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Advancing Integrated Environmental and Nutritional Life Cycle Assessments for Local Food Systems

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Abstract

Accelerating sustainable food system transitions requires spatially explicit integration of local production conditions and nutritional priorities, yet such assessments remain scarce, particularly for low- and middle-income countries. We developed an open-source, reproducible nutritional Life Cycle Assessment model – Local Environmental and Nutritional Scoring (LENS) – and analyzed sub-national food supply chains across six environmental impact categories in Kenya and Rwanda. Results reveal strong context dependency: terrestrial animal products show comparable impacts to most plant-source foods when comprehensively assessed. Enviro-nutritional efficiencies tend to be highest for wild-caught fish and seafood, pulses, fruit and vegetables from low-input systems, and lowest for starchy staples and poultry. Substantial variation within food groups, between co-products, and across space necessitates interpreting scores at landscape level rather than as independent benchmarks for scaling production.

Keywords: life cycle analysis; environmental impact assessment; spatial analysis; greenhouse gas emissions; water use; water pollution; air pollution; biodiversity; agrifood systems; food supply chains; nutrition-sensitive agriculture; nutrient profiling; smallholders; low- and middle-income countries (LMIC); Africa South of Sahara; Kenya; Rwanda; open-source software

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1. Introduction

Life Cycle Assessment (LCA) provides a common methodology for quantifying environmental impacts across entire food supply chains, from primary inputs to waste disposal. These assessments typically operate as deterministic, steady-state analyses, extrapolating single data points across broader geographic areas (*1*). Spatially explicit approaches methodologically advance LCAs by focusing on single supply chains or aggregated economic activities within defined sub-national territories (*2*). Yet, they remain rare across sectors – a limitation particularly critical for agrifood systems, where heterogeneous agroecological conditions necessitate spatial precision (*3*, *4*). Concurrently, nutritional LCAs (nLCA) have emerged to improve the relevance of LCAs of foods and diets to a wider range of stakeholders beyond environmental scientists and engineers (*5*–*7*). By replacing mass- or energy-based reference units with nutritional metrics – single nutrients (e.g., protein (*8*)) or compound nutritional scores (*9*–*11*)) – nLCAs shift the analytical focus from quantity of food produced or caloric supply to nutritional quality, thereby revealing synergies and trade-offs between environmental integrity and human health. Separately, impact assessment approaches have advanced in reflecting regional variation in environmental sensitivity (*12*), while discussions surrounding integration of ecological carrying capacities and natural resource constraints into impact evaluation continue (*13*, *14*).

Despite this progress, LCAs, including spatially explicit LCAs and nLCAs, share several key limitations. These include heavy reliance on data from industrialized agrifood systems in high-income countries (*3*, *4*, *15*–*17*) even though low- and middle-income countries (LMIC) bear the greatest burden of both environmental degradation and malnutrition (*18*), and extensive dependence on proprietary data and software (*19*, *20*). Additionally, impact assessments typically focus on natural resource efficiency without regard to resource constraints and ecological thresholds (e.g., total vs. sustainable water use (*21*)), and rely on administrative borders rather than biophysical boundaries for impact assessment (e.g., countries vs. river basins (*22*)).

Here we introduce Local Environmental and Nutritional Scoring (LENS), a model designed to address these limitations through four key innovations. First, LENS is a fully reproducible, open-source LCA model providing global coverage with default inventory data (base year 2020), representing local production conditions, and offering scalable assessment capabilities for sub-national implementation. Second, this sub-national scalability is achieved through seamless integration of high-resolution geospatial datasets on climate, soil, water, and land use, capturing agroecological heterogeneity and leveraging advances in environmental data availability and spatial precision. Third, the model employs a novel compound nutritional score as standardized reference basis, tailored to regional dietary patterns and malnutrition profiles. This enhances applicability to traditional smallholder and transitional agricultural systems (*23*) in LMICs, as demonstrated for Kenya and Rwanda. Fourth, LENS implements a target-based normalization to compare foods' enviro-nutritional efficiency against sustainability thresholds. Unlike traditional LCA normalization, which expresses impacts as dimensionless fractions of total resource use or monetary values (*24*, *25*) before aggregating into single scores, our approach employs the most spatially resolved policy goals and safe operating spaces for each indicator. This provides more contextually relevant guidance for decision-making across governance levels.

2. Case Study Context and Analytical Framework

We apply LENS in Kenya and Rwanda, two East African countries that share persistent food and nutrition challenges. Despite progress, over 25% of the population still consume diets lacking sufficient quantities of nutrient-rich foods (e.g., meat, dairy, vegetables) (*26*). Dietary diversity is constrained by staple crop overdependence (maize, beans, and potatoes in Kenya; cassava, bananas, and sweet potatoes in Rwanda), limiting dietary supply of high-quality protein and essential nutrients (*27*). Yet the two countries offer contrasting food system contexts, allowing us to demonstrate LENS' capacity to capture diverse sub-national food system dynamics. Kenya is characterized by a large diversity of agroecological zones – from pastoral systems across arid and semi-arid lands (*28*) to large-scale Rift Valley cereal production (*29*) and export-oriented sectors including tea, coffee, and horticulture (*30*). Rwanda, by contrast, has nearly six times Kenya's population density, making it one of Africa's most densely populated countries, with limited pastoral production (*31*) and an even greater reliance on smallholders, of whom 90% farm on hillsides (*32*).

LENS employs the Nutritional Value Score (NVS) as a standardized reference basis (functional unit), marking one of the first applications of this metric in an LCA model. The NVS integrates multiple health-relevant nutritional indicators, accounting for both density of nutrients commonly lacking in diets globally and dietary factors linked to noncommunicable disease risk (*33*). On a 1-100 scale, an NVS of 100 represents the highest relative nutritional value among a given set of food products. Specifically, we apply regional NVS for Sub-Saharan African foods to derive the quantity of food (in grams) required to achieve an NVS of 100 in this world region (see *Materials* and *Methods*

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for a detailed description). The model assesses six food-level environmental impacts: greenhouse gas (GHG) emissions, water use, water pollution (i.e., marine and freshwater eutrophication potential, ocean acidification potential), biodiversity loss (i.e., potential species loss), and non-GHG air pollution (i.e., particulate matter (PM) emissions); and also accounts for major international food imports (see *Materials* and *Methods for details*). To normalize and aggregate these impacts into single scores, we use location- and sector-specific policy targets (e.g., national GHG emission goals) and environmental thresholds (e.g., the planetary boundary for ocean acidification) (see *Materials* and *Methods* and *Table S3* for a detailed description).

3. Food System Profiles by Country and Food Group

We analyzed 163 domestically produced foods in Kenya and 75 in Rwanda, organizing them in eleven categories (*Fig. 1*). These include commonly consumed unprocessed, minimally processed, and processed foods, including indigenous crops and traditional foods rarely represented in global food composition and life cycle inventory databases (e.g., dried lake sardine, jute mallow, camel milk). *Fig. 1A* presents the complex relationship between nutritional quality [100 NVS] and combined environmental impacts by food group. Environmental impacts are expressed as dimensionless fractions of sustainability thresholds, aggregated and scaled by 10^6 per kilogram of food [ppm per kg]. Kenyan data include both high-input (H) production (i.e., irrigation, farm machinery use) and low-input (L) systems, while Rwandan data represent exclusively smallholder, low-input production. *Fig. 1B* integrates nutritional and environmental dimensions by rescaling impacts to the functional unit of 100 NVS (e-100NVS [ppm per 100 NVS]). Smaller values indicate greater enviro-nutritional efficiency, i.e., less environmental impact per unit nutritional value. Rwanda's overall efficiencies are considerably higher than Kenya's (Mdn: 1.30×10^{-2} ppm vs. 5.41×10^{-1} ppm), driven primarily by the country's far greater physical water availability rather than differences in modeled farming practices.

Despite this variation, several common patterns emerge across both countries: wild-caught fish and seafood (Mdn: 1.64×10^{-3}–1.26×10^{-2} ppm), fruit (Mdn: 2.25×10^{-3}–1.09×10^{-2} ppm), and vegetables, including green leafy vegetables (Mdn: 1.16×10^{-2}–8.90×10^{-2} ppm), from low-input systems show highest enviro-nutritional efficiencies. In Kenya, pulses (Mdn: 7.48×10^{-2} ppm) follow the same pattern. By contrast, starchy staples (starchy roots and tubers, Kenyan cereals) (Mdn: 3.12×10^{-2}–1.24 ppm), poultry (Mdn: 9.18×10^{-2}–4.28 ppm), and nuts and seeds (Mdn: 2.60×10^{-2}–3.7 ppm) tend to show relatively low efficiencies, though results for the latter should be interpreted cautiously given limited sample sizes (see *Supplementary File S3* for complete national datasets).

Uncertainties are on average higher for terrestrial animal products than plant-source foods, stemming from local yield variations (mean SD: $2.40\text{x}10^{-2}$-2.93 ppm vs. $5.37\text{x}10^{-3}$-1.94 ppm). Though scores vary across individual foods and food groups, they cluster closely together overall, and no clear pattern distinguishes most plant from terrestrial animal products. Some ruminant and other foregut-fermenting herbivore products (e.g., camel, included for Kenya), however, rank higher in enviro-nutritional efficiency than monogastric animal products and plant-source foods. For example, Kenyan beef (across both systems) scores higher than chicken meat or peanuts, while Rwandan goat/sheep milk ranks above pork or sweet potatoes (both white and orange varieties). Additionally, allocation of resources and emissions between co-products – such as milk and meat from the same animals, or roots and tubers and their leaves from the same plant – can lead to considerable individual score differences, further highlighting the complexity of modelling mixed crop-livestock systems. For Kenya, the inclusion of high-input production systems adds additional heterogeneity: high-input foods often rank lower overall (Mdn: 2.07 (H) vs. $3.01\text{x}10^{-1}$ (L) ppm), driven primarily by irrigation water requirements. Notably, ruminant products from extensive (low-input) and intensive (high-input) livestock systems rank similarly (Mdn: $5.66\text{x}10^{-1}$ (L) vs. $5.46\text{x}10^{-1}$ (H) ppm). Although intensive systems achieve higher feed-to-output efficiency per animal, this advantage is offset by the environmental impacts of domestic feed production. Extensive systems, by contrast, rely predominantly on grass, crop residues, and food waste as feed. High-fiber diets result in slower weight gain and higher enteric emissions, but both systems largely operate within national carrying capacities, primarily drawing on locally available feed resources with minimal reliance on inorganic

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fertilizer (*34*). Thus, associated environmental impacts are largely contained within the landscape where production occurs.

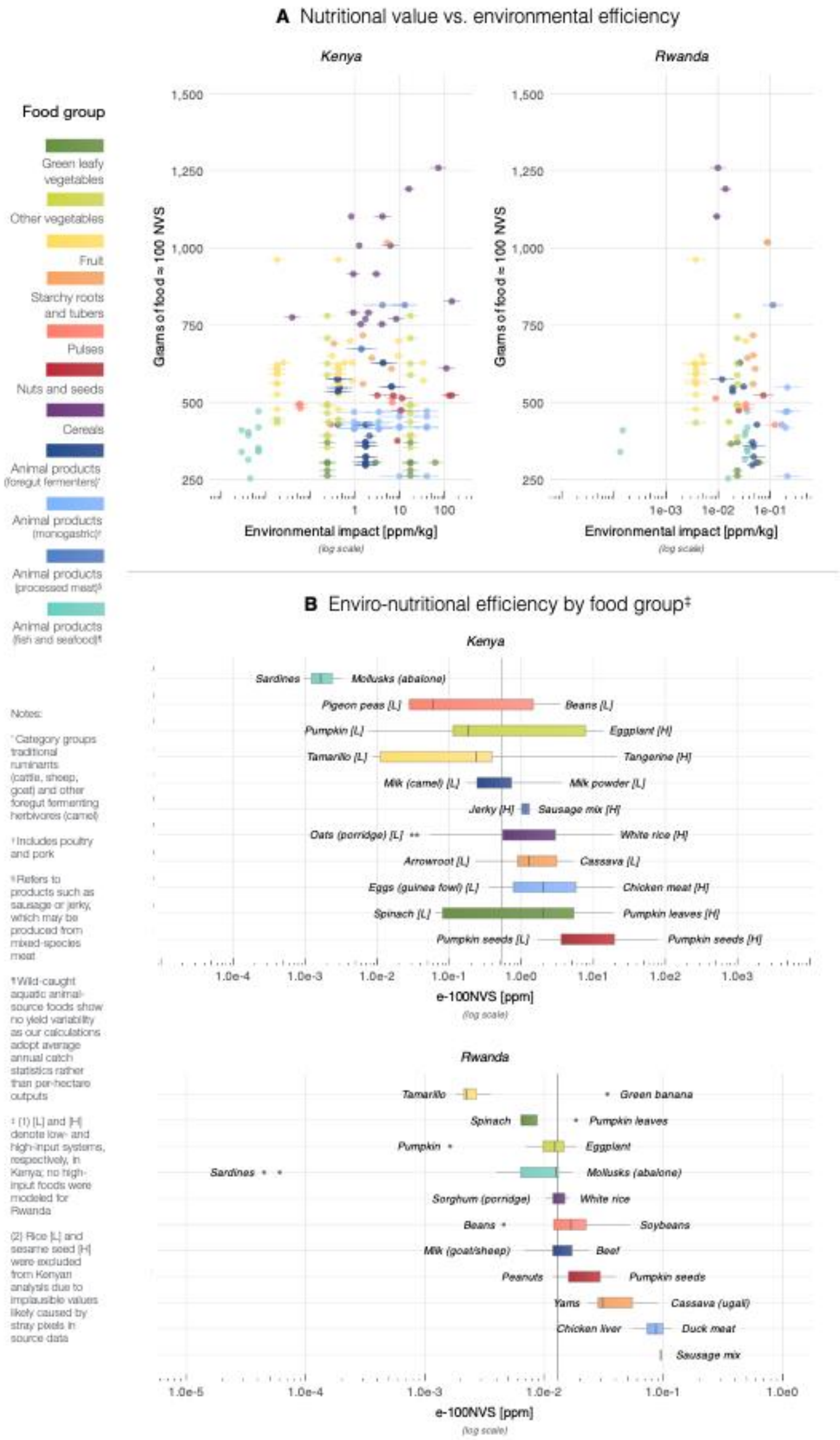

Figure 1. Complex synergies and tradeoffs between nutritional and environmental dimensions by food group and country. (A) Large variation in both environmental impacts [ppm/kg] and nutritional value of foods within and across countries (Kenya: n = 163 / Rwanda: n = 75). Error bars show ±1 SD based on per-hectare yield. **(B)** National e-100NVS [ppm] by food group reveal a common pattern: wild-caught aquatic animal products, pulses, fruit and vegetables from low-input systems tend to show greatest enviro-nutritional efficiencies, while poultry and starchy staples tend to rank lower. Rwanda shows higher efficiencies overall (Mdn: 1.30×10^{-2}, Range: 4.49×10^{-5} - 1.17×10^{-1} ppm) than Kenya (Mdn: 5.41×10^{-1}, Range: 9.73×10^{-4} - 7.90×10^{1} ppm). Food groups are ordered by median from highest enviro-nutritional efficiency (top) to lowest (bottom), showing interquartile ranges;

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points indicate outliers; the vertical line denotes the total national median. Within each food group, the specific foods labeled represent the minimum and maximum e-100NVS values.

3.1. Spatial Heterogeneity and Impact Contributions by Supply Chain Stage

Fig. 2 presents sub-national median e-100NVS for locally produced food products. Regional median scores range from 6.38×10^{-2} to 2.44×10^{2} ppm in Kenya (*Fig. 2A*, aggregated to former provinces) and from 6.07×10^{-3} to 1.72×10^{-2} ppm in Rwanda (*Fig. 2B,* province-level aggregation). In Rwanda, where all provinces include the same number of foods (n = 75), this variation reflects differences in production conditions across space. In Kenya, regional variation is driven by both crop mix and agroecological context (n = 132-163), as provinces with greater crop diversity – notably more cereals, legumes, and starchy roots and tubers – coincide with higher-yielding zones. The comparison highlights systemic, region- or impact-specific environmental hotspots that vary across foods and across both production conditions and systems. For box plots of enviro-nutritional efficiencies by food group and province, see *Supplementary Figures S2-S14*; for complete sub-national datasets by country, see *Supplementary File S3*. While impact category contributions show similar patterns across both countries, inter-provincial variation is considerable. Kenya’s national median e-100NVS is similar to scores in the Eastern and Coast provinces, while central and western regions – covering most national cropland area (*35*) – show higher enviro-nutritional efficiencies. Foods produced in the North-Eastern province rank significantly lower mainly due to limited regional water availability. Water use and climate change dominate most provincial scores, reflecting normalization choices applied at scales matching each impact's spatial dynamics: provincial water availability and national emission targets (see *Materials* and *Methods* and *Table S3*). The risk of species loss increases toward the western provinces, driven by both land use change and terrestrial acidification. Rwanda’s provincial median e-100NVS are less variable than Kenya’s and reflect generally greater efficiencies, with southeastern provinces ranking marginally higher. As in Kenya, water use and GHG emissions drive overall scores, but air pollution from PM emissions plays a more important role in Rwanda due to a combination of lower total e-100NVS and its smaller geographic area, the latter resulting in higher PM impacts per unit area when normalized against World Health Organization air pollution thresholds (*36*).

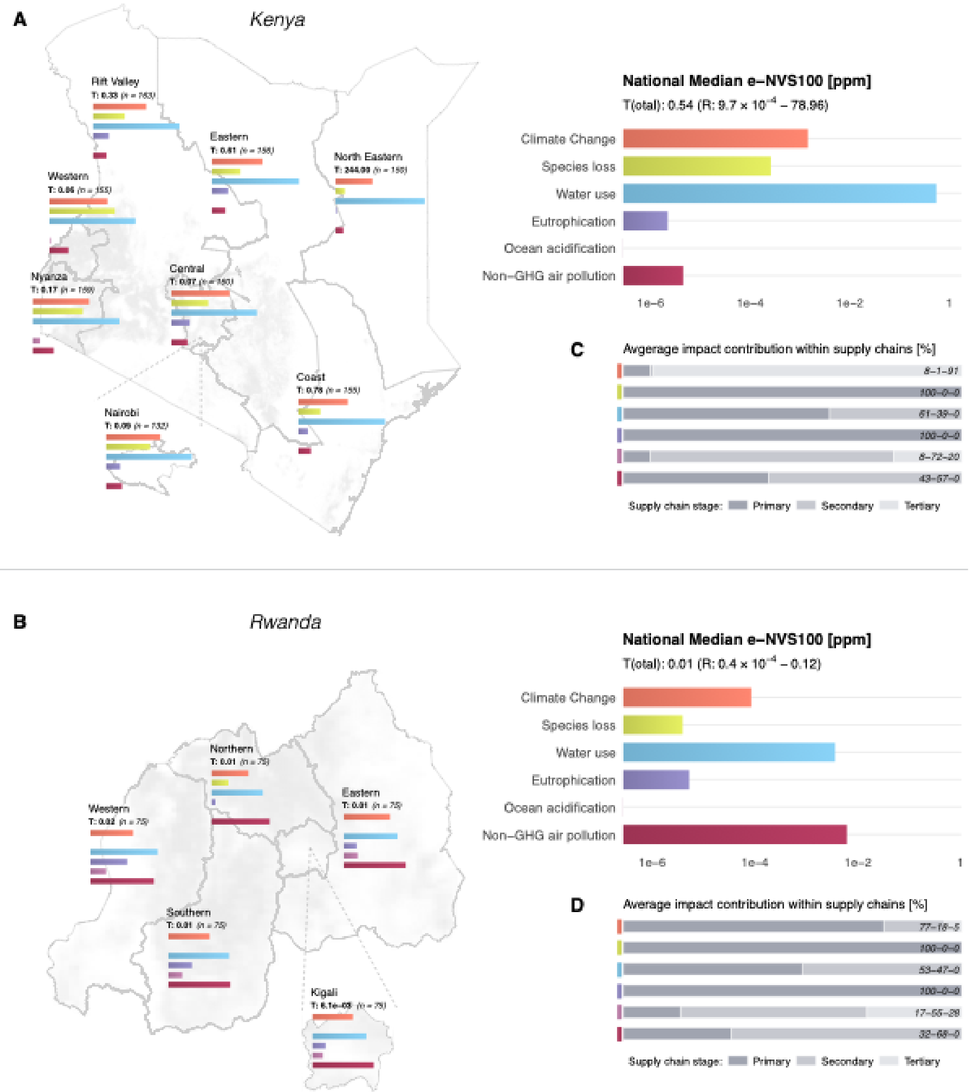

Figure 2. Inter-provincial variations in locally produced foods are considerable despite similar patterns in how environmental impact categories contribute relatively to national scores. (A) Kenya's 47 counties were aggregated to eight former provincial boundaries to improve accuracy, as uncertainties in underlying data could generate less reliable results at the county scale. The country's western regions achieve the highest enviro-nutritional efficiencies. Water use and GHG emissions dominate overall impacts in most provinces, though species loss risk increases westward. (B) Rwanda's provincial median e-100NVSs are less variable than Kenya's and reflect generally greater efficiencies, with southeastern provinces ranking marginally higher; species loss risk increases towards the north. Particulate matter plays a more prominent role than in Kenya. (C, D) Potential species loss, water use, and water pollution occur mainly during primary production and processing in both countries, while climate change, ocean acidification potential, and particulate matter show more heterogeneous patterns across supply chain stages.

Average relative contributions of individual impact categories by supply chain stage reveal that potential biodiversity loss and eutrophication are limited to primary crop production and processing in both countries (Figs. 2C and 2D). Primarily land use change (between 2000 and 2020) drives potential species loss. Most water use (53-61%) also occurs during primary stages. For certain pulses, including capillary rise in total crop water requirements (an advancement in crop modeling (37)) sharply differentiates scores within this food group despite very low absolute water use. GHG emissions show a more heterogeneous pattern. In Kenya, emissions from waste disposal dominate (91%), reflecting sector-specific emissions targets that limit waste more strictly than agriculture, thereby also reducing the relative impact of enteric methane emissions from ruminants and rice paddies. In Rwanda, by contrast, primary supply chain stages dominate GHG emissions (77%), driven mainly by soil emissions and land use change against relatively low emissions targets. Particulate matter emissions occur predominantly during food preparation due to widespread use of charcoal and gas stoves in both countries (38). Eutrophication and ocean acidification potentials contribute minimally to overall scores.

3.2. Variation in Enviro-Nutritional Efficiency and Ecosystem Functions Across Foods

Fig. 3 and *Fig. 4* present selected foods for Kenya and Rwanda, respectively, displaying e-100NVS values alongside traditional culinary uses and potential ecosystem functions beyond food provision. Based on CICES 2025 (39), we included all functional groups relevant to ecosystem regulation and maintenance for the sampled foods – recognizing that many plant and livestock species can fulfill multiple ecosystem roles. Heatmaps depict each food's relative deviation from its food-group median, revealing several patterns. First, co-products from the same source can show divergent enviro-nutritional efficiencies, yet are produced together in practice. Second, foods with contrasting scores are often combined in traditional dishes: for example, Kenyan Nyama Choma (roasted meat, e-100NVS (goat) = 0.604 (H) – 0.626 (L) ppm) served with maize ugali (0.553 (L) – 1.802 (H) ppm) and Sukuma wiki (sautéed collard greens, e-100NVS = 0.09 (L) – 6.48 (H) ppm), or Rwandan Brochette (meat skewers, e-100NVS (beef) = 0.024 ppm) paired with Igitoki (green banana, e-100NVS = 0.034 ppm) and Kachumbari (fresh salad, e-100NVS (tomato) = 0.007 ppm). Third, some foods with lower enviro-nutritional efficiency can still provide critical ecological functions, such as legumes contributing to nitrogen fixation and pest control, or tree crops supporting carbon sequestration, soil erosion control, and water cycle regulation. Fourth, impact-specific deviations can contradict overall rankings, e.g., Kenyan mango [L] ranking worse than passion fruit [H] in four out of six impact categories (*Fig. 3*).

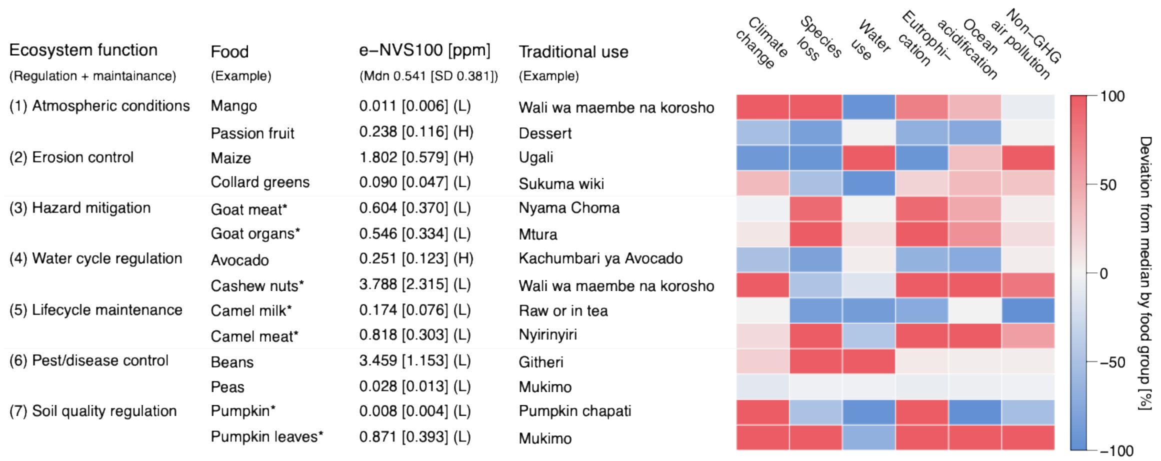

Figure 3. Selected foods for Kenya, showing their e-100NVS, select ecosystem functions, and traditional culinary uses. Asterisks (*) refer to co-products from a common plant or animal. Key ecological functions include: (1) trees sequestering and storing carbon; (2) intercropped maize or maize with undersown cover crops, and vegetables, preventing soil erosion via root systems; (3) goats consuming dry vegetation, reducing wild fire risk; (4) trees regulating local water cycles by moderating soil moisture and water flow; (5) camels supporting seed dispersal; (6) legumes - when grown in rotation with other crops - disrupting pest life cycles; and (7) pumpkins as cover crops reducing erosion and suppressing weeds. See footnote for an explanation of included example dish names[1]. A heatmap shows how each food deviates from the median e-100NVS of its respective food group by impact category.

[1] Wali wa maembe na korosho = mango and cashew nut rice, Ugali = stiff maize porridge, *Sukuma wiki* = sautéed collard greens, Nyama Choma = grilled meat, Mtura = blood sausage, Kachumbari ya Avocado = fresh vegetable salad, Nyirinyiri = sun-dried and deep-fried meat, Githeri = maize and

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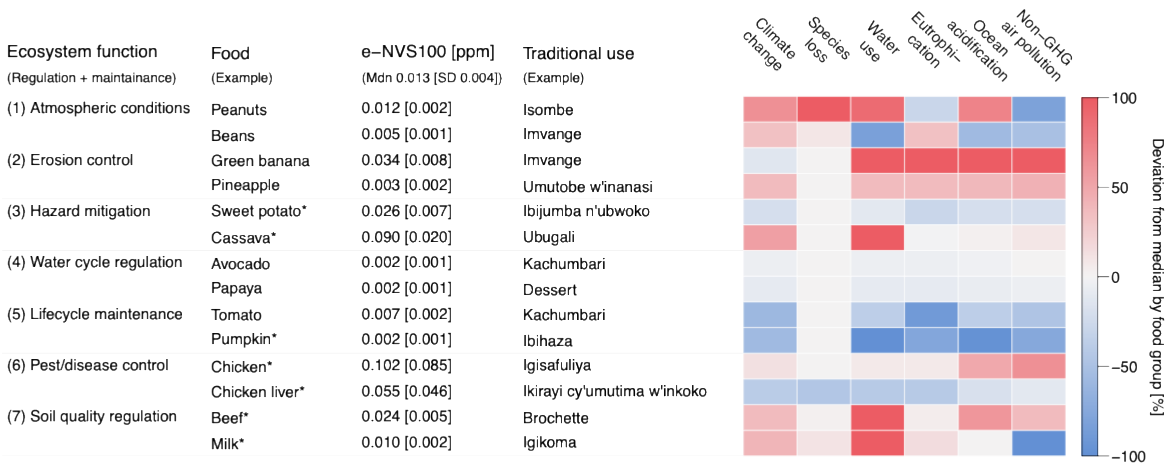

Figure 4. Selected foods for Rwanda, showing their e-100NVS, select ecosystem functions, and traditional culinary uses. Asterisks (*) refer to co-products from a common plant or animal. Key ecological functions include: (1) legumes reducing soil nitrogen (N) emissions through N fixation; (2) trees and shrubs preventing soil erosion via root systems; (3) drought-resistant starchy roots and tubers providing resilience against weather hazards; (4) trees regulating local water cycles by moderating soil moisture and water flow; (5) flowering vegetables supporting pollinators; (6) poultry controlling weeds and pests (insects); and (7) livestock manure enhancing soil fertility. See footnote for an explanation of included example dish names[2]. A heatmap shows how each food deviates from the median e-100NVS of its food group by impact category.

4. Discussion

LENS advances current (n)LCA approaches for food system analysis by capturing spatial agroecological heterogeneity, production contexts, and local nutritional priorities that existing models and metrics incompletely address. Our application in Kenya and Rwanda reveals how prioritizing nutrient-rich foods in assessments uncovers distinct enviro-nutritional synergies and trade-offs in smallholder-dominated systems with low external inputs and integrated crop-livestock production. These patterns differ from conventional LCA findings for industrialized agrifood systems (*15*, *16*, *21*). Using a comprehensive nutrition-focused functional unit rather than mass or energy, representing smallholder systems, and normalizing multiple environmental impacts against sustainability thresholds, we find that wild-caught aquatic animal products, pulses, and fruit and vegetables from low-input systems tend to score higher. By contrast, starchy staples and poultry tend to show lower efficiencies. Notably, ruminant products from extensive systems match or outperform those from more intensive systems – contrasting with traditional efficiency metrics (*15*, *16*, *40*).

The substantial heterogeneity within food groups, between co-products, and across space underscores that enviro-nutritional efficiency metrics are context-dependent and therefore cannot guide interventions in isolation. Model results should be interpreted as indicative of broader patterns rather than exact quantifications at individual food level. Each food's e-100NVS reflects the output of complex, interdependent agrifood systems. Altering production (and processing) scales, spatial distribution, or practices can therefore affect other products' efficiency – for example, by adjusting fertilizer application rates, feed availability, or required energy inputs, as shown in our low-input vs.

bean dish, Mukimo = mashed potatoes, peas, and green vegetables, Pumpkin chapati = chapatis blended with pumpkin

[2] Isombe = cassava leaf stew with peanut butter, Imvange = bean stew with green banana, potato and vegetables, Umutobe w'inanasi = pineapple juice, Ibijumba n'ubwoko = sweet potato and mushroom dish, Ubugali = dense cassava porridge, Kachamburi = fresh vegetable salad, Ibihaza = bean and pumpkin stew, Igisafuliya = chicken stew, Ikirayi cy'umutima w'inkoko = chicken heart/liver curry, Brochette = grilled meat skewers, Igikoma = millet porridge

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high-input system comparison. Solely relying on scaling production based on such values – expanding more efficient foods, reducing less efficient ones – risks rebound and spillover effects, where efficiency gains trigger increased production or land use that can ultimately drive further deforestation or heightened vulnerability to natural hazards (*41*, *42*). Broader, landscape-level objectives should precede agronomic specifications, such as promoting particular crop varieties or livestock breeds. The e-100NVS can thus serve primarily as diagnostic indicator to guide mitigation and adaptation strategies, while accounting for other ecological dimensions essential to ecosystem functioning and climate adaptation (*43*), as well as cultural values, including local culinary traditions, and economic considerations shaping livelihoods (*44*).

Being adaptable to other world regions and production systems, LENS also includes the assessment of major international food imports, e.g., wheat from Turkey, temperate fruit from South Africa (results available in *Supplementary File S3*). We encourage users to review and verify available data sources and modeling approaches for specific study contexts. The number of environmental impact categories, inventory datasets, and assessment approaches are adjustable and expandable as needed. Both functional unit and normalization approach can be modified to align with different analytical objectives. Normalization choices strongly influence individual impact contributions to final single scores (*45*). We set sustainability thresholds at different geographic scales: for example, water use budgets reflect provincial availability, while GHG emissions rely on national targets aligned with Paris Agreement goals. This illustrates how spatial boundary decisions affect results. Additionally, water use budgets rely on physical availability rather than management constraints or infrastructure limitations. These can restrict effective access even when total resources appear adequate – a particular concern in Rwanda given its dense population and rapid surface runoff from hillside farmland (*46*). Thresholds represent the latest available sustainability targets to ensure policy relevance (see *Materials* and *Methods* and *Table S3*). For each indicator, we apply a single threshold at its respective geographic scale as only one national policy target, natural resource budget, or planetary boundary estimate exists at each scale.

Uncertainty ranges represent one standard deviation based on local yield variability, which we identified as the dominant source of variance (compare (*47*)). Since all impacts for terrestrial food products are modeled per hectare, yield variability affects all impact categories – unlike uncertainties arising from individual data sources such as soil or hydrological model outputs (for a full list of data sources see *Supplementary File S2*, *Tables S2-S3*). Existing assessments show low uncertainty in crop production model outputs for our case studies (*48*, *49*). Wild-caught aquatic animal products preclude meaningful uncertainty analysis as catch data and processing inventory are reported per kilogram rather than per area. Additional uncertainty arises from food loss and waste rate estimates (*34*, *50*), for which we were unable to identify multiple data sources, and uncertainty is rarely reported. In extensive pastoral systems such as those prevalent in Kenya, emissions from ruminants and camels at least partially substitute for natural wildlife emission baselines, aspects discussed further in *Materials* and *Methods*. Nevertheless, LENS' structure allows for straightforward updates as more recent or precise data and modeling approaches become available.

The patterns revealed for Kenya and Rwanda – where low-input systems can outperform high-input ones, co-products show contrasting efficiencies, and culturally important dishes can span the full spectrum of enviro-nutritional profiles – demonstrate why context-specific assessment is essential for evidence-based interventions addressing both malnutrition and environmental degradation. We make our model openly available to encourage broader application across LMICs (and beyond) and continued methodological refinement. LENS may thereby support food system transitions oriented towards resilience and food sovereignty, where efficiency is evaluated only insofar as it respects both ecological carrying capacities and the complexity of diverse nutritional, socio-economic, cultural, and geopolitical contexts.

Supplementary Materials: Materials and Methods. Figs. S1 to S15. Tables S1 to S3. References (51-160). Data S3.

Author Contributions: Conceptualization: KD, FO, TB, JC. Methodology: KD, FO, TB, CGF, GM. Visualization: KD, TB. Project administration: JC Writing – original draft: KD, FO, GM, CGF, HV, PM, OM, FW, JC, TB.

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Data Availability Statement: We developed LENS with a particular focus on applicability in data-scarce environments, though analyses can be run and updated for any part of the world. The entire model code (v1.0) implemented in R, all accompanying datasets, and case study outputs can be accessed under the Creative Commons license CC-BY 4.0 International, archived in Zenodo (https://doi.org/10.5281/zenodo.18875992). Supplementary Figure S15 (see Supplementary File S2) provides an overview of the folder structure, distinguishing which datasets are already included as input data and underwent transformation, and which have to be manually retrieved by users from public repositories. Supplementary File S3 aggregates all final model outputs by country and province. Regional NVS datasets are publicly available via Dataverse (https://doi.org/10.7910/DVN/HJJR2V).

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Conflict of Interests: The authors declare no competing interests.

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