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Simulation-Based Evaluation of Offline Web Mapping for Agricultural Land Inventory: Usability and Data Quality**Sanriomi Sintaro^{1*}, Saroyo², Ricardo Gianluigi Tindi³**¹Information Systems Study Program, Faculty of Mathematics and Natural Sciences, Sam Ratulangi University²Biology Study Program, Faculty of Mathematics and Natural Sciences, Sam Ratulangi University³Management Study Program, Faculty of Economics and Business, Sam Ratulangi University*Corresponding author:
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Abstract. Agricultural land inventories require reliable spatial records, accessible software, and consistent data validation. This study assessed AgriMap Field version 1.2, a self-contained offline web mapping application, through a computational simulation designed to examine its evaluation procedures before field deployment. A structured simulation dataset comprised 30 hypothetical user profiles, 120 task attempts across four inventory activities, 30 ten-item System Usability Scale (SUS) response sets, 30 agricultural plot records, and paired geographic coordinates. Task completion was assessed using recorded success and a stricter definition requiring completion within the specified time without assistance. SUS scoring and internal consistency were recalculated, and coordinate-pair distances were independently verified using the haversine formula. Recorded task success was 88.3% (106/120), while strict independent success was 80.0% (96/120); spatial location retrieval had the lowest strict success (70.0%). The simulated SUS mean was 73.0 (standard deviation 9.01), with Cronbach's alpha of 0.774. All 30 simulated inventory records contained the six mandatory fields, and the mean distance between paired coordinates was 6.43 m; 25 of 30 pairs were separated by less than 10 m. Separately, all 61 predefined software regression checks passed. These findings support the internal consistency of the evaluation framework and identify mapping navigation as a priority for subsequent testing. Because the user responses and geographic reference records were simulated, these measures do not represent observed farmer usability or independently measured field positional accuracy.

Keywords: Agricultural inventory; Data quality; Offline web mapping; Simulation; Usability.

INTRODUCTION

Agricultural land inventories support crop surveillance, local resource allocation, and spatially explicit decisions, yet their usefulness depends on the availability of accurate, well-described field observations. Agronomic information often remains aggregated or absent at the level needed by local stakeholders. Tenorio et al. (2024) proposed a minimum-data approach to closing this gap, while Chamorro-Padial et al. (2024) identified persistent limitations in the availability and reuse of agricultural datasets. An operational inventory

therefore requires not only a spatial display but also an accessible procedure for recording location, crop identity, and observation metadata.

Mobile geographic information systems have expanded opportunities to collect spatial observations using widely available devices. Nowak et al. (2020) reviewed environmental field-mapping applications, emphasizing the value of integrated location and descriptive data. Lamb et al. (2022) demonstrated software support for agricultural sampling navigation, whereas Zhou et al. (2024) linked smartphone observations with spatial analysis for pest management.

Agricultural data-collection platforms may also require flexible workflows and heterogeneous attribute structures (Liu *et al.*, 2024). These approaches illustrate technological diversity, but each deployment faces distinct connectivity, equipment, maintenance, and training requirements.

Low-infrastructure design is particularly relevant when spatial data must be captured or inspected in settings with intermittent connectivity. Moinard *et al.* (2025) demonstrated a low-cost acquisition chain that used smartphones and precision positioning equipment, while Minallah *et al.* (2024) described a cloud-based survey application capable of recording agricultural polygons. Such solutions are valuable but are not interchangeable with a self-contained web application operating entirely on locally bundled resources. The role of accessible technology in agricultural systems has also been illustrated by Lamaega *et al.* (2026), whose low-cost postharvest-processing prototype highlighted the value of matching design decisions to constrained operational contexts, although their study did not investigate geospatial mapping.

Data validation represents a second challenge. A visually plausible point may contain incomplete metadata, a duplicated plot identifier, a miscoded commodity, or coordinates that are numerically valid but spatially misplaced. Reviews of volunteered geographic information have stressed the importance of distinguishing internal quality indicators from comparison with independent reference information (Senaratne *et al.*, 2017). Agricultural data-management studies likewise demonstrate the importance of contextual metadata and interoperable records (Krisnawijaya *et al.*, 2025; Basir *et al.*, 2025). These considerations call for transparent completeness rules, traceable validation, and careful interpretation of positional differences.

The practical suitability of a mapping application further depends on task-based usability. The System Usability Scale (SUS) is a widely used standardized measure of perceived usability (Lewis, 2018), with extensive empirical experience supporting score interpretation (Bangor *et al.*, 2008). Nevertheless, questionnaire scores should not replace direct observations of task completion and assistance requirements. Sample-size considerations for later field studies should also be justified against the intended inferential goal rather than inferred from a convenient simulated sample (Faulkner, 2003; Lakens, 2022).

Although digital tools can support agricultural mapping, evidence about their intended evaluation procedures should be distinguished from evidence of performance in real field conditions. This study addresses the pre-deployment need for a coherent, reproducible framework linking offline mapping functions with task outcomes, SUS scoring, inventory validation, and geographic-coordinate checks. AgriMap Field v1.2 was assessed using constructed agricultural inventory scenarios rather than recruited participants. The objectives were to (1) evaluate simulated task outcomes under recorded and independent-success criteria, (2) verify SUS scoring and internal-consistency calculations, (3) assess the completeness and consistency of simulated inventory attributes and coordinate pairs, and (4) determine the methodological implications for future field-based evaluation.

MATERIAL AND METHODS

Research Design and Simulation Data

A simulation-based computational study was conducted to assess the pre-deployment evaluation procedures for AgriMap Field v1.2. The fixed analytical dataset consisted of eight related data components covering study guidance, hypothetical user profiles, task outcomes,



SUS responses, agricultural plot attributes, coordinate-reference pairs, summary metrics, and variable definitions. It comprised 30 constructed profiles (P01–P30), four simulated tasks for each profile (120 task attempts), 30 complete ten-item SUS response sets, 30 agricultural plot records, and 30 linked coordinate pairs. The scenario used the location codes MIN, MINUT, and TOM and July–August 2026 dates as synthetic descriptors, not as locations or dates of completed fieldwork. No farmers were recruited, questionnaires administered to actual users, or smartphone and Garmin positions independently observed. Accordingly, the 30 profiles constitute a methodological scenario rather than a sample representing farmers in North Sulawesi (Lakens, 2022).

The analysis used three distinct units: a simulated user profile for SUS statistics ($n = 30$), a user–task attempt for task outcomes ($n = 120$), and a constructed agricultural plot for attribute and coordinate checks ($n = 30$). The four tasks associated with one profile were treated as repeated scenarios rather than observations from independent respondents. Explicit variable definitions, task criteria, and data provenance supported transparent recalculation and interpretation (Anderson *et al.*, 2024; Chamorro-Padial *et al.*, 2024).

The simulation records were provided as a fixed analytical case with defined variables and record-level observations. Their origin as constructed values is acknowledged explicitly. Although the original generation code, random seed, and probability distributions were not available, the task, SUS, attribute-completeness, and haversine analyses can be reproduced using the specified calculations and the preserved case data. Therefore, this study assesses reproducibility of the analytical procedure rather than independent regeneration of the original synthetic scenarios. No assumptions were introduced about

unrecorded sampling or data-generation mechanisms.

Application and Inventory Structure

AgriMap Field v1.2 is a standalone browser-based inventory application built with locally bundled HTML, CSS, JavaScript, and vector basemap geometries. The application provides an offline world/coastal map, marker-based records, an agricultural commodity legend, local storage and JSON backup, CSV/TXT import, CSV/GeoJSON export, and an internal data-quality panel. It stores observations as points in geographic coordinates (WGS84); imported GeoJSON may provide contextual boundaries, but the application does not automatically survey plot polygons, calculate cadastral area, or supply satellite images. This scope is narrower than polygon-survey systems (Minallah *et al.*, 2024) and high-precision agricultural acquisition chains (Moinard *et al.*, 2025).

Inventory fields were plot code, commodity, village, latitude, longitude, survey date, observer identifier, respondent identifier, stated area (ha), condition, and notes. The application's required-field measure covers the first six fields only. Area values, where entered, are externally provided attributes rather than areas calculated from boundary geometry. The synthetic records represented multiple commodities and locations across site codes. Design choices align with research emphasizing structured geospatial fieldwork (Lamb *et al.*, 2022; Liu *et al.*, 2024; Nowak *et al.*, 2020) and traceable agricultural metadata (Basir *et al.*, 2025; Brodeur *et al.*, 2019).

Task Scenarios and Success Criteria

Four standardized agricultural inventory scenarios were evaluated: T1, registering a plot record; T2, locating a plot on the map; T3, identifying and correcting an invalid record; and T4, exporting inventory data. Task-specific time limits were 360, 180, 300, and 180



seconds, respectively. Each simulated attempt included completion status, elapsed time, assistance requirement, navigation errors, entry errors, and a technical-incident indicator. These variables enabled consistent application of predefined assessment rules without treating the constructed profiles as observed users (Faulkner, 2003; Lewis, 2018).

Recorded success was calculated as the proportion of attempts classified as completed. Strict independent success additionally required completion within the task-specific time limit without operational assistance. For task j , strict success (%) = $100 \times \Sigma[\text{success} = 1 \wedge \text{duration} \leq \text{limit}_j \wedge \text{assistance} = 0] / n_j$. Mean and median durations were reported to characterize the constructed task scenarios. Inferential tests and confidence intervals for a farmer population were not performed because these observations were simulated (Lakens, 2022).

SUS Scoring and Reliability

Each synthetic user profile contained responses to ten SUS questions on a five-point ordinal scale. Scores were independently recalculated using the standard alternating rule: adjusted contribution _{i} = response _{i} – 1 for odd-numbered items and 5 – response _{i} for even-numbered items. Total SUS score = $2.5 \times \Sigma$ adjusted contributions _{i} , yielding a scale from 0 to 100. All item responses were checked for valid range and completeness. The sample mean, median, standard deviation, and range were recomputed, and Cronbach's alpha was derived from the ten consistently oriented item contributions (Lewis, 2018; Bangor et al., 2008). The calculated alpha describes coherence within the simulated response matrix; it does not establish actual respondent comprehension or psychometric reliability in a recruited population.

Inventory-Quality and Coordinate Audit

Required-field completeness (%) = $100 \times \text{populated mandatory cells} / (\text{six required fields} \times \text{number of records})$. The assessment also inspected quality-control flags, repeated plot identifiers, and agreement between simulated commodity labels and their paired reference classifications. Records without flagged issues were considered internally compliant with the predefined rules; such compliance does not establish their accuracy against actual agricultural conditions. Because the inventory scenario contained no independently confirmed erroneous plot entries, its sensitivity and specificity for real-world error detection could not be estimated (Senaratne et al., 2017; Krisnawijaya et al., 2025).

The geographic consistency assessment calculated haversine great-circle distances: $d = 2R \arcsin[\sqrt{(\sin^2(\Delta\phi/2) + \cos\phi_1 \cos\phi_2 \sin^2(\Delta\lambda/2))}]$, where ϕ and λ are latitude and longitude in radians and $R = 6,371,000$ m. Recomputed separations were compared with the distance values assigned to the same synthetic coordinate pairs, taking the original one-decimal-metre precision into account. Mean, median, standard deviation, range, root-mean-square distance, and proportions below 5, 10, and 15 m were reported. The calculations assess consistency between constructed coordinates and recorded separations, not the horizontal accuracy of a smartphone or reference receiver (Brodeur et al., 2019; Senaratne et al., 2017).

Controlled Software Verification and Analysis

Software verification was undertaken separately from the simulation-based task and inventory analysis using the frozen AgriMap Field v1.2.0 single-file HTML build. The documented environment consisted of automated Playwright-



controlled Chromium 144.0.7559.96 on Linux 6.18.55 (x86_64; Python 3.13.5). Since the test sandbox restricted direct file:// and local-server navigation, the same application HTML was loaded using Playwright page.set_content with external requests blocked. This configuration tested browser functionality without internet resources but did not verify file:// persistence after browser restart. The 61 predefined checks covered application initialization, map navigation, record creation/editing/search, import/export, local geographic layers, quality-control rules, research-instrument calculations, and controlled error handling. Each test was accepted when the observed result matched a predefined expected outcome or rejection criterion.

Software quality-control verification additionally used 22 synthetic records: four valid controls, 17 deliberately invalid records within the audit scope, and one geographically misplaced yet numerically valid coordinate outside that scope. A separate nine-case regression set assessed

commodity-category and calendar-date validation after known defects in v1.1 had been corrected. The software passed 61 of 61 functional checks and detected 17 of 17 in-scope faults. These results were analyzed independently from the 30-profile evaluation scenario. Regression logs, input-expected-output comparisons, the application build checksum, and export artifacts provided traceable evidence for the software checks; Python numerical routines were used for the descriptive simulation analyses (Krisnawijaya et al., 2025; Tenorio et al., 2024).

RESULTS AND DISCUSSION

Results

Implementation and Regression Verification

The locally bundled offline map and synthetic agricultural plot markers in AgriMap Field v1.2.0 are illustrated in Figure 1.



Figure 1. Enlarged field-map panel of AgriMap Field v1.2.0, showing offline coastal geometry, synthetic agricultural observation markers, map navigation, and geographic coordinates (cropped from the software verification screenshot).

The application displayed inventory and quality-control summaries and supported record editing and export. The enlarged map-panel screenshot highlights plot markers, coastlines, and navigation controls. Indonesian navigation labels elsewhere in the interface include Peta Lapangan (Field Map), Inventaris Lahan (Land Inventory), and Kualitas Data (Data Quality). The separate regression log documents all 61 predefined checks as passed and no observed external network requests under restricted testing conditions. These results verify specified functions in that environment rather than general performance in field deployments.

Simulated Task Outcomes

The four agricultural task scenarios are summarized in Table 1 using recorded completion, strict independent completion, assistance, and duration. Overall, 106 of 120 task attempts met the

recorded-success criterion (88.3%), whereas 96 met the stricter independent-success criterion (80.0%). All completed attempts remained within their designated time limits; the ten-attempt difference resulted from recorded assistance. Location retrieval (T2) produced the lowest strict success (70.0%), while exporting data (T4) produced the highest (86.7%). These task patterns reflect constructed evaluation scenarios rather than observed user performance.

Simulated mean task durations were 140.8 s for T1, 124.7 s for T2, 100.3 s for T3, and 41.1 s for T4. The lower T2 median (67.0 s) indicates that a subset of longer assigned durations increased its mean. Figure 2 depicts only the percentage-point reduction between the two definitions of success, complementing the counts and durations in Table 1.

Table 1. Outcomes of the four simulated tasks (30 attempts per task)

Task	Success n (%)	Strict n (%)	Assisted n	Mean time (s)	Median (s)
T1 — Enter	27 (90.0)	24 (80.0)	6	140.8	123.0
T2 — Locate	22 (73.3)	21 (70.0)	9	124.7	67.0
T3 — Correct	27 (90.0)	25 (83.3)	5	100.3	80.5
T4 — Export	30 (100.0)	26 (86.7)	4	41.1	40.5
All tasks	106 (88.3)	96 (80.0)	24	—	—

Note. Recorded success is the completion status assigned in the simulation dataset. Strict success additionally requires compliance with the task-specific time limit and completion without assistance. Assistance flags may also occur on unsuccessful attempts. All outcomes are simulated.

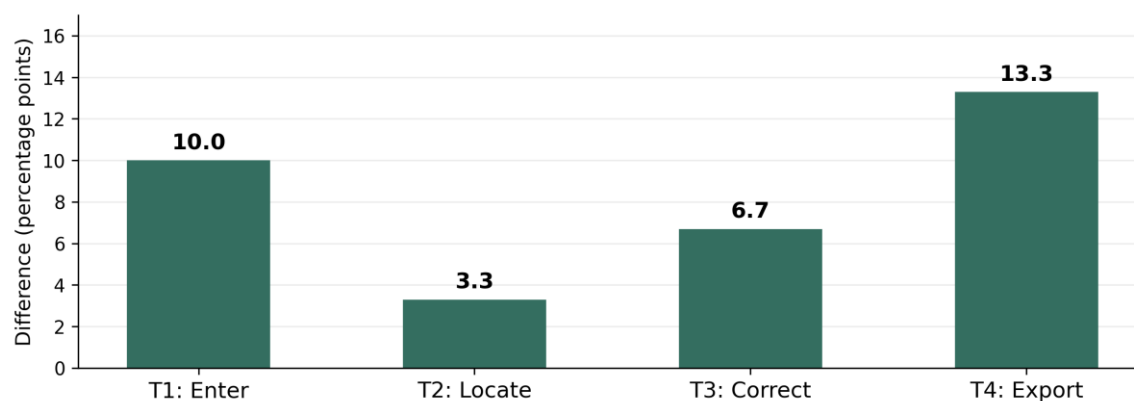


Figure 2. Reduction from recorded to strict task success by task (percentage points; simulated data). Counts, assistance, and durations are given in Table 1.

Simulated Usability Scale

The simulation included 30 complete SUS response profiles, with each of the ten items scored within the valid range of 1–5. Independent application of the standard scoring formula reproduced the original totals. The mean SUS score was 73.0 (SD 9.01), with a median of 72.5 and a range of 60.0–95.0 (Table 2). Cronbach's alpha for the adjusted item responses was 0.774. Under common interpretive conventions, a score around 73 may be described as broadly acceptable (Bangor *et al.*, 2008); however, this simulated score does not demonstrate actual user acceptance or instrument reliability among recruited farmers.

Table 2. Descriptive statistics of simulated System Usability Scale responses

Indicator	Value
Simulated user profiles	30
Complete SUS response sets	30/30
Mean SUS score	73.00
Standard deviation	9.01
Median	72.50
Range	60.00–95.00
Cronbach's alpha (10 adjusted items)	0.774

Simulated Inventory Integrity

All 30 constructed agricultural plot records contained the six mandatory attributes, producing 180 populated cells

out of 180 required cells (100% completeness). No duplicate plot identifiers or application quality-control flags were recorded. Commodity classifications agreed across the paired synthetic inventory and reference records (30/30). The scenario included 25 plots classified as being in good condition and five classified as mildly damaged. These results establish internal consistency of the constructed inventory only; no independently verified farm census or erroneous field observations were available to assess real-world omission or classification error.

Coordinate-Pair Recalculation

Haversine recalculation for the 30 constructed geographic-coordinate pairs yielded a mean separation of 6.43 m (SD 2.94 m; median 6.16 m; range 2.64–11.50 m; root-mean-square distance 7.05 m). The corresponding reference values supplied with the simulation averaged 6.41 m; the approximately 0.02-m difference between the two means is consistent with their recorded precision. Twelve pairs were separated by less than 5 m, 25 by less than 10 m, and all 30 by less than 15 m (Table 3). These results verify distance-calculation consistency but cannot establish actual device positioning accuracy against field reference points.

Table 3. Distances between pairs of constructed geographic coordinates (n = 30)

Measure	Value
Mean recomputed distance	6.43 m
Mean recorded reference distance	6.41 m
Difference between mean values	0.02 m
Median (recomputed)	6.16 m
Standard deviation (recomputed)	2.94 m
Minimum–maximum	2.64–11.50 m
Root-mean-square distance	7.05 m
Distance < 5 m	12/30 (40.0%)
Distance < 10 m	25/30 (83.3%)
Distance < 15 m	30/30 (100.0%)

Discussion

The evaluation demonstrated two distinct levels of technical evidence: functional verification of an offline agricultural mapping application and consistency checks of a simulation-based evaluation procedure. The software tests supported the application's ability to display local map features, manage point records, apply validation rules, and export inventory data. The task, SUS, and coordinate scenarios produced reproducible analytical summaries. However, these outcomes cannot replace field observations, which remain essential for determining how intended agricultural users interact with the application under actual working conditions (Nowak *et al.*, 2020; Lamb *et al.*, 2022).

The difference between recorded completion (88.3%) and strict independent completion (80.0%) illustrates the methodological importance of distinguishing completed tasks from tasks completed without assistance. The highest simulated assistance burden was associated with location retrieval (T2), indicating that navigation, marker selection, and search feedback deserve attention during future user evaluation. Table 1 preserves the detailed task outcomes, whereas Figure 2 provides a concise visual comparison of the change introduced by the stricter definition. These values are scenario outputs, not observed difficulties among farmers (Faulkner, 2003; Lakens, 2022).

A mean simulated SUS score of 73.0 may appear favorable relative to conventional SUS interpretation, and the calculated alpha of 0.774 exceeds a frequently used internal-consistency reference of 0.70. Neither statement demonstrates that participants understood the alternating positively and negatively worded items: a simulated matrix has no cognitive response process. Cronbach's alpha alone cannot establish validity or unidimensionality of a measure. Field

evaluation should administer a documented Indonesian-language SUS version after task completion, preserve item-level responses, and investigate any unusually uniform or contradictory response patterns. SUS results should then be interpreted alongside task success, time, and assistance rather than used as an isolated product-quality guarantee (Bangor *et al.*, 2008; Lewis, 2018).

The 100% required-field completeness in the simulated plot records confirms only that the example database satisfies a predetermined six-field rule. It neither tests detection under varying levels of missingness nor validates agricultural content against independent sources. Work on FAIR-oriented agricultural data management emphasizes provenance, context, and interoperability beyond surface-level file completeness (Krisnawijaya *et al.*, 2025), while metadata-capture tools such as Meta Ag demonstrate how additional context can support trustworthy agricultural records (Basir *et al.*, 2025). Future validation should deliberately include verified omissions, duplicate plot identifiers, inconsistent crop classifications, implausible survey dates, and wrong-location records, then report sensitivity and specificity for each validation class.

The mean coordinate-pair distance of 6.43 m requires a similarly restricted interpretation. The values were computed from constructed geographic positions and do not represent measured differences between actual smartphone and Garmin observations. Consequently, they cannot be used to claim horizontal GPS accuracy, farm-boundary accuracy, or reliable agricultural area estimation. AgriMap is designed for point-based inventory rather than cadastral mapping. Its intended scope differs from RTK-supported field acquisition (Moinard *et al.*, 2025) and polygon-oriented survey applications (Minallah *et al.*, 2024). Any future positional-accuracy study will require



independently documented reference measurements and acquisition conditions.

The principal contribution of this research is an integrated, auditable approach for assessing an offline agricultural web mapping system before deployment. Separating software verification from simulated task outcomes, questionnaire scoring, attribute-completeness checks, and coordinate calculations helps prevent different forms of evidence from being conflated. This low-infrastructure design may be useful for agricultural inventory management, although operational feasibility must ultimately be established through direct user observations and independently verified land records. Future work should evaluate the frozen application with intended users and documented ground reference positions. The simulation results presented here must not be interpreted as field-derived findings (Liu *et al.*, 2024; Zhou *et al.*, 2024).

CONCLUSION

AgriMap Field application offers a self-contained offline platform for point-based agricultural land inventory. In a pre-deployment computational evaluation, the application passed 61 predefined functional tests, while 30 simulated user profiles and agricultural records generated internally consistent analytical results. Recorded and strict independent task success were 88.3% and 80.0%, respectively; the simulated SUS mean was 73.0 (Cronbach's $\alpha = 0.774$), all mandatory inventory attributes were populated, and the mean separation between constructed coordinate pairs was 6.43 m. Spatial location retrieval was the lowest-performing task scenario and merits priority in subsequent field testing. These findings establish the reproducibility of the technical evaluation framework, not actual farmer acceptance, field GPS accuracy, or cadastral

suitability. Real-world effectiveness requires observation of intended users and verification against independently measured agricultural reference data.

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REFERENCES

- Anderson, E., Lybbert, T. J., Shenoy, A., Singh, R., & Stein, D. (2024). Does survey mode matter? Comparing in-person and phone agricultural surveys in India. *Journal of Development Economics*, 166, 103199. <https://doi.org/10.1016/j.jdeveco.2023.103199>
- Bangor, A., Kortum, P. T., & Miller, J. T. (2008). An empirical evaluation of the System Usability Scale. *International Journal of Human-Computer Interaction*, 24(6), 574–594. <https://doi.org/10.1080/10447310802205776>
- Basir, M. S., Zhang, Y., Buckmaster, D., Raturi, A., & Krogmeier, J. V. (2025). Meta Ag: An automatic agricultural contextual metadata collection app. *Smart Agricultural Technology*, 12, 101073. <https://doi.org/10.1016/j.atech.2025.101073>
- Brodeur, J., Coetzee, S., Danko, D., Garcia, S., & Hjelmager, J. (2019). Geographic information metadata—An outlook from the international standardization perspective. *ISPRS*



- International Journal of Geo-Information, 8(6), 280.
<https://doi.org/10.3390/ijgi8060280>
- Chamorro-Padial, J., García, R., & Gil, R. (2024). A systematic review of open data in agriculture. *Computers and Electronics in Agriculture*, 219, 108775.
<https://doi.org/10.1016/j.compag.2024.108775>
- Faulkner, L. (2003). Beyond the five-user assumption: Benefits of increased sample sizes in usability testing. *Behavior Research Methods, Instruments, & Computers*, 35(3), 379–383.
<https://doi.org/10.3758/BF03195514>
- Krisnawijaya, N. N. K., Tekinerdogan, B., Catal, C., van der Tol, R., & Herdiyeni, Y. (2025). Implementing FAIR principles in data management systems: A multi-case study in precision farming. *Computers and Electronics in Agriculture*, 230, 109855.
<https://doi.org/10.1016/j.compag.2024.109855>
- Lakens, D. (2022). Sample size justification. *Collabra: Psychology*, 8(1), 33267.
<https://doi.org/10.1525/collabra.33267>
- Lamaega, J. C. E., Paat, F. J., Sintaro, S. S., & Saroinsong, D. (2026). Development and performance evaluation of a low-cost, energy-efficient air fryer prototype using incandescent bulb heating for oil-free food processing. *Jurnal Agroekoteknologi Terapan*, 7(1), 38–51.
<https://doi.org/10.35791/jat.v7i1.66252>
- Lamb, J. R., Araújo, E. C., Bazzi, C. L., & Maggi, M. F. (2022). Sampling in precision agriculture: A software for navigation in field activities. *Sustainable Computing: Informatics and Systems*, 36, 100804.
<https://doi.org/10.1016/j.suscom.2022.100804>
- Lewis, J. R. (2018). The System Usability Scale: Past, present, and future. *International Journal of Human–Computer Interaction*, 34(7), 577–590.
<https://doi.org/10.1080/10447318.2018.1455307>
- Liu, S., Li, B., Chen, Y., & Cai, Z. (2024). Establishing a generic geographic information collection platform for heterogeneous data. *Applied Sciences*, 14(13), 5416.
<https://doi.org/10.3390/app14135416>
- Minallah, N., Khan, W., Zeeshan, M., & Ahmad, T. (2024). GeoSurvey: A cloud-based mobile app for efficient land surveys and big data collection. *Software Impacts*, 19, 100620.
<https://doi.org/10.1016/j.simpa.2024.100620>
- Moinard, S., Oger, B., Brunel, G., Ducanhez, A., Crestey, T., Faure, P., Pichon, L., & Tisseyre, B. (2025). A collaborative and low cost acquisition chain for collecting spatialized observations in agriculture. *Computers and Electronics in Agriculture*, 239, 111113.
<https://doi.org/10.1016/j.compag.2025.111113>
- Nowak, M. M., Dziób, K., Ludwisiak, Ł., & Chmiel, J. (2020). Mobile GIS applications for environmental field surveys: A state of the art. *Global Ecology and Conservation*, 23, e01089.
<https://doi.org/10.1016/j.gecco.2020.e01089>
- Senaratne, H., Mobasher, A., Ali, A. L.,



- Capineri, C., & Haklay, M. (2017). A review of volunteered geographic information quality assessment methods. *International Journal of Geographical Information Science*, 31(1), 139–167. <https://doi.org/10.1080/13658816.2016.1189556>
- Tenorio, F. A. M., Rattalino Edreira, J. I., Monzon, J. P., Aramburu-Merlos, F., Dobermann, A., Gruere, A., Brihet, J. M., Gayo, S., Conley, S., Mourtzinis, S., Mashingaidze, N., Sananka, A., Aston, S., Ojeda, J. J., & Grassini, P. (2024). Filling the agronomic data gap through a minimum data collection approach. *Field Crops Research*, 308, 109278. <https://doi.org/10.1016/j.fcr.2024.109278>
- Zhou, C., Lee, W. S., Zhang, S., Liburd, O. E., Pourreza, A., Schueller, J. K., & Ampatzidis, Y. (2024). A smartphone application for site-specific pest management based on deep learning and spatial interpolation. *Computers and Electronics in Agriculture*, 218, 108726. <https://doi.org/10.1016/j.compag.2024.108726>