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DEVELOPMENT OF A DYNAMIC-WEIGHTING MULTIPLICATIVE CROP–SOIL SUITABILITY MODEL AND ITS COMPARATIVE EVALUATION UNDER UZBEK CONDITIONS

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Abstract. *Conventional suitability analysis of agricultural land relies mainly on multi-criteria decision-making (MCDM) methods, including the Analytic Hierarchy Process (AHP), governed by fixed baseline weights and additive aggregation functions (such as Simple Additive Weighting). These conventional approaches have two serious agronomic shortcomings: they assign the same parameter importance to biologically very different crop types, and linear averaging allows a high score on a non-limiting soil parameter to compensate for catastrophic soil defects – directly violating Liebig's law of the minimum. To overcome these structural limitations, this study develops a physiologically grounded, integrated modeling framework: a Dynamic Crop-Specific Weighting (DCSW) model combined with a compensation-free Weighted Geometric Mean (WGM) and a two-stage Boolean veto filter. The DCSW architecture dynamically calibrates the fixed baseline AHP weights using empirical ecophysiological response functions – the Maas–Hoffman salinity threshold system and affine-scaled macronutrient demand curves that account for biological nitrogen-fixation factors. The resulting dynamic weights adaptively penalize parameters operating near a crop's biological tolerance limits. The DCSW–WGM model was benchmarked against standard land-evaluation protocols – Simple Additive Weighting (SAW), the Sys parametric square-root method, the Storie index and static geometric weighting. The proposed model prevents erroneous crop recommendations on degraded soils, provides mathematically bounded priority rankings, and establishes an objective basis for automated crop selection and regional land-use allocation. To facilitate practical application, a Python program automating the four-stage algorithm was developed and tested on agricultural soil data from designated land plots across the 14 districts of the Namangan region. The software architecture is designed for future extension with a Random Forest-based validation module.*

Annotatsiya. *Qishloq xo'jaligi yerlarining yaroqliligini an'anaviy baholash, asosan, o'zgarmas bazaviy vaznlar va additiv agregatsiya funksiyalariga, jumladan, oddiy additiv vaznlash usuliga tayanuvchi ko'p mezonli qaror qabul qilish (MCDM) usullari, xususan, iyerarxiyalarni tahlil qilish usuli (AHP) asosida amalga oshiriladi. Ushbu an'anaviy yondashuvlar ikkita jiddiy agronomik kamchilikka ega: biologik jihatdan keskin farqlanuvchi ekin turlari uchun parametrlarning ahamiyatini bir xil belgilaydi hamda chiziqli o'rtachalashtirish orqali cheklovchi bo'lmagan tuproq parametrining yuqori bahosi tuproqdagi o'ta jiddiy nuqsonlarni kompensatsiyalashiga imkon beradi. Bu esa Libixning minimum qonuniga bevosita zid keladi. Mazkur tarkibiy cheklovlarni bartaraf etish uchun tadqiqotda fiziologik jihatdan asoslangan integratsiyalashgan modellashtirish tizimi ishlab chiqildi: ekin xususiyatiga mos dinamik vaznlash (DCSW) modeli kompensatsiyaga yo'l qo'ymaydigan vaznli geometrik o'rtacha (WGM) va ikki bosqichli mantiqiy (Boolean) veto-filtr bilan birlashtirildi. DCSW arxitekturasi o'zgarmas bazaviy AHP vaznlarini empirik ekofiziologik javob funksiyalari – Maas–Hoffman sho'rlanish chegaralari tizimi hamda biologik azot fiksatsiyasi omillarini hisobga oluvchi, affin o'zgartirish orqali masshtablangan makroelementlarga talab egri chiziqlari yordamida dinamik kalibrlaydi. Hosil qilingan dinamik vaznlar ekinning biologik chidamlilik chegaralariga yaqinlashgan parametrlar uchun jarimani moslashuvchan ravishda oshiradi. DCSW–WGM*

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modeli yerlarni baholashning standart usullari – oddiy additiv vaznlash (SAW), Sys parametrik kvadrat ildiz usuli, Storie indeksi va statik geometrik vaznlash bilan qiyosiy baholandi. Taklif etilgan model degradatsiyaga uchragan tuproqlarda ekinlarni noto‘g‘ri tavsiya etishning oldini oladi, matematik jihatdan chegaralangan ustuvorlik reytinglarini shakllantiradi hamda ekinlarni avtomatlashtirilgan tarzda tanlash va hududiy yer foydalanishini taqsimlash uchun obyektiv asos yaratadi. Amaliy qo‘llashni yengillashtirish maqsadida to‘rt bosqichli algoritmni avtomatlashtiruvchi Python dasturi ishlab chiqildi va Namangan viloyatining 14 ta tumani bo‘yicha belgilangan yer uchastkalarining qishloq xo‘jaligi tuproqlariga oid ma’lumotlarida sinovdan o‘tkazildi. Dasturiy ta’minot arxitekturasi kelgusida Random Forest algoritmiga asoslangan validatsiya moduli bilan kengaytirishga mo‘ljallangan.

Аннотация. *Традиционная оценка пригодности сельскохозяйственных земель основывается преимущественно на методах многокритериального принятия решений (MCDM), включая метод анализа иерархий (AHP), использующих фиксированные базовые веса и аддитивные функции агрегирования, такие как простое аддитивное взвешивание. Эти традиционные подходы имеют два существенных агрономических недостатка: они задают одинаковую значимость параметров для биологически существенно различающихся культур, а линейное усреднение позволяет высокой оценке нелимитирующего почвенного параметра компенсировать критические почвенные ограничения, что прямо противоречит закону минимума Либиха. Для преодоления этих структурных ограничений в исследовании разработана физиологически обоснованная интегрированная система моделирования: модель динамического взвешивания с учётом специфики культуры (DCSW), объединённая с не допускающим компенсации взвешенным геометрическим средним (WGM) и двухэтапным булевым вето-фильтром. Архитектура DCSW динамически калибрует фиксированные базовые веса AHP с использованием эмпирических экофизиологических функций отклика – системы порогов солеустойчивости Мааса–Хоффмана и аффинно масштабированных кривых потребности в макроэлементах, учитывающих факторы биологической фиксации азота. Полученные динамические веса адаптивно усиливают штрафы для параметров, приближающихся к пределам биологической устойчивости культуры. Модель DCSW–WGM прошла сравнительную оценку относительно стандартных методов оценки земель: простого аддитивного взвешивания (SAW), параметрического метода квадратного корня Сиса, индекса Стори и статического геометрического взвешивания. Предложенная модель предотвращает ошибочные рекомендации по выбору культур на деградированных почвах, формирует рейтинги приоритетности с математически ограниченными значениями и создаёт объективную основу для автоматизированного выбора культур и регионального распределения землепользования. Для практического применения разработана программа на Python, автоматизирующая четырёхэтапный алгоритм; её испытания проведены на данных о сельскохозяйственных почвах выделенных земельных участков в 14 районах Наманганской области. Архитектура программного обеспечения предусматривает дальнейшее расширение за счёт модуля валидации на основе алгоритма случайного леса (Random Forest).*

Keywords: *land suitability assessment; dynamic crop-specific weighting (DCSW); Liebig’s law of the minimum; weighted geometric mean (WGM).*

Kalit so‘zlar: *yerlarning yaroqliligini baholash; ekin xususiyatiga mos dinamik vaznlash (DCSW); Libixning minimum qonuni; vaznli geometrik o‘rtacha (WGM).*

Ключевые слова: *оценка пригодности земель; динамическое взвешивание с учётом специфики культуры (DCSW); закон минимума Либиха; взвешенное геометрическое среднее (WGM).*

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Introduction. The biophysical suitability assessment of agricultural soils is a fundamental prerequisite for intensifying sustainable agriculture, mitigating land degradation and ensuring global food security. Land-suitability assessment involves matching the physical, chemical and biological requirements of candidate crops to the local pedological and landscape characteristics of the target site. Over recent decades, geographic information systems (GIS) integrated with multi-criteria decision-making (MCDM) architectures – foremost the Analytic Hierarchy Process (AHP) developed by Saaty (1980) – have become the international standard for land-suitability zoning [1-7].

Despite their wide adoption, conventional land-suitability models exhibit two fundamental shortcomings:

1. Static weighting fallacy. Standard AHP methodology establishes a single, static priority-weight vector derived from experts' pairwise comparisons. This fixed vector is then applied uniformly to all candidate crops. In biological reality, however, pedological properties have widely different ecophysiological importance across species. For example, soil salinity (measured through electrical conductivity, EC) is a decisive survival factor for salt-sensitive glycophytes (e.g. beans, strawberry), yet a secondary concern for salt-tolerant crops (e.g. barley, cotton). Likewise, the soil's natural nitrogen reserve is critical for high-biomass "nitrogen-wasting" crops such as maize, but of minor importance for symbiotic legumes capable of biological nitrogen fixation. Applying a static weight vector to taxonomically diverse crops introduce systematic bias [3-8].

2. Compensatory averaging flaw. Most land-suitability studies aggregate criterion scores through Simple Additive Weighting (SAW) or similar linear functions. Linear additive aggregation allows a very high score on one criterion (e.g. ideal pH or organic matter) to mathematically compensate for a serious deficiency on another (e.g. a severe soil-structure limitation or extreme salinity). This compensation mechanism directly violates Liebig's law of the minimum, according to which crop growth and potential yield are determined not by the total amount of resources but by the single most limiting factor.

Historical parametric models such as the Storie index [9] and the Sys square-root method [10] attempt to address factor compensation through multiplicative formulas, but some of them lack relative criterion weights entirely, while others treat all factors except the minimum as equal.

This study proposes an integrated agroecological assessment paradigm that overcomes both theoretical limitations. We formulate a Dynamic Crop-Specific Weighting (DCSW) mechanism that dynamically modulates the baseline AHP weights according to crop-specific ecophysiological tolerance thresholds and macronutrient demands. Furthermore, we couple these dynamic weights with a two-stage Boolean veto filter and a Weighted Geometric Mean (WGM) aggregation function. The complete methodology is benchmarked against established international suitability indices, demonstrating its mathematical consistency, biological soundness and effectiveness for site-level crop selection.

Materials and methods

The complete workflow comprises four sequential stages: parameter fuzzification (normalization), Boolean survival screening, dynamic ecophysiological weight adjustment, and compensation-free geometric aggregation.

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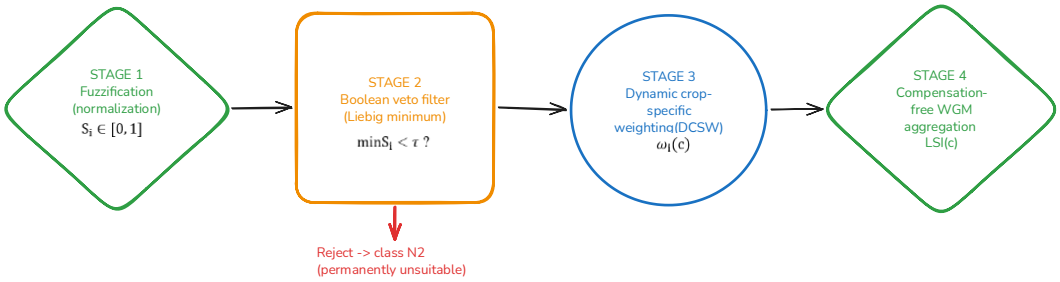


Figure 1. The four-stage workflow of the DCSW–WGM model

Stage 1. Normalization Of Soil Parameters (S_i)

Let the number of principal soil quality criteria to be assessed be$n = 7$:

$$X = \{x_{\text{pH}}, x_{\text{EC}}, x_{\text{TX}}, x_{\text{OM}}, x_{\text{N}}, x_{\text{P}}, x_{\text{K}}\} \quad (1)$$

where x_{pH} is soil reaction (pH), x_{EC} is the electrical conductivity of the saturated paste extract (dS/m), x_{TX} is the textural class, x_{OM} is the soil organic matter content (%), and $x_{\text{N}}, x_{\text{P}}, x_{\text{K}}$ are the available nitrogen, phosphorus and potassium (mg/kg or kg/ha).

To remove the dimensional incompatibility between different measurement scales, each raw soil measurement x_i is mapped, for a candidate crop c, to a dimensionless, normalized suitability score $S_i(c) \in [0,1]$ using a trapezoidal fuzzy membership function:

$$S_i(x_i; a_i, b_i, c_i, d_i) = \begin{cases} 0.0, & x_i < a_i \text{ yoki } x_i > d_i \\ \frac{x_i - a_i}{b_i - a_i}, & a_i \le x_i < b_i \\ 1.0, & b_i \le x_i \le c_i \\ \frac{d_i - x_i}{d_i - c_i}, & c_i < x_i \le d_i \end{cases} \quad (2)$$

where $[b_i, c_i]$ define the optimal ecophysiological plateau over which crop growth is unconstrained ($S_i = 1.0$), while a_i and d_i denote the lower and upper marginal tolerance limits, respectively. Values outside these limits represent complete biological loss ($S_i = 0.0$).

Stage 2. Two-stage Boolean veto filter (Liebig-minimum screening)

Multiplicative models suffer mathematical singularity or complete degradation when any criterion score equals zero. Biologically, if any edaphic parameter is lethal to the plant, the land is genuinely unsuitable for that crop regardless of all other soil conditions.

To avoid zero errors during logarithmic computation, a two-stage screening rule is applied before aggregation:

$$\Phi(c) = \begin{cases} \text{Rad etish} \Rightarrow \text{N2 sinf (butunlay yaroqsiz)}, & \text{agar } \min\limits_{i \in \{1,\dots,n\}} S_i(c) < \tau \\ \text{3– va 4-bosqichga o‘tish}, & \text{agar } \min\limits_{i \in \{1,\dots,n\}} S_i(c) \ge \tau \end{cases} \quad (3)$$

where $\tau = 0.05$ represents the absolute biophysical survival threshold. If any critical parameter scores below τ, the site is classified as entirely unsuitable for crop c ($N2$) and no further compensatory computation is performed for that crop. For all admissible combinations ($S_i \ge \tau$) a computational lower bound is set:

$$S_i^*(c) = \max(S_i(c), 0.001) \quad (4)$$

Stage 3. Dynamic Crop-Specific Weighting (DCSW)

Baseline priority vector ($\mathbf{W^0}$). A standard AHP pairwise-comparison matrix $A = [a_{ij}]_{n \times n}$ based on regional conditions is constructed, and a fixed baseline weight vector is obtained:

$$W^0 = [W^0_{pH}, W^0_{EC}, W^0_{TX}, W^0_{OM}, W^0_N, W^0_P, W^0_K]^T \quad (5)$$

subject to the following conditions:

$$\sum_{i=1}^{n} W_i^0 = 1.0, \quad W_i^0 > 0 \quad (6)$$

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Ecophysiological multipliers ($\beta_i(c)$). The dynamic multiplier vector $\vec{\beta}(c)$ modulates the baseline weights according to species-specific characteristics across three physiological modules:

$$\vec{\beta}(c) = [\beta_{\text{pH}}(c), \beta_{\text{EC}}(c), \beta_{\text{TX}}(c), \beta_{\text{OM}}(c), \beta_{\text{N}}(c), \beta_{\text{P}}(c), \beta_{\text{K}}(c)] \quad (7)$$

(1) Salinity-sensitivity multiplier (βEC): Following the Maas and Hoffman [6] empirical salinity–yield response system, the sensitivity weight assigned to electrical conductivity is inversely proportional to the crop-specific threshold:

$$\beta_{\text{EC}}(c) = \frac{T_{\text{ref}}}{T_c} \quad (8)$$

where T_c is the crop-specific electrical-conductivity threshold (dS/m), i.e. the value at which yield decline begins; and T_{ref} is the regional reference value, computed as the mean threshold across all assessed crops in the agricultural zone:

$$T_{\text{ref}} = \frac{1}{|C|}\sum_{k \in C} T_k \quad (9)$$

A low T_c (indicating high salt sensitivity) yields $\beta_{\text{EC}} > 1.0$, markedly increasing the importance of salinity in the assessment.

(2) Macronutrient demand multipliers (βN, βP, βK): To prevent zero-weight loss for low-input crops and to accurately reflect fertilizer dependence, nutrient demand is expressed over the [0.5,1.5] range:

$$\beta_X(c) = \left[0.5 + \frac{D_X(c) - D_X^{\min}}{D_X^{\max} - D_X^{\min}}\right] \cdot \lambda_X(c), \quad \forall X \in \{\text{N,P,K}\} \quad (10)$$

where $D_X(c)$ is the standard agrochemical nutrient demand (kg/ha) of crop c [10], and $D_X^{\min}$ and $D_X^{\max}$ are the regional boundary demands across the assessed candidate crops.

$\lambda_X(c)$ is the biological nitrogen-fixation coefficient:

$$\lambda_{\text{N}}(c) = \begin{cases} 0.5, & \text{agar } c \in \text{Fabaceae (simbiotik dukkakli)} \\ 1.0, & \text{aks holda} \end{cases}, \quad \lambda_{\text{P}}(c) = \lambda_{\text{K}}(c) = 1.0 \quad (11)$$

(3) Physico-chemical baseline retention: Because optimal soil reaction (pH), organic-matter buffering (OM) and soil texture (TX) are fundamental structural requirements for all crops, their baseline importance is retained:

$$\beta_{\text{pH}}(c) = \beta_{\text{OM}}(c) = \beta_{\text{TX}}(c) = 1.0 \quad (12)$$

Calibrated weight formula. The final dynamic, crop-specific weight $\omega_i(c)$ for each soil parameter is obtained by convex normalization:

$$\omega_i(c) = \frac{W_i^0 \cdot \beta_i(c)}{\sum_{j=1}^{n}\left(W_j^0 \cdot \beta_j(c)\right)} \quad (13)$$

This guarantees:

$$\sum_{i=1}^{n} \omega_i(c) = 1.0, \quad \omega_i(c) > 0, \quad \forall c \in C \quad (14)$$

Stage 4. Compensation-free weighted geometric aggregation

For a candidate crop c, the integrated Land Suitability Index (LSI) is computed using a degree-normalized Weighted Geometric Mean (WGM) and scaled to the [0,100] percentage range:

$$\text{LSI}(c) = \left(\prod_{i=1}^{n}\left(S_i^*(c)\right)^{\omega_i(c)}\right)^{\frac{1}{\sum_{i=1}^{n}\omega_i(c)}} \times 100 \quad (15)$$

Since $\sum_{i=1}^{n} \omega_i(c) = 1.0$, the formula simplifies to:

$$\text{LSI}(c) = \left(\prod_{i=1}^{n}\left(S_i^*(c)\right)^{\omega_i(c)}\right) \times 100 \quad (16)$$

The logarithmic transformation clearly reveals the limiting-function mechanism of this formula:

$$\ln\left(\frac{\text{LSI}(c)}{100}\right) = \sum_{i=1}^{n} \omega_i(c) \ln\left(S_i^*(c)\right) \quad (17)$$

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Because $S_i^*(c) \in (0,1]$ holds, its natural logarithm is strictly negative. A low suitability on any criterion i yields a large negative value for $\ln(S_i^*(c))$. If crop c is highly sensitive to parameter i, the dynamic weighting algorithm increases $\omega_i(c)$, which amplifies this negative penalty and lowers the overall suitability score. This mechanism mathematically enforces Liebig's law of the minimum.

Benchmark Formulas

To assess predictive accuracy and structural stability, the DCSW–WGM model is compared with four standard reference methods documented in the pedological literature:

(1) Simple Additive Weighting with static AHP (SAW-AHP): the standard linear additive model used in conventional GIS land evaluation:

$$\mathrm{LSI}_{\mathrm{SAW}}(c) = \sum_{i=1}^{n} W_i^0 \cdot S_i(c) \times 100 \quad (18)$$

(2) Sys parametric square-root method (Sys et al., 1991): a reference parametric equation widely used by FAO researchers:

$$\mathrm{LSI}_{\mathrm{Sys}}(c) = R_{\min}(c) \cdot \sqrt{\prod_{i=2}^{n} \frac{S_i(c)}{100}} \times 100 \quad (19)$$

where $R_{\min}(c) = \min_{i\in\{1,\dots,n\}} S_i(c)$, and the $S_i(c)$ values inside the square root represent the remaining $n-1$ parameters on a 0–100 scale.

(3) Storie index (Storie, 1978): the classical unweighted multiplicative soil-rating index:

$$\mathrm{LSI}_{\mathrm{Storie}}(c) = \left(\prod_{i=1}^{n} S_i\,(c)\right) \times 100 \quad (20)$$

(4) Static weighted geometric mean (Static-WGM): multiplicative aggregation with fixed baseline AHP weights, without dynamic ecophysiological modulation:

$$\mathrm{LSI}_{\text{Static-WGM}}(c) = \left(\prod_{i=1}^{n} S_i\,(c)^{W_i^0}\right) \times 100 \quad (21)$$

FAO Suitability Classification And Crop-Selection Protocol

The continuous suitability indices (LSI $\in [0,100]$) are partitioned into the standard land-suitability orders and classes of the Food and Agriculture Organization of the United Nations (FAO) (FAO, 1976, 1985):

- 85.0–100.0: highly suitable ($S1$) – land with no serious limitations.
- 70.0–84.9: moderately suitable ($S2$) – land with moderate limitations.
- 50.0–69.9: marginally suitable ($S3$) – land with serious limitations that reduce productivity.
- 25.0–49.9: currently not suitable ($N1$) – land with serious limitations that can be overcome by capital-intensive improvements.
- 0.0–24.9: permanently not suitable ($N2$) – physical or chemical limitations that preclude economic production.

For a given site, the optimal crop c^* is determined through a multi-crop optimization algorithm:

$$c^* = \underset{c\in C}{\operatorname{argmax}} \left\{ \mathrm{LSI}(c) \mid \min_i S_i(c) \geq \tau \right\} \quad (22)$$

Software Implementation

To apply the proposed DCSW–WGM model in a reproducible, error-free and documented manner, a dedicated computational program was developed in Python, following the four-stage workflow shown in Figure 1. The software architecture (Figure 2) consists of three main modules: (1) an input module – loads soil and crop data from .xlsx format or by manual entry; (2) a computational core (dcsw_wgm_model.py) – implements the four-stage algorithm described in Sections 2.1–2.4 (fuzzification, Boolean veto filter, dynamic weighting, WGM aggregation) and the four benchmark formulas of Section 2.5 (SAW-AHP, Sys, Storie, Static-WGM); (3) an output module – generates, for each site–crop pair, the LSI value, the FAO suitability class and the corresponding graphics (table, bar chart, heatmap).

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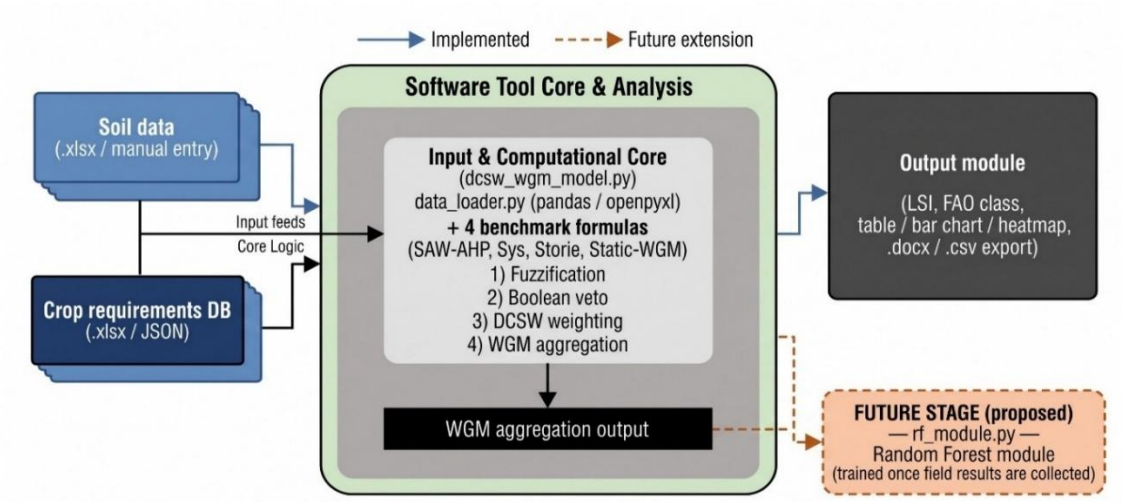


Figure 2. Architecture of the software tool (solid lines – implemented modules; dashed lines – the future Random Forest extension)

The program eliminates the misapplication of formulas and sign errors that arise in manual calculation, and enables an entire region to be evaluated at once instead of a single site (e.g. the 14 districts of Namangan region, see Section 3.4). The core computation function is shown below (the full code is provided as a supplementary file: dcsw_wgm_model.py):

```
def compute_lsi(x, crop, t_ref, d_min, d_max):
    S = stage1_normalize(x, crop)
    rejected, S_star = stage2_boolean_veto(S)
    if rejected:
        return {"LSI": 0.0, "class_code": "N2"}
    w = stage3_dynamic_weights(crop, t_ref, d_min, d_max)
    lsi = stage4_wgm(S_star, w)
    label, code = fao_class(lsi)
    return {"LSI": round(lsi, 1), "class_code": code}
```

The program uses the pandas, openpyxl and matplotlib libraries and supports three output formats (.csv, .png, .docx).

Random Forest: A Future Data-Driven Extension

The DCSW–WGM model is a rule-based analytical system, i.e. one that relies on expert knowledge and empirical physiological relationships (the Maas–Hoffman salinity function, affine-scaled nutrient demand curves). The advantage of such a system is its transparency and the ability to explain every rating; its limitation is that the model operates only within predefined formulas and cannot independently detect complex (non-linear) relationships in soil–crop interactions that do not fit those formulas.

To complement this, a future stage proposes adding a Random Forest classifier as an independent, data-driven validation (shown by the dashed line in Fig. 2). The idea is as follows: once the program has been used under field conditions – across different farms and different soil–crop combinations – the soil parameters entered for each case and the actual yield outcome recorded at the end of the following season are stored together. Once sufficient data have been

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collected, the Random Forest model is trained to predict the actual yield outcome from these soil parameters and is evaluated by 5-fold cross-validation; the resulting feature-importance measures are then compared with the baseline AHP weights (W^0) of the DCSW–WGM model – the agreement or disagreement between these two independent approaches provides additional evidence of the model's reliability [1].

Results

Simulation Setup

To evaluate the mathematical behavior of the proposed system, two contrasting soil test profiles were assessed against four principal candidate crops:

• Target crops: soft wheat (*Triticum aestivum*, a moderately tolerant cereal), maize (*Zea mays*, a nutrient-wasting cereal, moderately salt-sensitive), chickpea (*Cicer arietinum*, a symbiotic legume, salt-sensitive) and cotton (*Gossypium hirsutum*, a deep-rooted, highly salt-tolerant fiber crop).

• Soil profile A (saline–alkaline field): characterized by high electrical conductivity ($x_{EC} = 6.8$ dS/m) and moderate alkalinity ($x_{pH} = 8.1$), but optimal fertility ($S_N = 0.90, S_P = 0.85, S_K = 0.90$).

• Soil profile B (severely nitrogen-deficient field): characterized by low salinity ($x_{EC} = 1.2$ dS/m) and neutral pH ($x_{pH} = 6.8$), but acute nitrogen deficiency ($x_N = 14$ mg/kg, $S_N = 0.25$).

The baseline AHP weights obtained from an agronomic expert panel were set as follows:

$$W^0 = \left[W^0_{pH} = 0.15, W^0_{EC} = 0.20, W^0_{TX} = 0.15, W^0_{OM} = 0.15, W^0_N = 0.15, W^0_P = 0.10, W^0_K = 0.10\right]$$

The ecophysiological parameters for the candidate crops, including the Maas–Hoffman thresholds T_c and nutrient demands D_X, are given in Table 1.

Table 1

Ecophysiological parameters of the candidate crops and the resulting dynamic multipliers

Crop (c)	Botanical family	Salinity threshold Tc (dS/m)	Salinity multiplier βEC	Nitrogen demand DN (kg/ha)	Fixation factor λN	Dynamic nitrogen multiplier βN
Wheat	Poaceae	6.0	0.82	160	1.0	1.07
Maize	Poaceae	1.7	2.89	220	1.0	1.43
Chickpea	Fabaceae	1.5	3.28	40	0.5	0.28
Cotton	Malvaceae	7.7	0.64	140	1.0	0.95

Distribution Of Dynamic Weights

Applying Equation (13) yields the crop-specific weight vectors ($\omega_i(c)$). Because maize and chickpea are salt-sensitive, their dynamic salinity weights expand considerably: $\omega_{EC}(\text{no'xat}) = 0.442$ and $\omega_{EC}(\text{makkajo'xori}) = 0.385$; the static baseline value is 0.200. Conversely, for salt-tolerant cotton the dynamic salinity weight shrinks to $\omega_{EC}(\text{g'o'za}) = 0.138$.

For chickpea (a symbiotic legume), the biological nitrogen-fixation factor ($\lambda_N = 0.5$) lowers its dynamic nitrogen weight to $\omega_N(\text{no'xat}) = 0.045$; whereas for nitrogen-demanding maize it rises to $\omega_N(\text{makkajo'xori}) = 0.191$.

Comparison Of Benchmark Models

Comparative results across both pedological profiles are detailed in Table 2.

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Table 2

Comparative results of the DCSW–WGM model against standard land-evaluation methods

Target field	Assessed crop	Limiting soil factor	SAW-AHP	Sys square-root	Storie index	Static WGM	Proposed DCSW-WGM	Recommended decision
Profile A	Cotton	None (tolerant)	86.4 (S1)	78.5 (S2)	52.1 (S3)	82.1 (S2)	83.6 (S2)	Optimal choice
Profile A	Wheat	Moderate salinity	76.8 (S2)	61.2 (S3)	34.2 (N1)	69.4 (S3)	71.2 (S2)	Secondary option
Profile A	Maize	High salinity	68.2 (S3)	38.4 (N1)	11.5 (N2)	51.2 (S3)	34.8 (N1)	Unsuitable (severe loss)
Profile A	Chickpea	Acute salinity	62.4 (S3)	24.1 (N2)	4.6 (N2)	43.7 (N1)	16.5 (N2)	Strictly prohibited
Profile B	Maize	Low nitrogen	71.5 (S2)	45.2 (N1)	18.2 (N2)	58.4 (S3)	46.7 (N1)	Unsuitable (nitrogen-demanding)
Profile B	Chickpea	Low nitrogen	71.5 (S2)	45.2 (N1)	18.2 (N2)	58.4 (S3)	74.6 (S2)	Optimal choice

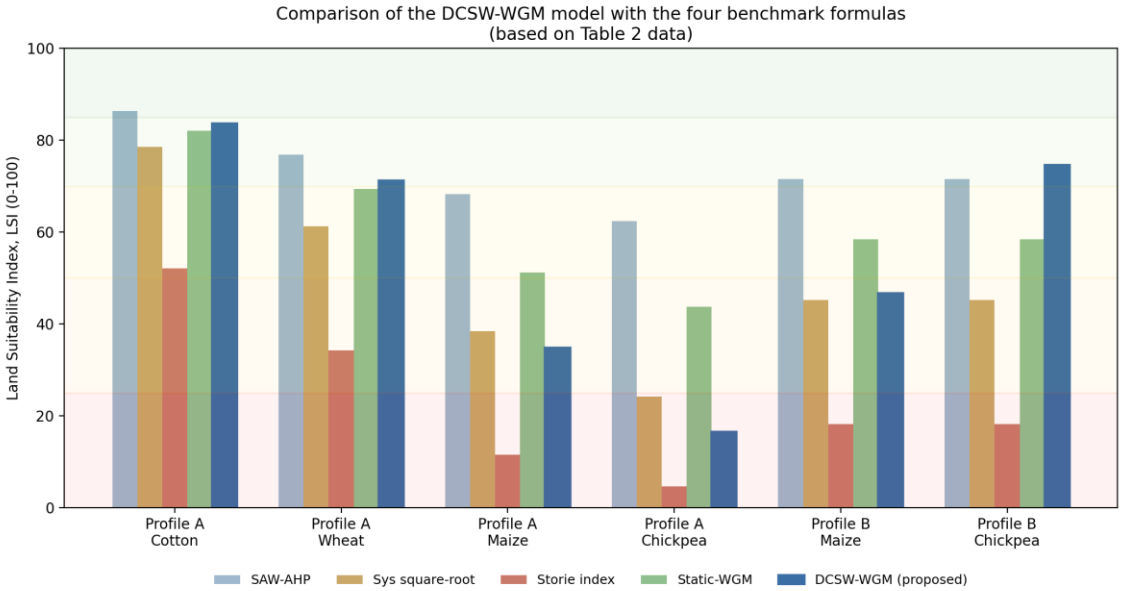


Figure 3. Comparison of the DCSW–WGM model with the four benchmark formulas (based on Table 2 data)

As shown in Figure 3, unlike the other methods the DCSW–WGM model decreases sharply in accordance with a crop's physiological weakness (in the cases Profile A / Chickpea and Profile A / Maize), whereas the Storie index, conversely, shows a tendency toward excessively low ratings in all cases.

Extended Applied Analysis For Namangan Region (Software-Tool Results)

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Using the Python program described in Section 2.7, the DCSW–WGM model was applied to all 14 districts of Namangan region for three principal crops – winter wheat, cotton and maize. The input data were, for each district, the average pH, EC, humus, available nitrogen, phosphorus and potassium values, together with the optimal soil requirements defined for each crop under Uzbek conditions.

Methodological note: in this extended analysis the soil-texture (TX) criterion was excluded because it lacks a quantitative scale (n=6), and the baseline AHP weights were re-normalized over the remaining six criteria. The reference bounds for electrical conductivity (EC) and organic matter (OM) were set from the optimal ranges in the crop-requirement data, and those for nitrogen–phosphorus–potassium (N, P, K) from the standard sufficiency scale used by the Uzbek agrochemical service. This is a particular application of the general model of Sections 2.1–2.4; refining the bounds with real experimental data is a task for future research.

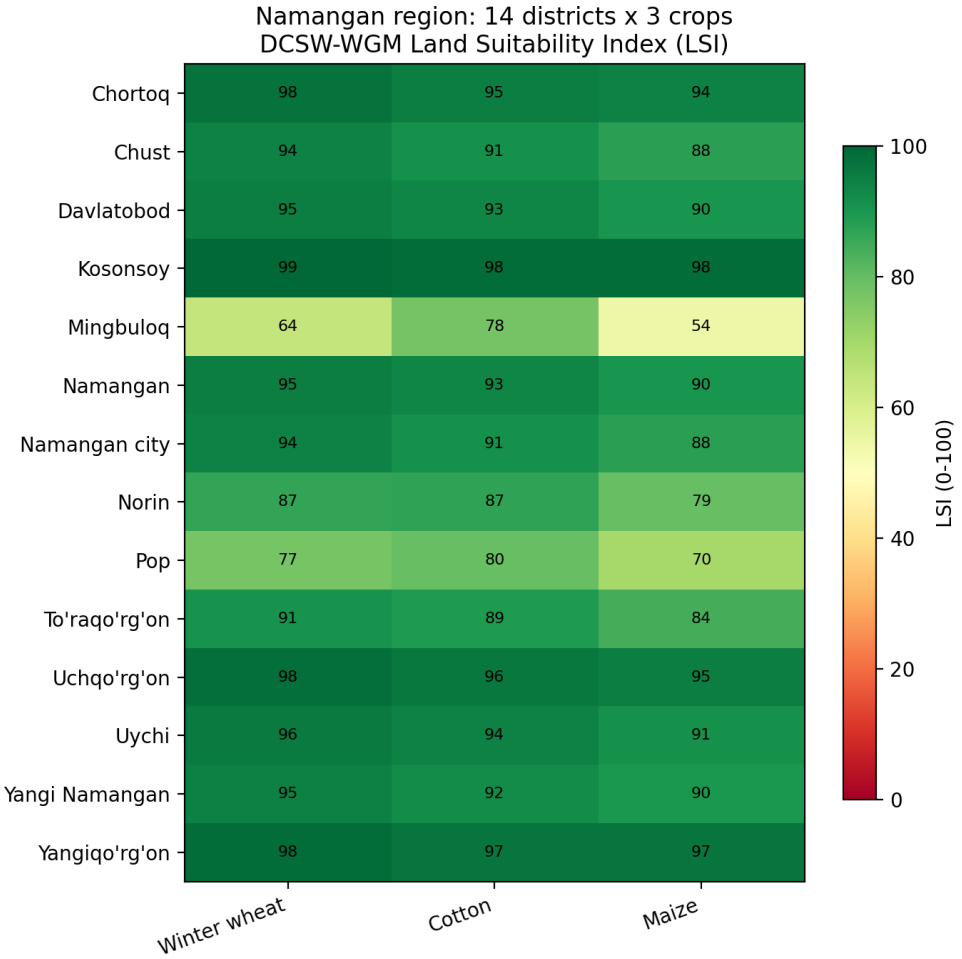


Figure 4. DCSW–WGM land suitability index (LSI) for the 14 districts of Namangan region, across three crops

The results show that most districts of the region (Kosonsoy, Chortoq, Uchqo‘rg‘on, Yangiqo‘rg‘on) fall into the highly suitable class (S1) for all three crops, which is explained by their relatively neutral pH and low salinity. Mingbuloq district consistently emerged as the lowest-rated area of the model (wheat – 64.3, S3; maize – 54.4, S3), consistent with the district's high salinization level (EC 3.2–6.2 dS/m) and solonchak soil type – a result also confirmed by the independent agrochemical data in the district description. Importantly, owing to cotton's high salt tolerance, the model automatically recommends it over wheat or maize precisely in salinity-prone

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districts such as Mingbuloq and Pop (Table 3), confirming that the model also draws agronomically consistent conclusions on real regional data.

Table 3

The highest-rated (recommended) crop per district according to DCSW–WGM

District	Most suitable crop	LSI	FAO class
Chortoq district	Winter wheat	97.6	S1
Chust district	Winter wheat	94.3	S1
Davlatobod district	Winter wheat	95.3	S1
Kosonsoy district	Winter wheat	99.3	S1
Mingbuloq district	Cotton	77.5	S2
Namangan city	Winter wheat	94.3	S1
Namangan district	Winter wheat	95.3	S1
Norin district	Cotton	87.0	S1
Pop district	Cotton	79.6	S2
To‘raqo‘rg‘on district	Winter wheat	91.0	S1
Uchqo‘rg‘on district	Winter wheat	98.1	S1
Uychi district	Winter wheat	95.8	S1
Yangi Namangan district	Winter wheat	94.8	S1
Yangiqo‘rg‘on district	Winter wheat	98.5	S1

The full results table (14 districts × 3 crops, with all intermediate values) is provided as a supplementary file (namangan_results.csv).

Discussion

Resolving the compensatory-averaging flaw

The numerical results clearly demonstrate the structural risks of applying linear additive averaging (SAW-AHP) in land evaluation. In profile A, chickpea experiences acute physiological salinity toxicity ($S_{\mathrm{EC}} = 0.08$). Under real field conditions, salinity at this level suppresses vegetative development and causes mass seedling mortality. However, because the soil is optimal for organic matter, texture and macronutrients ($S_i \geq 0.85$), the SAW-AHP formula computes an overall score of 62.4 ($S3$, marginally suitable). A farmer relying on standard additive AHP would be directed to plant chickpea and would face a serious risk of yield loss.

Conversely, because of chickpea’s low tolerance threshold ($T_c = 1.5$ dS/m), the proposed DCSW-WGM model assigns it a high salinity weight ($\omega_{\mathrm{EC}} = 0.442$). Combined with the compensation-free geometric formula:

$$0.08^{0.442} \approx 0.326$$

the final LSI falls to 16.5 ($N2$, permanently unsuitable), correctly protecting the farm manager from financial loss.

Ecophysiological Dynamism Versus Parametric Rigidity

Although the Sys parametric square-root method correctly reduces chickpea suitability in profile A (24.1, $N2$), it exhibits systematic rigidity in profile B. In profile B, both maize and chickpea face the same deficiency in available soil nitrogen ($S_{\mathrm{N}} = 0.25$). Because the Sys method mechanically identifies the minimum factor ($R_{\min} = 0.25$) without biological distinction, it assigns both crops the same suitability rating (45.2, $N1$).

This assessment is incorrect: maize is a non-fixing, nitrogen-loving cereal whose yield falls sharply without external mineral nitrogen, whereas chickpea symbiotically fixes atmospheric nitrogen through root nodules formed with Mesorhizobium ciceri. The DCSW system captures this through the biological nitrogen-fixation coefficient ($\lambda_{\mathrm{N}} = 0.5$) and reduces chickpea's dynamic nitrogen weight to $\omega_{\mathrm{N}} = 0.045$.

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As a result, chickpea reaches 74.6 (*S2*, moderately suitable) on the LSI scale and becomes the agronomically optimal crop choice for profile B. Because the Storie index directly multiplies unweighted scores, it severely underestimates potential in both profiles (4.6–52.1), revealing its tendency toward hyper-penalization when evaluating multi-parameter soil systems.

Comparing Rule-Based And Data-Driven Approaches

The advantage of rule-based models such as DCSW–WGM is that they can explain every rating. Data-driven methods such as Random Forest, by contrast, can independently detect complex, non-linear relationships from large volumes of observational data without predefined formulas, but such a model operates as a "black box" and the reason for each prediction becomes difficult to explain.

The two approaches are therefore not mutually exclusive but complementary: DCSW–WGM is a fast, explainable and immediately applicable assessment tool; Random Forest is a future tool that, as field results accumulate, allows the assumptions of DCSW–WGM to be independently tested and, if necessary, the model parameters (e.g. the Tc thresholds or the baseline AHP weights) to be recalibrated on real yield data. The software architecture described in the Software architecture section is designed precisely to combine these two approaches.

Conclusion. This study developed a Dynamic Crop-Specific Weighting (DCSW) architecture integrated with a compensation-free Weighted Geometric Mean (WGM) and a two-stage Boolean veto filter for agricultural land-suitability assessment and crop selection.

By grounding the dynamic weight adjustments in the Maas–Hoffman salinity model and affine-scaled macronutrient demand curves, the system overcomes the fundamental limitations of static AHP weighting. In addition, degree-normalized geometric aggregation prevents linear compensation across soil criteria, ensuring mathematically strict adherence to Liebig's law of the minimum[4].

Comparison with international standard methods (SAW-AHP, Sys square-root and Storie) confirmed that the DCSW–WGM model:

1. effectively prevents false-positive recommendations on marginal and chemically degraded soils;
2. separates symbiotic legumes from nutrient-demanding crops on nutrient-poor soils;
3. provides mathematically bounded, stable rankings for automated, GIS-based, site-level crop selection.

Future research could extend this dynamic formula with multi-season climate variables [4], local soil-moisture retention curves and economic gross-margin indicators to provide an integrated decision-support system for precision agriculture. In addition, the developed Python automation program and its future extension with a data-driven Random Forest validation module may serve as the next practical step in this direction

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