

SOIL SALINITY MAPPING USING POINT TO FIELD LEVEL REMOTE SENSING TECHNIQUES

CARTOGRAPHIE DE LA SALINITÉ DES SOLS AU MOYEN DE TECHNIQUES DE TÉLÉDÉTECTION, DE L'ÉCHELLE PONCTUELLE À L'ÉCHELLE DE LA PARCELLE

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ABSTRACT

Soil salinity constrains crop production in irrigated, semi-arid regions by reducing plant water uptake, altering nutrient availability, and potentially degrading soil structure. In Colorado's South Platte River Basin (SPRB), salinity risk is shaped by an intensively managed stream-aquifer system, irrigation return flows through salt-bearing geologic formations, shallow groundwater, and progressive reuse of water as it moves downstream. This paper presents a multi-scale study effort to map soil salinity expressed as electrical conductivity of the saturated paste extract (EC_e , dS/m) by linking point observations, field-scale ground surveys, satellite remote sensing, and controlled-environment hyperspectral data analysis. Two existing remote sensing-based soil salinity algorithms were evaluated using Landsat 8/9 (2000–2023) and PlanetDove mini-satellites (2020–2024) surface reflectance products, depicting a weak transferability to the SPRB conditions. In a first phase, locally calibrated, crop-specific regression EC_e models were then developed for irrigated maize using vegetation indices (NDVI, Crop Response to Salinity Index, and Crop Water Stress Index) combined with weather variables, producing improved performance with R^2 values approaching 0.64 and normalized errors near 6% for the best EC_e model. Then, in a second phase, a greenhouse experiment (five irrigation-water salinity levels) was implemented to identify salinity effects on maize plants across the hyperspectral (350–2500 nm) electromagnetic spectrum. Sensitivity analyses helped identify salinity-sensitive visible-edge and near-infrared (VIS/NIR) wavelengths and supported selection of several greenhouse-derived wavelengths (bandwidths) for future field EC_e modeling. Using field leaf spectra paired with location-specific soil EC_e observations and leave-one-out cross-validation, preliminary candidate equations achieved small errors ($RMSE \approx 0.71$ dS m^{-1}), but normalized errors remained somewhat high, indicating the need for expanded ground truth and independent validation before operational mapping can be implemented at a large scale.

Keywords: Soil salinity mapping; Remote sensing techniques; Semi-arid regions; Reuse of water; Salinity effects on maize plants.

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RÉSUMÉ

La salinité des sols limite la production végétale dans les régions irriguées semi-arides en réduisant l'absorption de l'eau par les plantes, en modifiant la disponibilité des nutriments et en pouvant dégrader la structure du sol. Dans le bassin de la South Platte (SPRB), au Colorado, le risque de salinité est déterminé par un système cours d'eau-aquifère géré de manière intensive, par les retours d'irrigation traversant des formations géologiques salifères, par la faible profondeur de la nappe et par la réutilisation progressive de l'eau à mesure qu'elle s'écoule vers l'aval. Cet article présente une étude multi-échelle visant à cartographier la salinité du sol, exprimée par la conductivité électrique de l'extrait de pâte saturée (EC_e , dS/m), en reliant des observations ponctuelles, des relevés de terrain à l'échelle de la parcelle, la télédétection satellitaire et l'analyse de données hyperspectrales en environnement contrôlé. Deux algorithmes existants de salinité des sols fondés sur la télédétection ont été évalués à l'aide de produits de réflectance de surface issus de Landsat 8/9 (2000–2023) et des minisatellites PlanetDove (2020–2024), ce qui a révélé une faible transférabilité aux conditions du SPRB. Dans une première phase, des modèles de régression de l' EC_e , étalonnés localement et propres au maïs irrigué, ont ensuite été élaborés au moyen d'indices de végétation (NDVI, Crop Response to Salinity Index et Crop Water Stress Index) combinés à des variables météorologiques ; les performances se sont améliorées, avec des valeurs de R^2 proches de 0,64 et des erreurs normalisées d'environ 6 % pour le meilleur modèle d' EC_e . Dans une deuxième phase, une expérience en serre comportant cinq niveaux de salinité de l'eau d'irrigation a été réalisée afin d'identifier les effets de la salinité sur les plants de maïs dans l'ensemble du spectre électromagnétique hyperspectral (350–2500 nm). Les analyses de sensibilité ont permis d'identifier des longueurs d'onde sensibles à la salinité dans la bordure du visible et le proche infrarouge (VIS/NIR), et ont guidé la sélection de plusieurs longueurs d'onde (bandes passantes) issues des essais en serre pour la future modélisation de l' EC_e au champ. À partir de spectres foliaires mesurés au champ, associés à des observations de l' EC_e du sol propres à chaque emplacement, et d'une validation croisée par retrait d'une observation, les premières équations candidates ont obtenu de faibles erreurs ($RMSE \approx 0,71 \text{ dS m}^{-1}$), mais les erreurs normalisées sont restées relativement élevées, ce qui indique qu'il faut davantage de données de terrain et une validation indépendante avant de pouvoir mettre en œuvre une cartographie opérationnelle à grande échelle.

Mots clés : Cartographie de la salinité des sols; Techniques de télédétection; Régions semi-arides; Réutilisation de l'eau; Effets de la salinité sur les plants de maïs.

1. INTRODUCTION

Irrigation can mobilize and concentrate salts in the root zone when leaching is insufficient or when shallow groundwater and drainage conditions limit salt export. As salinity increases, crops experience osmotic stress and ion toxicity that reduce canopy vigor and yield. Because salinity is spatially heterogeneous within fields, conventional soil sampling can miss fine-scale variability needed for management interventions such as variable-rate leaching, drainage improvement, or crop selection.

The SPRB is an intensively irrigated stream-aquifer system where water is repeatedly diverted, applied, and returned through surface and subsurface pathways through weathered and unweathered geologic formations containing salt minerals. These processes can increase salt loading downstream and elevate both irrigation-water salinity and soil salinity risk. Remote sensing (RS) offers spatially continuous information related indirectly to soil salinity through crop response and canopy water status; however, RS-based models are often site- and crop-specific, and model transferability may be limited by differences in soils, climate, management, crop type, and phenology.

This work integrates field-based surveys of soil saturation extract electrical conductivity (EC_e , dS/m), satellite-based vegetation indices, crop water stress index, and a controlled greenhouse hyperspectral (HS) experiment data to improve agricultural soils salinity mapping (modeling) efforts, and to support the use of multi-platform RS data for subsequent regular field EC_e mapping at regional scales. Figure 1 shows the study location of the SPRB in northern Colorado (CO), USA.

The objectives of the study were to: (1) evaluate selected satellite-based soil salinity models for transferability to SPRB conditions; (2) develop locally calibrated, crop-specific RS regression models for estimating EC_e using vegetation indices and weather variables; (3) quantify maize spectral responses to soil/water salinity controlled greenhouse conditions; (4) identify visible-edge and near-infra-red (VIS/NIR) wavelengths that are sensitive (responsive) to salinity effects on maize using a sensitivity analysis; and (5) to preliminarily develop a new field applicable EC_e model based on HS-based indices developed using results from objective 4 above.



Figure 1. South Platte River Basin area in northern Colorado. Source: U.S. Environmental Protection Agency (EPA).

2. MATERIALS AND METHODS

The first phase (FP) of the study evaluated and calibrated EC_e models using satellite (Landsat 2000-2023 and PlanetDove mini-satellite 2020-2024 datasets) RS surface reflectance imagery-based soil salinity in the SPRB of northeastern Colorado (CO), USA. Two existing soil salinity (EC_e) mapping models were evaluated, which included algorithms developed by Scudiero et al. (2015) in California, and Craig (2023) in Colorado. These models are shown below as equations 1 (R^2 of 0.73) and 2 (RMSE of 0.84 dS/m), respectively. The first model, developed by Scudiero et al. (2015), estimates EC_e using the crop response to salinity index (CRSI) in combination with annual rainfall (R, mm), annual average minimum air temperature (Temp, °C), and surface type (β_{Crop} , which is -100.76 for cropped land and -93.40 for fallow land). The second model, developed by Craig (2023), estimates EC_e using the normalized difference vegetation index (NDVI), CRSI, and the crop water stress index (CWSI) determined for the maize midseason growth stage.

$$EC_e = 26.3 + (\beta_{Crop} \times CRSI) + (0.025 \times R) + (3.35 \times Temp) \quad (1)$$

$$\ln(EC_e) = -306.8 + (586.8 \times CWSI) + (316.7 \times \ln(CRSI)) + (327.6 \times \ln(NDVI) - 600.3 \times CWSI \times \ln(CRSI)) - (616.1 \times CWSI \times \ln(NDVI)) - (337.1 \times \ln(CRSI) \times \ln(NDVI)) + (630.6 \times CWSI \times \ln(CRSI) \times \ln(NDVI)) \quad (2)$$

Both models were initially applied to the SPRB without any modification. Subsequently, due to poor agreement with field-measured EC_e values, model coefficients were recalibrated using locally derived soil and RS data (Karpa, 2025). Recalibration included restricting vegetation indices and weather variables to the development and midseason growth phases and re-estimating coefficients through nonlinear optimization to minimize the sum of squared errors between predicted and observed EC_e values (Karpa, 2025).

2.1 Ground truth soil salinity

For the FP, ground truth salinity was represented as EC_e (dS m⁻¹) derived from field-scale electromagnetic induction (EM) surveys (using an EM-38-MK2 sensor, Geonics Limited, Mississauga, Ontario, Canada) calibrated with lab-measured soil EC_e at selected sampling points, producing spatial

EC_e maps for RS-based EC_e model calibration. Figure 2 provides an example of such soil salinity map for a maize field within the SPRB. In the FP, twelve farmers' managed fields, within the SPRB area, were surveyed to determine "measured" EC_e for the evaluation of existing EC_e models and for the development of new ones. The 12 fields were maize (4), alfalfa (3), onion (1), cabbage (1), soybean (1), and grass hay (1).

For the second phase (SP) field-model screening, field location-level observations pairing leaf HS reflectance with laboratory-measured EC_e from collected soil samples were compiled for conservative candidate equation development.

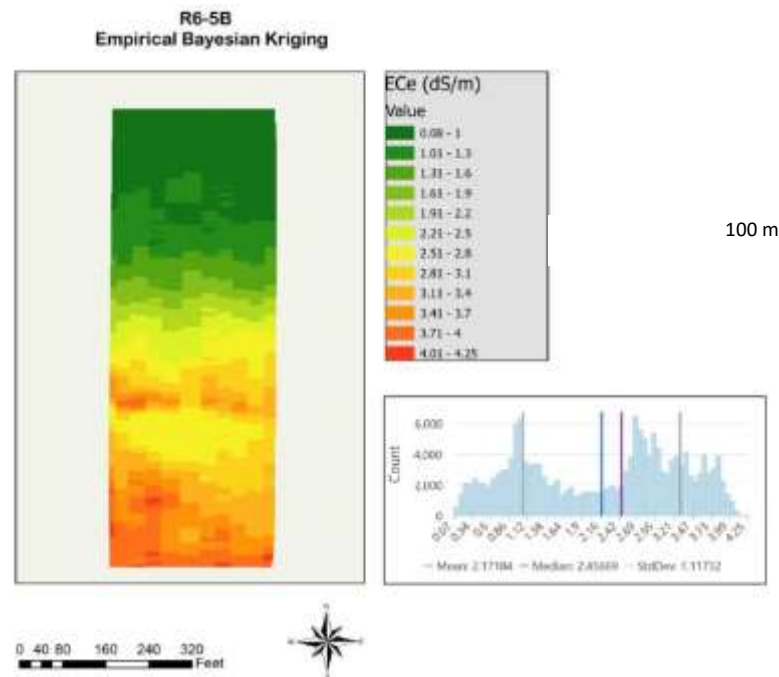


Figure 2. Soil salinity map produced from calibrated EM-38-MK2 electro-magnetic induction EC_e data.

2.2 Satellite remote sensing and vegetation indices - FP

Satellite surface reflectance imagery from Landsat (2000–2023) and PlanetDove (2020–2024) were used to compute vegetation indices representing canopy vigor, salinity response, and water status (NDVI, CRSI, and CWSI). These indices were used both to test existing algorithms and to develop locally calibrated multivariate regressions for irrigated maize within the SPRB.

2.3 Greenhouse experiment - SP

A second research phase (SP) was developed incorporating a greenhouse RS-based HS experiment given the limited results obtained during the first phase. Thus, a controlled greenhouse experiment was conducted in 2025. The greenhouse was managed by the United States Department of Agriculture (USDA) – Agricultural Research Service (ARS) in Fort Collins, CO, USA. The experiment used a Pioneer 487Q maize drought tolerant variety.

Salts (combination of sodium chloride NaCl and calcium chloride CaCl₂) were added to the plant pots (Fig. 3) through the drip irrigation-water. Five irrigation water salinity levels, with electrical conductivity (EC_w) of 0.8, 2, 4, 6, and 8 dS m⁻¹ were imposed, each replicated 5 times. Salinity inputs and drainage water salinity (EC_d), pH, and leachate volume were also measured. Weekly maize leaf spectral reflectance responses were measured using a HS spectroradiometer (ASD FieldSpec 4 Hi-Res, ASD

Inc. / Malvern Panalytical, Boulder, CO, USA) equipped with a leaf clip assembly. Hyperspectral (350–2500 nm) leaf-point measurements were collected alongside supporting plant physiological and environmental measurements. Figure 3 shows the greenhouse experiment used to identify HS bands sensitive to vegetation salinity effects.



Figure 3. Greenhouse maize experiment.

2.3.1 *Greenhouse spectral preprocessing and quality control*

The analysis dataset contained 148 observations and 2,151 wavelength columns, with measurements retained from six collection dates: April 2, 9, 16, 23, and 30, and May 7, 2025. Before performing the sensitivity analysis, the dataset was organized by plant label, collection date, salinity treatment, and wavelength-specific reflectance. Wavelength columns were checked to confirm the 350-2500 nm spectral range. Reflectance values were then normalized within each collection date to reduce the influence of plant age, growth stage, and date-specific measurement conditions.

This date-normalized dataset was used as the primary basis for identifying wavelengths responsive to salinity treatment. The normalization procedure included subtracting average reflectance values (from all observation on a given day) from reflectance values from each wavelength, and by dividing the result by the reflectance standard deviation, following a similar approach as the one described in Rinnan et al. (2009).

2.3.2 *Salinity sensitivity analysis and band selection*

Salinity treatment was used as the response variable for wavelength screening. Each wavelength was evaluated using multiple sensitivity indicators, including Spearman correlation, ANOVA/effect size, Kruskal-Wallis testing, mutual information, and the mean reflectance difference between the highest and lowest salinity treatments. The individual indicators were scaled and combined into a composite salinity sensitivity score for each wavelength. Representative wavelengths were selected from high-scoring salinity-sensitive regions using a minimum 10 nm separation rule. This avoided selecting only adjacent wavelengths from the same narrow spectral region. The final selected wavelengths were 355, 972, 983, 1026, 1090, 1100, 1111, and 1121 nm.

2.3.3 *Field EC_e and hyperspectral data preparation*

The selected greenhouse-derived HS wavelengths were used in the SPRB field experiment (FE) to develop and calibrate an RS-based EC_e model through narrow-band HS vegetation indices. The field dataset was obtained from two farmer-managed irrigated maize fields within the SPRB. One field was sprinkler irrigated through a center-pivot system, while the second field was furrow irrigated. The dataset contained 18 field-level (paired) observations with laboratory-measured EC_e (from soil

samples) and HS maize reflectance from 350 to 2500 nm, using the same HS instrument as in the greenhouse experiment. The laboratory-measured EC_e values ranged from 0.95 to 4.01 dS/m, with a mean value of 1.82 dS/m.

Because EC_e was measured at the field (location specific) scale, field EC_e modeling was conducted using data from field-level maize rows. This avoided treating repeated plant or scan measurements from the same location as independent EC_e observations. This format was therefore used as the conservative modeling unit for leave-one-out validation.

2.3.4 Greenhouse-derived vegetation index construction

Field spectral indices were constructed only from the eight greenhouse-derived wavelengths selected from the salinity sensitivity analysis. This constrained the field model search to wavelengths identified under controlled greenhouse salinity conditions, rather than allowing unrestricted feature selection from the full hyperspectral spectrum. Candidate index families included normalized-difference, ratio, difference, product, square-root product, sum, three-band, normalized-difference three-band, three-band ratio, and three-band difference formulations. Additional combined features were constructed from the strongest base indices.

2.4 Evaluation metrics

Candidate EC_e models were evaluated using leave-one-out cross-validation (LOOCV) by field observation location. In each LOOCV iteration, one field observation was withheld, the model was fitted using the remaining observations, and EC_e was predicted for the withheld location. The withheld predictions were then used to calculate RMSE, MAE, MBE, NRMSE, NMBE, and cross-validated R^2 . Training RMSE and training R^2 were reported only as secondary context. Model selection was based primarily on LOOCV RMSE, with preference given to simpler model forms when performance was comparable. The selected EC_e model is therefore interpreted as a preliminary candidate function developed from greenhouse-guided salinity-sensitive wavelengths, not as an independently validated operational salinity mapping model. Model performance was evaluated using R^2 , root mean square error (RMSE), and mean bias error (MBE), along with normalized metrics, following definitions by Willmott (1981). For the field level study, small site-specific datasets included paired new HS vegetation indices and 'measured' EC_e values. In this case, the leave-one-out cross-validation (LOOCV) was used to estimate out-of-sample error. Below, Table 1 summarizes the different levels of data and salinity modeling investigated in the study.

Table 1. Summary of datasets and roles in the integrated salinity mapping effort.

Dataset / measurement	Scale	Key variables	Primary use
Field soil salinity mapping	Field	EC_e from calibrated EM surveys	Ground truth for RS models
Satellite surface reflectance	Field	Landsat and Planet reflectance; NDVI/CRSI/CWSI	Predictors for EC_e regression
Greenhouse experiment	Plant/pot	EC_w and EC_d levels; hyperspectral, HS	Identify HS bands sensitive to veg salinity
Field leaf hyperspectral observations	Point/location	Leaf reflectance paired with EC_e	Candidate EC_e model screening (LOOCV)

3. RESULTS

3.1 Existing model transferability

The Scudiero et al. (2015) RS-based EC_e model was applied directly to the SPRB using Landsat-derived CRSI and locally measured weather data. The model produced implausible EC_e estimates. The model was rerun restricting meteorological inputs to the local growing season. Recalibrating coefficients reduced bias but did not improve much the overall EC_e model performance ($R^2 \approx 0.25$) and exhibited unacceptable error levels (NRMSE $\approx 44\%$), Karpa (2025).

The Craig (2023) EC_e model, developed for maize fields in Colorado's Lower Arkansas River Valley, was similarly evaluated. While the model produced EC_e values within a plausible expected numerical range, large portions of the basin contained undefined or near-zero estimates due to log-transformed vegetation indices approaching zero. After recalibration, the optimized model showed modest improvements but remained weakly correlated with observed EC_e ($R^2 \approx 0.25$) and exhibited systematic underestimation.

Thus, existing regional salinity algorithms tested with SPRB imagery showed weak transferability, indicating that performance is strongly affected by regional conditions and crop/management context. For this reason, a new FP calibration approach was pursued.

3.2 Locally calibrated satellite-index models – FP

Because neither published model produced acceptable results, new regression-based EC_e models were developed using locally measured EC_e (EM38 surveys) data, Planet Dove satellite-derived vegetation indices (NDVI, CRSI, CWSI), and weather variables.

Locally calibrated multivariate regressions for irrigated maize improved skill relative to transferred models. NDVI appeared in most top-performing formulations, with CRSI and CWSI also frequently contributing. In general, models incorporating vegetation indices from the crop development phase consistently outperformed those using full-season or midseason data. Weather variables—particularly minimum temperature and precipitation—were included in nearly all top-performing regressions, indicating that climatic context remains an important predictor of soil salinity patterns.

The best-performing EC_e model (Eq. 3) explained a moderate proportion of the variance in observed EC_e values ($R^2 = 0.63$). This model exhibited low bias (NMBE within $\pm 6\%$) and RMSE values near 1 dS/m, suggesting they may be suitable for regional-scale salinity assessment. However, spatial variability within fields was poorly represented, with model outputs tending toward field average.

$$\ln(EC_e) = -0.727 - 3.215 \times NDVI + 1.679 \times CWSI + 2.4 \times \ln(NDVI) - 0.0163 \times \ln(CWSI) + 0.0382 \times \text{Precipitation (mm)} + 0.267 \times \text{Temperature (}^\circ\text{C)} \quad (3)$$

3.3 Greenhouse experiment results- SP

After spectral preprocessing and date-normalized salinity sensitivity analysis, eight wavelengths were selected for field EC_e model screening: 355, 972, 983, 1026, 1090, 1100, 1111, and 1121 nm. These wavelengths were primarily within the visible-edge and near-infrared portions of the spectrum and represented high-scoring salinity-sensitive regions while maintaining at least 10 nm separation between selected bands.

Figure 4 depicts the greenhouse sensitivity results and the selected wavelength set. These bandwidths were used in the SPRB field experiment (FE) to develop a model to map soil salinity through the identification of new narrow-bands SWIR HS-based vegetation indices.

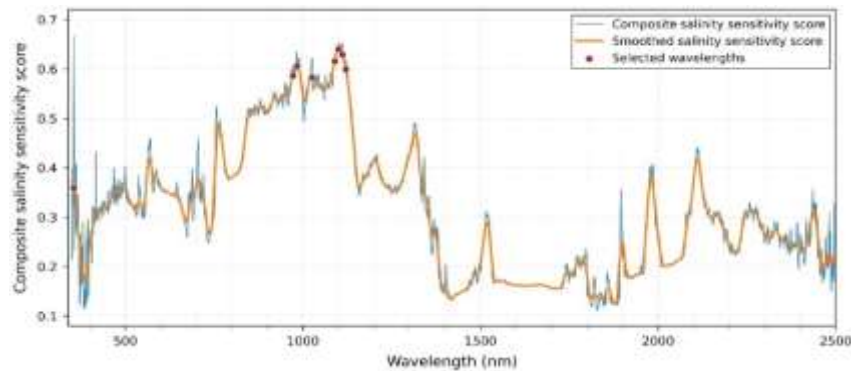


Figure 4. Greenhouse sensitivity analysis highlighting spectral regions responsive to soil salinity through maize leaves reflectance values.

3.4 Field-level EC_e modelling

Using the eight greenhouse-derived hyperspectral wavelengths selected from the salinity sensitivity analysis, candidate spectral-index models were screened with the location-level field EC_e dataset using leave-one-out cross-validation (LOOCV). The selected EC_e model was a quadratic three-band index (QTBI) EC_e model based on reflectance at 983, 1090, and 355 nm. The model produced LOOCV RMSE = 0.71 dS m⁻¹, MAE = 0.55 dS m⁻¹, MBE = -0.034 dS m⁻¹, NRMSE = 38.96%, NMBE = -1.87%, and $R^2 = 0.17$. Training RMSE was 0.58 dS m⁻¹ with training $R^2 = 0.44$. The selected EC_e model was:

$$EC_e = -1.155889 - 351.09289 \times TBI_{983_1090_355} - 8556.835 \times TBI_{983_1090_355}^2 \quad (4)$$

where three-band index (TBI) was defined as $TBI_{983_1090_355} = (R_{983} - R_{1090}) / R_{355}$. R_λ denotes leaf reflectance at wavelength λ (nm).

DISCUSSION

Results confirm that local calibration is essential for RS-based salinity estimation in irrigated systems. Differences in groundwater influence, irrigation practices, soils, plant types, and phenology can alter the relationship between soil salinity and vegetation canopy reflectance, limiting direct transfer of EC_e models developed elsewhere.

The greenhouse experiment provides a defensible controlled pathway to interpret salinity effects on vegetation reflectance through the application of different concentration of salts in the irrigation water and using hyperspectral RS. The greenhouse-guided wavelengths identification was consistent with salinity impacts on plant reflectance properties. These findings are consistent with results obtained by El-Hendawy et al. (2021) in a salinity study involving two wheat genotypes.

The identified (candidate) leaf-spectra-based EC_e equation is preliminary and should be interpreted as trend-level evidence. Its normalized error indicates the need for additional field observations, and independent validation before field-scale operational use.

A third phase of the study will include the collection of a wider range of field-level EC_e values, incorporating a larger number of farmers' managed irrigated fields (~15), a larger number of soil samples and EM-38 surveys, as well as different levels of HS RS data acquisition (i.e., handheld sensor, UAS-based and/or Satellite-based).

CONCLUSIONS

A point-to-field-scale study was carried out for soil salinity assessment in the SPRB using field EC_e mapping, satellite indices, and greenhouse hyperspectral data analysis. Existing EC_e models showed limited transferability, while locally calibrated maize-based RS regressions improved performance (best R² approaching 0.63 with ~6% normalized error). A greenhouse sensitivity analysis identified wavelengths responsive to salinity effect on maize leaves light reflectance and supported selection of eight wavelengths for candidate field screening. A preliminary field-derived maize leaf-spectra equation achieved an RMSE near 0.71 dS m⁻¹ under LOOCV but retained high normalized errors, underscoring the need for expanded ground truth and independent validation. Future work should expand field datasets and integrate spatial mapping products with uncertainty communication.

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