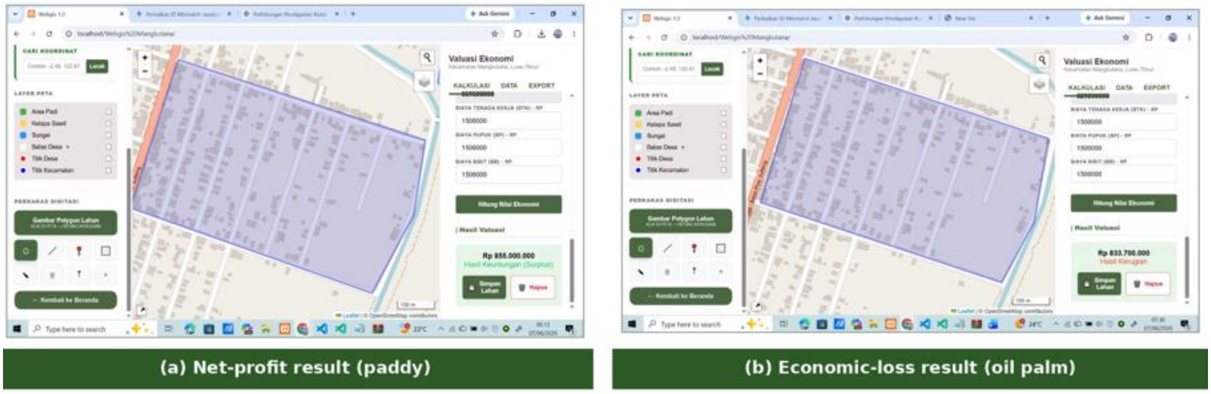

Figure 6. Valuation outputs: (a) net-profit result for a paddy parcel and (b) economic-loss result for an oil-palm parcel

Table 2. Illustrative valuation of two representative land parcels.

Parameter	Paddy parcel	Oil-palm parcel
Land area (ha)	28.65	27.64
Productivity (ton/ha)	15	15
Commodity price (Rp/ton)	2,000,000	2,000,000
Gross revenue, NE (Rp)	859,500,000	829,200,000
Total production cost (Rp)	4,500,000	4,500,000
Valuation scheme	Profit (surplus)	Loss (affected)
System output (Rp)	855,000,000	833,700,000

Finding 5: One-click documentation and export. Calculated parcels are saved and recapitulated under the Data tab; a per-parcel report carries the parcel identity, the reference formula, and a mini-map, and results are exported to both PDF and spreadsheet formats (Figures 7 and 8).

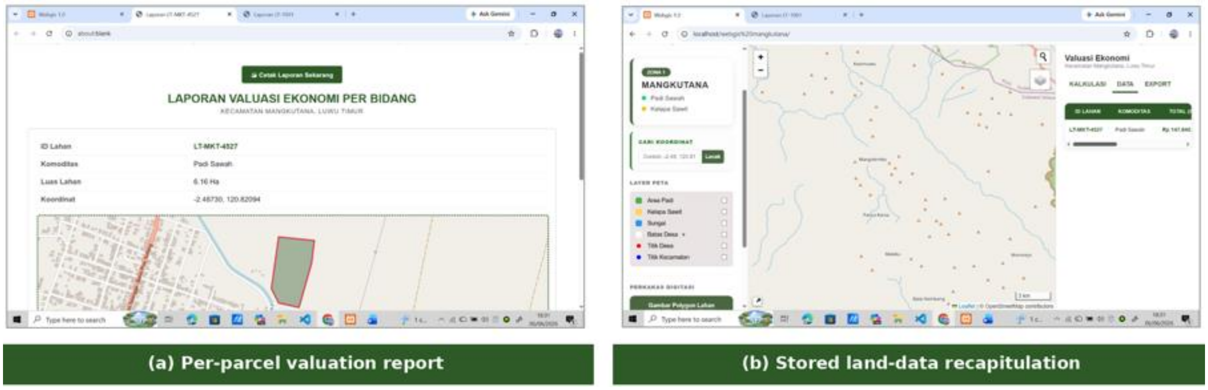

Figure 7. Documentation features: (a) per-parcel valuation report and (b) the stored land-data recapitulation table

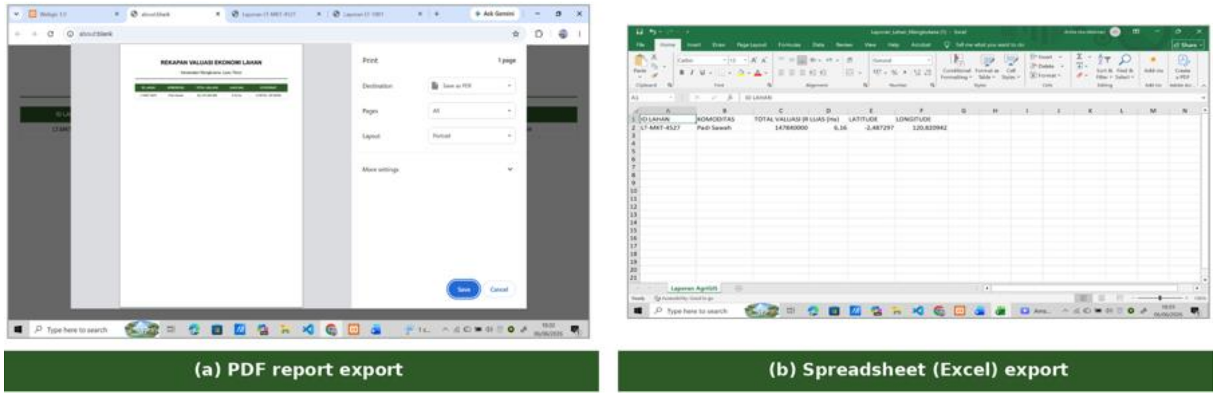

Figure 8. Report export of the valuation results into (a) PDF and (b) spreadsheet formats

Finding 6: Verified functionality and user acceptance. Black-Box testing returned the expected result for every core feature, all rated Valid (Table 3), and the User Acceptance Test scores for ease of use and usefulness sat above the 75-percent feasibility threshold, which indicates that extension officers can accept the interface as a decision-support aid.

Table 3. Summary of Black-Box functional testing.

No.	Tested feature	Expected result	Status
1	Parcel digitization	Polygon drawn and stored	Valid
2	Automatic area computation	Area shown in hectares	Valid
3	Gross-revenue calculation	NE displayed in Rupiah	Valid
4	Profit and loss valuation	Correct profit/loss value	Valid
5	Per-parcel report	The report opened with a map	Valid
6	Export to PDF and Excel	File generated correctly	Valid

Read together, the six findings answer a gap that earlier tools leave open. Three shortfalls define it. First, conventional agricultural GIS maps location but not value, stopping at description (Daud et al., 2024; Panda et al., 2025). Second, the loss calculators that are available work aspatially, computing value apart from a parcel's true area and position (Mueller et al., 2024). Third, manual paper recapitulation is slow and error-prone, delaying both relief and insurance claims. Figure 9 maps these shortfalls onto the contributions SIKAVALTA makes, and Table 4 sets its position against the earlier approaches.

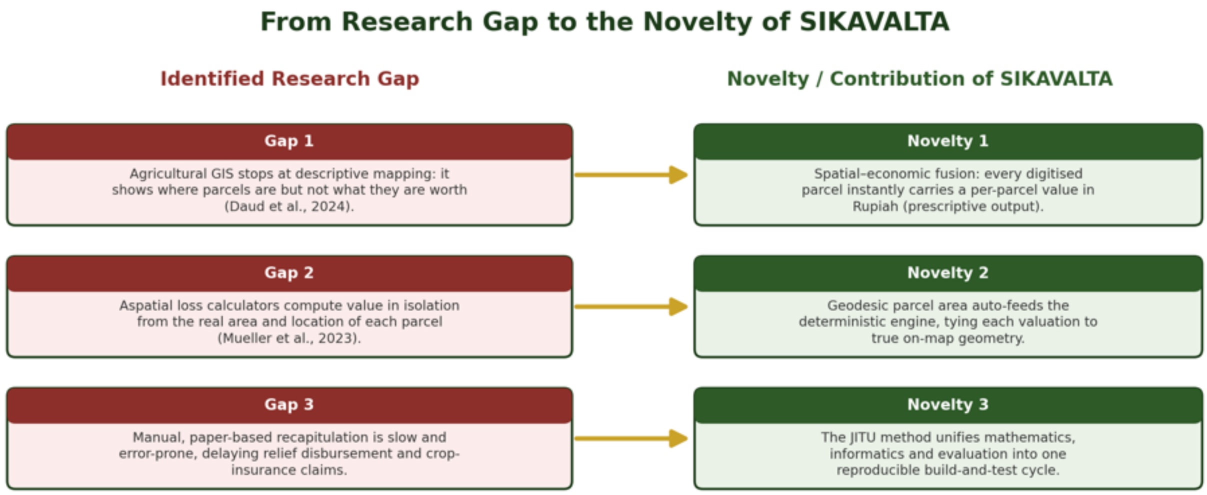

Figure 9. Mapping of the identified research gap to the novel contributions of SIKAVALTA

Table 4. Positioning of SIKAVALTA relative to prior spatial and valuation approaches

Aspect	Conventional GIS	Aspatial loss calculator	SIKAVALTA
Spatial mapping	Yes	No	Yes
Per-parcel monetary value	No	Partial	Yes
Automatic area input	No	No	Yes
Profit and loss schemes	No	Partial	Yes
Mobile-first field access	Limited	Limited	Yes
Output orientation	Descriptive	Statistical	Prescriptive

The novelty therefore separates into three layers. It is prescriptive because fusing space and economics gives every digitised parcel an immediate per-parcel value in Rupiah rather than leaving it a shape on a map. It is methodological at the data level, because a parcel's geodesic area feeds the deterministic engine automatically, binding each loss figure to real field geometry the same tight coupling of geospatial data and analysis that recent land-suitability and precision-agriculture systems pursue with GIS and machine learning(Jurisic et al., 2022; Youssef et al., 2024; Shokr et al., 2023; J. Wang et al., 2024). And it is integrative, because JITU threads mathematics, informatics, and evaluation into one compact, retraceable build-and-test cycle.

These results sit within a literature that has stressed spatial decision support for disaster and hazard management(Daud et al., 2024; Zhang et al., 2022a) and for precision agriculture (Panda et al., 2025; Teucher et al., 2022), while answering the specific limitation of loss calculators that stand apart from spatial data (Mueller et al., 2024). By producing a timely, parcel-level monetary figure, the system speaks directly to the needs of index and bundled crop-insurance schemes, whose fairness hinges on fast, spatially grounded loss estimates (Aina et al., 2024; Amarnath et al., 2023; Madaki et al., 2023).

The study's limits are worth stating plainly. The system still relies on static attribute data, covers only two commodities, and carries no real-time sensor feed, disaster-prediction simulation, or machine learning boundaries consistent with a TRL 3 proof of concept. The clearest paths forward therefore run toward connected field sensing and cloud integration (Dhanaraju et al., 2022; Maraveas et al., 2022; Rehman et al., 2022; Snieg et al., 2025; Thilakarathne et al., 2023), remote-sensing and machine-learning layers for damage prediction and early warning (Badehian et al., 2025; Chandel, 2025; Le Page & Zribi, 2019; Olson & Anderson, 2021; Ouhami et al., 2021), and a wider set of commodities and regions, so that the tool's usefulness can grow in stages(Ahmed et al., 2024; Assimakopoulos et al., 2024; Benos et al., 2021; Javaid et al., 2023; Khanna et al., 2024).

CONCLUSION

This research produced SIKAVALTA, a responsive WebGIS that turns physical damage to farmland, whether from pests or from hydrometeorological disaster, into an economic loss figure in Rupiah, read straight off the map. The mathematical valuation model was built from deterministic formulas linking parcel area, productivity, price, and production cost, and was then digitalised into an adaptive web interface. Functional testing showed every feature working to specification, and user validation cleared the feasibility threshold, so the objectives were met at the proof-of-concept level.

The novelty rests on the prescriptive character of the valuation and on the JITU framework that unites mathematics, informatics, and evaluation in a single thread. The system should shorten the once-manual preparation of loss reports and, with it, speed relief and insurance claims for farmers. The next steps run toward microclimate-sensor integration, predictive intelligence for early warning, and a broader reach across commodities and regions.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

REFERENCES

Abebaw, S. E. (2025). A Global Review of the Impacts of Climate Change and Variability on Agricultural Productivity and Farmers' Adaptation Strategies. *Food Science & Nutrition*, *13*(5).

Ahmed, S., Marwat, S. N. K., Brahim, G. Ben, Khan, W. U., Khan, S., Al-Fuqaha, A., & Koziel, S. (2024). IoT based intelligent pest management system for precision agriculture. *Scientific Reports*, *14*(1), 31917.

Aina, I., Ayinde, O., Thiam, D., & Miranda, M. (2024). Crop index insurance as a tool for climate resilience: lessons from smallholder farmers in Nigeria. *Natural Hazards*, *120*(5), 4811–4828.

Akpan, A. I., & Zikos, D. (2023). Rural Agriculture and Poverty Trap: Can Climate-Smart Innovations Provide Breakeven Solutions to Smallholder Farmers? *Environments*, *10*(4), 57.

Amarnath, G., Taron, A., Alahacoon, N., & Ghosh, S. (2023). Bundled climate-smart agricultural solutions for smallholder farmers in Sri Lanka. *Frontiers in Sustainable Food Systems*, *7*.

Aryal, J. P., Sapkota, T. B., Rahut, D. B., Marenya, P., & Stirling, C. M. (2021). Climate risks and adaptation strategies of farmers in East Africa and South Asia. *Scientific Reports*, *11*(1), 10489.

Assimakopoulos, F., Vassilakis, C., Margaris, D., Kotis, K., & Spiliotopoulos, D. (2024). The Implementation of "Smart" Technologies in the Agricultural Sector: A Review. *Information*, *15*(8), 466.

Badehian, Z., & Ghobadi, M. (2025). Assessment of agricultural drought severity using multi-temporal remote sensing data in Lorestan region. *Scientific Reports*, *15*(1), 18528.

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine Learning in Agriculture: A Comprehensive Updated Review. *Sensors*, *21*(11), 3758.

Chandel, A. S. (2025). Mapping drought risks in agriculture: a GIS and remote sensing study of Nagele Arsi district, Ethiopia. *Cogent Food & Agriculture*, *11*(1).

Daud, M., Ugliotti, F. M., & Osello, A. (2024). Comprehensive Analysis of the Use of Web-GIS for Natural Hazard Management: A Systematic Review. *Sustainability*, *16*(10), 4238.

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. *Agriculture*, *12*(10), 1745.

Erickson, B., & Fausti, S. W. (2021). The role of precision agriculture in food security. *Agronomy Journal*, *113*(6), 4455–4462.

Feizizadeh, B., Omarzadeh, D., Mohammadzadeh Alajujeh, K., Blaschke, T., & Makki, M. (2022). Impacts of the Urmia Lake Drought on Soil Salinity and Degradation Risk: An Integrated Geoinformatics Analysis and Monitoring Approach. *Remote Sensing*, *14*(14), 3407.

Habib-ur-Rahman, M., Ahmad, A., Raza, A., Hasnain, M. U., Alharby, H. F., Alzahrani, Y. M., Bamagoos, A. A., Hakeem, K. R., Ahmad, S., Nasim, W., Ali, S., Mansour, F., & EL Sabagh, A. (2022). Impact of climate change on agricultural production; Issues, challenges, and opportunities in Asia. *Frontiers in Plant Science*, *13*.

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, *2*(1), 15–30.

Jurisic, M., & Radocaj, D. (2022). GIS-Based Cropland Suitability Prediction Using Machine Learning: A Novel Approach to Sustainable Agricultural Production. *Agronomy*, *12*(9), 2210.

Khanna, M., Atallah, S. S., Heckelei, T., Wu, L., & Storm, H. (2024). Economics of the Adoption of Artificial Intelligence–Based Digital Technologies in Agriculture. *Annual Review of Resource Economics*, *16*(1), 41–61.

Le Page, M., & Zribi, M. (2019). Analysis and Predictability of Drought In Northwest Africa Using Optical and Microwave Satellite Remote Sensing Products. *Scientific Reports*, *9*(1), 1466.

Liu, Y., Yang, Q., Du, T., Li, N., Liang, J., Javed, T., Wang, H., & Guo, J. (2023). Bibliometric Analysis on the Impact of Climate Change on Crop Pest and Disease. *Agronomy*, *13*(3), 920.

Ma, C.-S., Wang, B.-X., Wang, X.-J., Lin, Q.-C., Zhang, W., Yang, X.-F., van Baaren, J., Bebber, D. P., Eigenbrode, S. D., Zalucki, M. P., Zeng, J., & Ma, G. (2025). Crop pest responses to global changes in climate and land management. *Nature Reviews Earth & Environment*, *6*(4), 264–283.

Madaki, M. Y., Kaechele, H., & Bavorova, M. (2023). Agricultural insurance as a climate risk adaptation strategy in developing countries: a case of Nigeria. *Climate Policy*, *23*(6), 747–762.

Malhi, G., Kaur, M., & Kaushik, P. (2021). Impact of Climate Change on Agriculture and Its Mitigation Strategies: A Review. *Sustainability*, *13*(3), 1318.

Maraveas, C., Piromalis, D., Arvanitis, K. G., Bartzanas, T., & Loukatos, D. (2022). Applications of IoT for optimized greenhouse environment and resources management. *Computers and Electronics in Agriculture*, *198*, 106993.

Mthethwa, K. N., Ngidi, M. S. C., Ojo, T. O., & Hlatshwayo, S. I. (2022). The Determinants of Adoption and Intensity of Climate-Smart Agricultural Practices among Smallholder Maize Farmers. *Sustainability*, *14*(24), 16926.

Mueller, D. S., Sisson, A. J., Eide, B., Allen, T. W., Bradley, C. A., Faske, T. R., Friskop, A., Lawrence, K., Musser, F., Reisig, D., Tenuta, A. U., & Wise, K. A. (2024). Field Crop Yield Loss Calculator for Disease and Invertebrate Pests: An Online Tool from the Crop Protection Network. *PhytoFrontiers™*, *4*(2), 255–258.

Mullapudi, A., Vibhute, A. D., Mali, S., & Patil, C. H. (2023). A review of agricultural drought assessment with remote sensing data: methods, issues, challenges and opportunities. *Applied Geomatics*, *15*(1), 1–13.

Olson, D., & Anderson, J. (2021). Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture. *Agronomy Journal*, *113*(2), 971–992.

Ouhami, M., Hafiane, A., Es-Saady, Y., El Hajji, M., & Canals, R. (2021). Computer Vision, IoT and Data Fusion for Crop Disease Detection Using Machine Learning: A Survey and Ongoing Research. *Remote Sensing*, *13*(13), 2486.

Panda, S. S., Siddique, A., Terrill, T. H., Mahapatra, A. K., Morgan, E., Pech-Cervantes, A. A., & van Wyk, J. A. (2025). Decision support system for Lespedeza cuneata production and quality evaluation: a WebGIS dashboard approach to precision agriculture. *Frontiers in Plant Science*, *16*.

Raza, A., Razzaq, A., Mehmood, S. S., Zou, X., Zhang, X., Lv, Y., & Xu, J. (2019). Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome: A Review. *Plants*, *8*(2), 34.

Rehman, A., Saba, T., Kashif, M., Fati, S. M., Bahaj, S. A., & Chaudhry, H. (2022). A Revisit of Internet of Things Technologies for Monitoring and Control Strategies in Smart Agriculture. *Agronomy*, *12*(1), 127.

Ricciardi, V., Ramankutty, N., Mehrabi, Z., Jarvis, L., & Chookolingo, B. (2018). How much of the world's food do smallholders produce? *Global Food Security*, *17*, 64–72.

Ristaino, J. B., Anderson, P. K., Bebber, D. P., Brauman, K. A., Cunniffe, N. J., Fedoroff, N. V., Finegold, C., Garrett, K. A., Gilligan, C. A., Jones, C. M., Martin, M. D., MacDonald, G. K., Neenan, P., Records, A., Schmale, D. G., Tateosian, L., & Wei, Q. (2021). The persistent threat of emerging plant disease pandemics to global food security. *Proceedings of the National Academy of Sciences*, *118*(23).

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, *3*(3), 430–439.

Shokr, M. S., El Behairy, R. A., Arwash, H. M. El, El Baroudy, A. A., Ibrahim, M. M., Mohamed, E. S., & Rebouh, N. Y. (2023). Artificial Intelligence Integrated GIS for

Land Suitability Assessment of Wheat Crop Growth in Arid Zones to Sustain Food Security. *Agronomy*, *13*(5), 1281.

Skendžić, S., Zovko, M., Živković, I. P., Lešić, V., & Lemić, D. (2021). The Impact of Climate Change on Agricultural Insect Pests. *Insects*, *12*(5), 440.

Śnieg, M., Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., & Łobodzińska, A. (2025). The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. *Sensors*, *25*(12), 3583.

Teucher, M., Thürkow, D., Alb, P., & Conrad, C. (2022). Digital In Situ Data Collection in Earth Observation, Monitoring and Agriculture—Progress towards Digital Agriculture. *Remote Sensing*, *14*(2), 393.

Thilakarathne, N. N., Bakar, M. S. A., Abas, P. E., & Yassin, H. (2023). Towards making the fields talks: A real-time cloud enabled IoT crop management platform for smart agriculture. *Frontiers in Plant Science*, *13*.

Wang, H., & Gai, Y. (2024). Plant Disease: A Growing Threat to Global Food Security. *Agronomy*, *14*(8), 1615.

Wang, J., Wang, Y., Li, G., & Qi, Z. (2024). Integration of Remote Sensing and Machine Learning for Precision Agriculture: A Comprehensive Perspective on Applications. *Agronomy*, *14*(9), 1975.

Youssef, Y. M., Sathiyamurthi, S., Subbarayan, S., Ramya, M., Sivasakthi, M., Gobi, R., Qaysi, S., Praveen Kumar, S., Lee, J., Alarifi, N., & Wahba, M. (2024). Advancing Agricultural Land Suitability in Urbanized Semi-Arid Environments: Insights from Geospatial and Machine Learning Approaches. *ISPRS International Journal of Geo-Information*, *13*(12), 436.

Zhang, C., Yang, Z., Di, L., Yu, E. G., Zhang, B., Han, W., Lin, L., & Guo, L. (2022). Near-real-time MODIS-derived vegetation index data products and online services for CONUS based on NASA LANCE. *Scientific Data*, *9*(1), 477.

Zhang, C., Yang, Z., Zhao, H., Sun, Z., Di, L., Bindlish, R., Liu, P.-W., Colliander, A., Mueller, R., Crow, W., Reichle, R. H., Bolten, J., & Yueh, S. H. (2022). Crop-CASMA: A web geoprocessing and map service based architecture and implementation for serving soil moisture and crop vegetation condition data over U.S. Cropland. *International Journal of Applied Earth Observation and Geoinformation*, *112*, 102902.