

Cropland Suitability Evaluation Related to Crop Yield Based on Geospatial Data

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Feeding a global population projected to exceed nine billion people within decades while limiting further conversion of natural ecosystems into farmland remains one of the defining challenges of this century [1]. Agricultural expansion has already reshaped a large share of the Earth's land surface, and the room for further horizontal growth is narrowing as remaining natural land increasingly overlaps with regions of high biodiversity value or fragile soils [2]. This tension between production and conservation is compounded by the looming scarcity of land suitable for cultivation once economic globalization and competing land uses are taken into account [3]. At the same time, a changing climate is altering the geography of what can be grown where, shifting historically reliable agroclimatic zones and eroding the yield gains achieved over preceding decades in some of the world's most productive regions [4].

Rooted in the qualitative land evaluation framework proposed by the Food and Agriculture Organization of the United Nations [5] and refined through subsequent theoretical treatments that formalized suitability as a function of matching land qualities to crop requirements [6], cropland suitability evaluation has evolved considerably since its origins in expert-based soil survey interpretation. Early quantitative approaches to digital soil mapping demonstrated that soil-forming factors could be modeled explicitly and spatially rather than inferred from coarse polygon-based soil maps [7], while the parallel development of geographic information system-based multicriteria decision analysis provided a transparent means of combining heterogeneous climatic, edaphic, and topographic layers into composite suitability indices [8]. These multicriteria frameworks, frequently implemented through the analytic hierarchy process, have since been applied across a wide range of agroecological contexts to rank land parcels according to their fitness for specific crops [9]. Global initiatives such as the Global Agroecological Zones framework have extended this logic to a planetary scale, offering harmonized, freely available suitability and potential-yield layers that underpin much of the comparative literature on land resource assessment [10].

The maturation of precision agriculture as a discipline has demonstrated that fine-scale spatial and temporal variability in crop performance, previously invisible at the scale of conventional soil surveys, can be captured, mapped, and acted upon [11]. This shift has been accelerated by the growing sophistication of earth observation data and machine learning methods applied to crop yield estimation, which are now capable of exploiting the high dimensionality of dense satellite image time series far more effectively than the linear regression frameworks that dominated the field only a decade ago [12]. The systematic bibliometric analysis of this literature contained within this Special Issue quanti-

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fies the scale of this transition [13]. Examining 1174 articles indexed in the Web of Science Core Collection between 2000 and 2025, the review finds that multispectral missions, particularly Sentinel-2, Landsat, and the Moderate Resolution Imaging Spectroradiometer, dominate the satellite-based crop yield prediction literature, while synthetic aperture radar is emerging as an increasingly important complementary data source in cloud-prone regions [13]. Precision agriculture applications of remote sensing have more broadly followed a comparable trajectory, moving from coarse-resolution vegetation indices toward multi-sensor frameworks capable of resolving management-relevant variability within individual fields [14].

The first contribution addresses a species rarely considered in the suitability literature—teak, a high-value timber species increasingly planted across the coastal lowlands of Ecuador [15]. Using the CAPFITOGEN toolkit to characterize the ecogeographic diversity of the cultivated landscape and the maximum entropy algorithm, originally developed for species distribution modeling in ecology [16], to project potential exploitation zones from a dataset of over a thousand georeferenced plantations, the study achieved a strong predictive accuracy and identified precipitation seasonality and elevation as the dominant drivers of teak suitability [15]. Species distribution models of this kind have proven broadly transferable across ecological explanation and prediction tasks [17], and their statistical underpinnings have been examined in detail to clarify how presence-only data can be used responsibly for spatial prediction [18]. The resulting maps, built on a digital elevation model derived from the Shuttle Radar Topography Mission [19], indicate that the suitable area for teak expansion considerably exceeds current cultivation, concentrated in already-deforested coastal provinces rather than in the ecologically sensitive Amazon basin, echoing climate-driven distribution work previously reported for the same species in tropical Asia [20]. The study illustrates how ecogeographic characterization combined with presence-only modeling can support forestry planning decisions that simultaneously pursue economic and conservation objectives.

A second contribution turns to the Canadian Prairies, where canola and flax represent economically vital but climatically sensitive oilseed crops [21]. Building on the Land Suitability Rating System long used by Canadian agricultural agencies to rate cropland by combining independently scored climate, soil, and landscape factors [22], the authors trained random forest models on historical crop density data to derive empirical, crop-specific weights for the climate and soil components of the rating system, departing from the fixed weighting schemes traditionally applied in this framework [21]. Climate variables accounted for the substantial majority of predictive importance for both crops, with canola suitability governed primarily by mid- to late-season precipitation and maximum temperature and flax suitability governed by growing-season minimum temperature, findings consistent with earlier work directly linking Prairie oilseed yields to temperature and precipitation variability [23]. Applying downscaled Coupled Model Intercomparison Project Phase 6 climate projections under three shared socioeconomic pathways [24,25], the study projects a progressive northward migration of high-suitability zones for both crops, with the most pronounced gains under higher-emission scenarios accompanied by marked declines across the traditionally productive southern Prairies [21]. The work exemplifies how machine learning can refine, rather than replace, an established and interpretable suitability rating methodology, extending its applicability into an explicitly future-oriented climate change adaptation context.

A third study refines the suitability question from to the within-field scale, examining how subsoil geological structure shapes the yield and wine quality of Merlot grapevines cultivated on a terraced Mediterranean slope in Israel [26]. Rather than relying on remotely sensed vegetation proxies, the authors applied electrical resistivity tomography and ground-penetrating radar, established non-invasive geophysical techniques for char-

acterizing subsurface soil-related terroir factors [27], to five adjacent vine rows subjected to identical irrigation management [26]. The geophysical surveys revealed a buried karst layer beneath the highest-yielding row and consolidated bedrock beneath the most severely water-stressed row. Electrical resistivity and radar reflectivity patterns tracked seasonal changes in subsurface moisture consistent with established interpretive frameworks for karst-system exploration [28] and for electrical resistivity applications in soil science more broadly [29]. Vines overlying the karst-influenced zone produced the highest yield but the most dilute berries and the lowest-scoring wine, whereas moderate water stress, in line with the physiological threshold long associated with elevated polyphenolic quality in Merlot [30], produced the best-balanced sensory outcome [26]. This work is a valuable reminder that the geospatial characterization underpinning cropland suitability need not always originate from an orbiting sensor; ground-based geophysical imaging offers comparably rich, spatially explicit information at scales below what any current satellite mission can resolve, and does so for a perennial crop in which fruit quality, not merely yield, is the economically relevant output.

Another contribution returns to the interface between empirical machine learning and mechanistic crop simulation, using the AquaCrop model, part of a family of process-based crop growth models that translate water availability into simulated biomass and yield according to well-established physiological principles [31], to generate a synthetic training dataset of 342 simulated instances of durum wheat yield, spanning combinations of soil, sowing date, and irrigation regime in the Capitanata plain of southern Italy [32]. Five machine learning algorithms of varying complexity, from linear regression to a multilayer perceptron, were trained as surrogate emulators of the process model, with the multilayer perceptron achieving the highest accuracy, consistent with the broader pattern by which deep learning architectures excel at capturing non-linear structures in high-dimensional data [33] at some cost to interpretability, a trade-off increasingly addressed through post hoc explanation methods such as Shapley additive explanations [34]. Notably, the four more-interpretable models converged on remarkably similar agronomic signals despite differing accuracy, correctly identifying standard and early sowing dates, supplemental irrigation at anthesis, and fine-textured soils as favorable for yield [32], a convergence that echoes the growing evidence that coupling machine learning with mechanistic crop models can improve, rather than merely automate, agronomic decision support [35]. The study demonstrates that the choice between black-box and interpretable models need not sacrifice agronomic insight when the training data itself derives from a physically grounded simulation, offering a template for extending suitability evaluation into scenario-based irrigation and sowing-date optimization.

A fifth contribution broadens the suitability question beyond a single crop to the allocation of cropland itself within a competitive coastal industrial landscape, using Nantong, in China's Jiangsu Province, as a case study [36]. Employing shift-share analysis to decompose growth in the region's agricultural sub-sectors and a multi-objective genetic algorithm to reconcile economic, social, ecological, and land-use efficiency objectives under coastal-specific constraints including soil salinity and tidal influence [36], the authors demonstrate that optimized allocation can reduce cropland area while improving alignment with industrial cluster demand and Pareto-efficiency metrics relative to conventional optimization benchmarks. This approach is conceptually aligned with knowledge-informed evolutionary methods developed for multi-objective land allocation [37] and with multi-objective land-use optimization frameworks reported for other rapidly urbanizing coastal regions [38]. This work extends cropland suitability evaluation from a biophysical question of where a crop can grow well to a socioeconomic question of how finite agricultural land should be distributed among competing uses under environmental and market constraints, a dimension of suitability assessment that is likely to grow in im-

portance as coastal and peri-urban agricultural land continues to face mounting non-agricultural pressure worldwide.

Overall, the six research articles collected in this Special Issue, “Cropland Suitability Evaluation Related to Crop Yield Based on Geospatial Data”, span perennial forestry species, temperate oilseeds, a Mediterranean fruit crop grown for wine, an irrigated cereal under a changing climate, and a coastal cropping mosaic shaped by competing industrial land demands, unified by the shared premise that geospatial data, properly integrated with agronomic and physiological knowledge, can meaningfully anticipate where and how well a crop will perform (Table 1). These contributions to this Special Issue illustrate both the breadth of contemporary cropland suitability research and the degree to which its methodological toolkit has converged on a common set of building blocks: freely available global soil and climate baselines derived from harmonized international databases [39,40], high-resolution digital elevation data [19], increasingly diverse machine learning architectures ranging from random forests to convolutional and recurrent neural networks, and, where appropriate, mechanistic process models that lend physiological grounding to purely data-driven predictions. What distinguishes the strongest contributions in this collection is not the sophistication of any single technique but the care with which each study matches its methodological choice to the scale and nature of the suitability question at hand, whether that is a continental ecogeographic characterization, a climate-adaptive rating system, a field-scale geophysical survey, a process-model emulator, or a multi-objective land-allocation optimization.

Table 1. Summary of the six contributions to this Special Issue.

No.	Crop/System	Study Area	Geospatial/Modeling Approach	Key Finding	Authors	Ref.
1	Satellite RS review (bibliometric)	Global (literature review)	Systematic review, 1174 WoS-indexed articles (2000–2025)	Sentinel-2/Landsat/MODIS dominate; SAR emerging in cloud-prone regions	Radočaj et al.	[13]
2	Teak (<i>Tectona grandis</i>)	Ecuador	CAPFITOGEN + MaxEnt SDM	Precipitation seasonality and elevation are dominant suitability drivers; large expansion potential outside Amazon basin	Borja et al.	[15]
3	Canola and flax	Canadian Prairies	Land Suitability Rating System + random forest, CMIP6 projections	Climate variables dominate; suitability zones migrate northward under warming	Nooris-ameleh et al.	[21]
4	Merlot grapevine	Israel	Electrical resistivity tomography + GPR	Karst layer related to highest yield, lowest wine quality; moderate water stress related to best wine quality	Simhayov et al.	[26]
5	Durum wheat	Capitanata plain, Italy	AquaCrop model + 5 ML algorithms (emulators)	MLP most accurate; sowing date, irrigation timing, and soil texture identified as key drivers	Garofalo et al.	[32]
6	Cropland allocation (multi-sector)	Nantong, Jiangsu, China	Shift-share analysis + multi-objective genetic algorithm	Optimized allocation cuts cropland area by 3.13% while improving industrial-cluster alignment (overall improvement index 0.847)	Lu et al.	[36]

Several avenues for future research follow directly from the gaps this Special Issue has helped to reveal. The persistent concentration of remote sensing-based yield and suitability research on a small number of staple cereals and data-rich countries, documented

quantitatively in this Special Issue [13], leaves specialty crops and large swaths of Africa and South America comparatively underserved despite their acute exposure to climate variability and food security risk. A recurring methodological concern across the broader literature on crop yield modeling is the tendency to overstate model transferability in the absence of spatially or temporally independent validation [41], a caution echoed by wider surveys of transferability in deep learning that emphasize how performance estimated within a single domain may not generalize to new regions or seasons [42]. It is encouraging that several contributions to this Special Issue already model this good practice by explicitly reporting the absence of spatial cross-validation or replicated vinifications as limitations of their own work [21,26], a transparency that should be encouraged rather than treated as a shortcoming during peer review. Extending the interpretable, empirically weighted suitability frameworks demonstrated here for oilseeds and forestry species to a wider range of crops, and validating them with more rigorous cross-validation designs, would meaningfully strengthen the evidentiary basis for land-use policy in underserved regions. Likewise, the integration of subsurface geophysical characterization with satellite-based canopy monitoring, so far explored largely in isolation from one another, represents a promising direction for reconciling the coarse spatial footprint of most Earth observation missions with the fine-scale heterogeneity that geophysical methods reveal to be agronomically decisive. As climate change continues to redraw the geography of agro-climatic suitability—consistent with the physical basis for continued warming and shifting precipitation regimes documented in the most recent international climate assessment [43], and as illustrated starkly by the projected northward migration of oilseed production zones in this Special Issue [21]—the capacity to anticipate these shifts with confidence, rather than merely observe them after the fact, will remain central to safeguarding both the productivity and the sustainability of global cropland.

As Guest Editors of this Special Issue, we are grateful to the authors for their rigorous and diverse contributions, and we hope that this collection encourages further cross-fertilization between geospatial data science, agronomic, and land evaluation communities in pursuit of more resilient and sustainable cropping systems worldwide.

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