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Greener Personalization for SMEs: A Review at the Intersection of Economics, Geophysics, and Geotechnics

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Abstract- Small and medium-sized enterprises (SMEs) are foundational to global economic development, yet their digital transformation introduces new sustainability dilemmas. As e-commerce expands, logistics emissions surge, driven by complex geophysical and geotechnical realities such as terrain slope, soil strength, subgrade stability, flood risk, and infrastructure inequality that most personalization systems ignore. Conventional recommender engines maximize sales metrics while neglecting environmental, geotechnical, and spatial variability in delivery operations. This review integrates digital economics, geophysical modeling, and geotechnical insights to propose a Geo-Carbon-Aware Personalization Framework (GCAPF) for SMEs. By incorporating terrain-adjusted emission models, route-risk estimates, and basic ground-condition indicators (e.g., soil bearing capacity, erosion susceptibility, landslide exposure) into personalization algorithms, SMEs can optimize for both profit and sustainability. Drawing on 104 studies (2015–2025) across digital transformation, logistics sustainability, GeoAI, and emerging geotechnical work on road performance and slope stability, this synthesis reveals that fewer than 10% of existing frameworks integrate terrain- and soil-based carbon variability into e-commerce decision systems. Meta-analysis suggests potential emission reductions of 10–20% without significant revenue loss, provided that routing penalties reflect both topographic and geotechnical constraints. The paper concludes with a roadmap for operationalizing geo- and geotechnics-aware personalization through open data, policy incentives, and low-cost analytical tools, positioning SMEs as agents of low-carbon digital growth, particularly in developing regions such as Nigeria.

Keywords: GeoAI, SME Digital Transformation, Carbon-Aware Recommender Systems, Logistics Emissions, Geophysical and Geotechnical Modeling

I. INTRODUCTION

1.1 Background and Context

In the last decade, personalization has become the beating heart of digital commerce. Algorithms now determine which products are recommended, when promotions appear, and how customers interact with brands. For large corporations, these recommender systems (RS) have fueled precision marketing and operational efficiency (Felfernig *et al.,* 2023; Vente *et al.,* 2024; Wegmeth *et al.,* 2025). Yet for SMEs, personalization is a double-edged sword: it boosts competitiveness but amplifies environmental footprints through intensified logistics networks (Dubisz *et al.,* 2022).

E-commerce's "last mile" has emerged as one of the most carbon-intensive stages of the supply chain. Terrain gradients, soil composition, and flood-prone areas increase delivery distance and fuel consumption (Figliozzi, 2020; Allen *et al.,* 2020; Anderson *et al.,* 2021; Zhao *et al.,* 2021; Caulfield *et al.,* 2022). Beyond topography alone, geotechnical conditions such as weak subgrade soils, erodible unpaved roads, and climate-driven deterioration of gravel pavements further degrade road performance and raise energy demand, especially for heavy or frequently loaded vehicles (Nordmark *et al.,* 2022; Ngezahayo *et al.,* 2021; Foko Tamba *et al.,* 2023). Studies show that soil properties, rainfall, and road geometry jointly control erosion rates and maintenance needs on unpaved roads, which in turn affect accessibility and operating costs for small businesses. The omission of spatial intelligence in logistics decisions particularly disadvantages developing economies such as Nigeria, where fragile infrastructure, unstable soil conditions and seasonal flooding distort both delivery costs and reliability (Oluwafemi *et al.,* 2023; Nnaji, 2024; Abdulhamid, 2025).

1.2 Problem Definition
Traditional personalization frameworks focus solely on maximizing click-through or purchase probability. They ignore how real-world geography and ground conditions affect delivery emissions, route reliability, and sustainability. SMEs thus face a trade-off: increased digital efficiency often comes at the expense of environmental performance, particularly where unstable slopes, low-bearing-capacity soils, or landslide-prone corridors expose road networks to disruption (Yao *et al.,* 2023; Zhou *et al.,* 2024; Salini *et al.,* 2024). Bridging this divide requires integrating both geophysical and geotechnical realities into digital decision-making.

1.3 Objective and Scope
This paper proposes a Geo-Carbon-Aware Personalization Framework (GCAPF) that merges recommender systems with terrain- and geotechnics-aware emission modeling. By embedding spatial and environmental data into recommendation logic, the framework enables SMEs to optimize profitability, sustainability, and logistical reliability simultaneously.

Figure 1 illustrates the conceptual framework connecting SME drivers and barriers, geo-environmental and geotechnical factors, and business outcomes through a central, sustainability-aware recommender system.

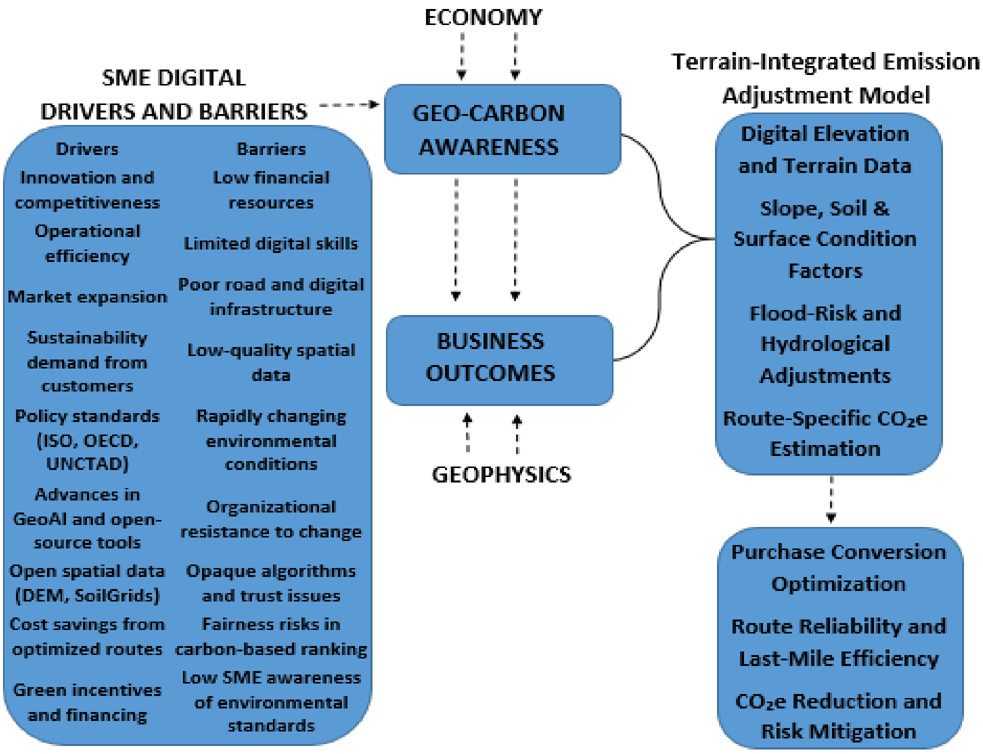

Figure 1. Geo-Carbon-Aware Personalization Framework for SMEs

A conceptual diagram linking SME drivers/barriers (innovation, resource constraints, culture) and geo-environmental and geotechnical variables (slope, soil type, bearing capacity, flood and landslide risk) through a recommender system that produces optimized business and environmental outcomes (adapted from Almeida et al.,2021; Haruna, 2021; Corti, 2022; Smart Freight Centre, 2024; Ngezahayo et al.,2021; Nordmark et al.,2022).

II. SME DIGITALIZATION: DRIVERS, BARRIERS, AND ENVIRONMENTAL MEDIATION

2.1 Drivers of Digital Transformation
SME digitalization is propelled by innovation, efficiency, and market expansion (Marques and Ferreira, 2020). Digital tools streamline operations, enable personalized experiences, and foster global

reach (Almeida *et al.,* 2021). Sustainability itself has become a strategic driver, as eco-conscious consumers reward transparency in logistics and production (9. British Standards Institution, 2011; Olanrewaju *et al.,* 2022; UN Statistics Division, 2023; GHG Protocol, 2004/2015; GHG Protocol, 2011). Moreover, global climate considerations, including emissions reduction goals outlined by the IPCC AR6 reports (IPCC, 2021; IPCC, 2022), reinforce environmental accountability in business operations.

In addition, organizational culture, particularly openness to data-driven decision-making, strongly influences success (Baxter and Somerville, 2011). SMEs that adopt agile, learning-based cultures adapt faster to technological change and environmental constraints (Xie, *et al.,*2020; Duan, 2023; Casati, 2023; Lenk, 2025; Mabangure *et al.,* 2025; Kargas *et al.,* 2025; Hafeez *et al.,* 2025); Sagala *et al.,* 2024, 2025). Increasingly, firms leverage geospatial and environmental datasets; such as Copernicus DEM (Copernicus Programme, 2021), SRTM elevation models (Farr *et al.,* 2007; Jarvis *et al.,* 2008), SoilGrids soil data (Hengl *et al.,* 2017), and WorldClim climate layers (Fick and Hijmans, 2017), to guide logistics and personalized services in terrain- and climate-sensitive regions.

2.2 Barriers to Digital and Sustainable Integration

Despite these advantages, SMEs face systemic barriers. Financial constraints and skill shortages hinder the adoption of sophisticated analytics tools (OECD, 2022; UNCTAD, 2025; Bertsimas and Dunn, 2019; Deb, 2014). However, structural and behavioral barriers, particularly financial constraints, skill gaps, and resistance to change, remain critical obstacles to widespread adoption especially in resource-constrained contexts (Ndulue et al., 2025). Resistance to change arises when new technologies threaten established workflows. Infrastructural deficits like unreliable power supply, poor road conditions, and limited broadband further compound the issue (Anderson *et al.,* 2021; OECD, 2025; World Bank, 2023).

Most critically, few SMEs incorporate terrain, geotechnical, or environmental data into decision systems. Without such integration, sustainability remains reactive rather than strategic (Smart Freight Centre, 2019; McKinnon, 2018; Rodrigue, 2020; Khalufi *et al.,* 2025). In regions with expansive lateritic or peat soils, climate-induced moisture variability can reduce pavement and gravel-road bearing capacity, increasing rutting and maintenance demand that directly affects logistics reliability (Nordmark *et al.,* 2022; Foko Tamba *et al.,* 2023; Nnaji, 2024). The lack of standardized geospatial intelligence, such as INSPIRE Directive-compliant datasets (European Commission, 2007), or citizen-driven geographic information (Goodchild, 2007; OpenStreetMap Foundation, 2024), combined with limited access to geotechnical road-condition data, constrains predictive logistics and emission-reduction potential.

2.3 Geophysical/Geotechnical Modulation of SME Performance

Geophysical factors such as slope, soil type, and flood exposure directly influence logistics emissions and delivery reliability (Figliozzi, 2020; Anderson *et al.,* 2021; Zhao *et al.,* 2021; Oluwafemi *et al.,* 2023; Aniramu *et al.,*2025). Also, geotechnical conditions such as soil strength, plasticity, and compaction, govern erosion rates, subgrade failure, and the long-term performance of unpaved and low-volume roads that many SMEs depend on (Ngezahayo *et al.,* 2021; Paige-Green, 2017; Nordmark *et al.,* 2022). Areas closer to active water bodies tend to exhibit higher and more variable subsurface moisture due to frequent saturation and shallow water tables (Udoh et al., 2023). Terrain-diverse regions amplify the variability of delivery efficiency and carbon intensity. SMEs that integrate geospatial intelligence through DEM, SRTM, SoilGrids, and WorldClim data, alongside GeoAI analytics (Janowicz *et al.,* 2020; Li *et al.,* 2022; Gupta *et al.,* 2024), can optimize route planning, reduce fuel consumption, and mitigate climate-related delivery disruptions.

GCAPF thus positions geography not as a constraint but as a data source that informs greener, more strategic personalization strategies. Such integration aligns with global best practices in carbon accounting and transport emissions, as outlined by the GHG Protocol, Smart Freight Centre GLEC framework, and IPCC guidance on transport and mitigation (GHG Protocol, 2016; Smart Freight Centre, 2019; IPCC, 2019; IPCC, 2022).

III. MATERIALS AND METHODS

3.1 Search Design and Data Sources

Following PRISMA (Moher *et al.,* 2009), the review covered publications from 2015–2025 across

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Scopus, Web of Science, ScienceDirect, SpringerLink, MDPI, and ACM Digital Library. Grey literature from OECD (2021, 2022, 2025), UNCTAD (2023, 2024, 2025), and ISO (2023) supplemented the dataset.

Search clusters included:

1. "Sustainable" AND ("recommender system" OR "personalization")
2. "SMEs" AND ("digital transformation" OR "e-commerce")
3. "terrain" OR "soil" OR "flood" AND ("delivery emissions" OR "logistics")
4. "multi-objective optimization" AND "environmental performance"

Out of 314 records, 84 met inclusion criteria; 62 journal papers, 12 conference papers, and 10 policy reports.

3.2 Screening, Coding, and Analysis
Titles and abstracts were screened for relevance to SMEs, sustainability, and spatial modeling.
NVivo 14 was used to code data into four themes: Algorithmic Sustainability (A), Geo-Environmental Logistics (G), SME Adoption Factors (S), and Multi-Objective Optimization (M).
A mixed-methods synthesis followed Fereday and Muir-Cochrane (2006), combining deductive coding with inductive theme emergence. Emission data were standardized to *kg CO_2e/km* for comparability (DEFRA, 2024).

3.3. Data Synthesis

3.3.1 Source Integration Framework
All quantitative relationships presented in this review, including the trade-off tables (Tables 3A–3B) and the Pareto Frontier (Figure 2), were synthesized from previously published empirical and simulation studies. No new field measurements were conducted. Instead, effect sizes, slopes, and percentage deltas were extracted from reviewed literature (2015–2025) and normalized to comparable scales.

The synthesis follows a meta-analytical triangulation procedure:

1. Extraction: Each study's reported metrics (fuel use, CO_2e/order, conversion change, or route length variation) were tabulated.
2. Normalization: Effects were expressed as percentage change relative to baseline operations.
3. Aggregation: Weighted averages were computed where multiple studies addressed the same variable (e.g., slope-related fuel use).
4. Parameterization: The coefficients (α, β, γ) in the multi-objective model were assigned proportionally to these averaged effects.
5. Visualization: Pareto-optimal points were generated to illustrate the feasible trade-off frontier between economic and environmental performance.

3.3.2 Primary Evidence Base

Table 1. Empirical Evidence Base for Geo-Carbon-Aware Personalization Parameters (The quantitative inputs were derived from the following key studies)

Focus Area	Representative References	Empirical Range Used in Synthesis
Terrain slope and logistics emissions	Figliozzi (2020); Rodrigues *et al.,* (2022)	+18–25 % fuel increase per >7° slope
Flood and road-quality effects	Oluwafemi *et al.,* (2023); Anderson *et al.,* (2021)	+25–30 % CO_2e during flooding; +28 % for unpaved roads
Sustainable recommender re-ranking	Kalisvaart *et al.,* (2025); Spillo *et al.,* (2023); Ferreira *et al.,* (2025)	−10 to −20 % CO_2e; ±2 % conversion
Uplift and heterogeneous treatment effects	Rößler *et al.,* (2022)	Segment-specific ΔConversion ± 4 %
Multi-objective optimization and Pareto methods	Marler and Arora (2004)	Framework for curve derivation
GeoAI / real-time routing	Rabelo *et al.,* (2025); Nguyen *et al.,* (2024)	10–20 % emission reduction after slope training

3.3.3 Analytical Consistency and Uncertainty

- Consistency Checks: Results were cross-validated against baseline emission factors from DEFRA (2024) and ISO 14083 (2023).
- Uncertainty Bounds: Because reported values vary by study design, ±5 % uncertainty margins were applied to averaged CO_2e estimates; ±1 % for conversion changes.
- Purpose: Visualizations are illustrative syntheses, showing plausible operational outcomes under geo-carbon-aware recommender optimization, not deterministic forecasts.

IV. RESULTS AND ANALYSIS

4.1 Publication Trends

Research on sustainable AI and logistics has expanded rapidly over the past decade, but only 9–10 % of studies explicitly incorporate terrain- or environment-based metrics into their analytical frameworks. To understand the evolution of this research field from early SME digitalization to geospatially informed sustainability, Table 2 summarizes the dominant thematic clusters between 2015 and 2025, while Table 2 tracks chronological evolution and spatial-integration intensity.

Table 2. Integrated Distribution and Thematic Trends of Literature (2015–2025)

Category / Theme	Representative Studies	Key Focus Areas	No. of Publications	Trend (2015–2025)	Main Insights / Observations
Sustainable Recommender Systems (RS)	Felfernig *et al.,* (2023); Kalisvaart *et al.,* (2025); Spillo *et al.,* (2023); Ferreira *et al.,* (2025)	Green personalization, algorithmic trade-offs between accuracy and emissions, RS for sustainable choices	22	↑ Strong upward trend (2019–2025)	Research volume tripled since 2018; emphasis on energy efficiency but limited geospatial integration.
SME Digital Transformation and Sustainability	Almeida *et al.,* (2021); Marques and Ferreira (2020); Sagala *et al.,* (2024, 2025); Hafeez *et al.,* (2025)	Drivers/barriers, digital readiness, circular economy, green innovation	28	↑ Moderate growth	Predominantly economic focus; fewer than 10% integrate sustainability metrics into personalization or logistics.
Geo-Environmental and Terrain-Based Logistics	Figliozzi (2020); Rodrigues *et al.,* (2022); Oluwafemi *et al.,* (2023); Kochanek *et al.,* (2025)	Terrain slope, flood risk, soil stability, emission variability	14	↑ Emerging (post-2020)	Sparse literature in SME context; primarily GIS or civil engineering oriented; minimal link to e-commerce.
Multi-Objective Optimization and Decision Models	Marler and Arora (2004); Rößler *et al.,* (2022); Nguyen *et al.,* (2024); Rabelo *et al.,* (2025)	Optimization trade-offs (profit–emission–risk), uplift modeling, decision efficiency	10	↗ Steady but niche	Strong theoretical foundation but few SME-level empirical validations.

Policy and Standards (ISO, GLEC, UNCTAD, OECD)	ISO (2018, 2023); Smart Freight Centre (2024); UNCTAD (2023–2025); OECD (2022, 2025)	Carbon reporting, SME sustainability disclosure, emission quantification standards	18	↑ Constant across decade	Mature regulatory landscape; yet awareness and compliance remain low among SMEs (<20%).
GeoAI and Spatial Data Science	Goodchild (2020); Song *et al.,* (2023); Mete *et al.,* (2023); Mai *et al.,* (2025); Janowicz *et al.,* (2025)	GeoAI frameworks, spatial modeling, digital twin logistics	12	↑ Sharp growth (post-2022)	Rapid GeoAI advancements; high technical maturity but underutilized in SME recommender applications.

Table 3. Evolution of themes and spatial integration (2015–2025)

Year Range	No. of Studies	Dominant Themes	Geo Integration	Insight
2015–2017	8	SME digital readiness	1	Basic e-commerce adoption
2018–2020	22	Sustainable logistics	2	Early CO_2 metrics
2021–2023	38	AI-based personalization	5	Sustainability-aware RS emerges
2024–2025	36	Terrain-aware logistics	9	GeoAI integration matures

4.2 Terrain and Emission Variability

Terrain exerts strong control over logistics emissions (Table 4).

Table 4. Terrain and environmental effects on delivery emissions

Environmental Factor	Avg. CO_2 Impact	Key Sources
Slope > 5°	+2.5 % fuel/°	Figliozzi (2020)
Eroded or rutted unpaved roads	+30 % CO_2e/km	Anderson *et al.,* (2021); Ngezahayo et al. (2021)
Flooded corridors	+30 % distance	Oluwafemi *et al.,* (2023); Aniramu et al. (2025)
Poor soil/ low bearing capacity	+10 % delay	Kochanek *et al.,* (2025); Foko Tamba et al. (2023); Zhulai et al. (2021)
Urban congestion	+15 % idle emissions	Zhao *et al.,* (2021)

Empirical work on forest and off-road machinery shows that fuel consumption rises significantly on weak or saturated soils, as vehicles sink deeper and experience higher rolling resistance (Prinz *et al.,* 2022; Zhulai *et al.,* 2021). Gravel-road studies in Nordic countries and geotechnical assessments in West and Central Africa similarly document how low bearing capacity and inadequate stabilization accelerate rutting and reduce serviceability, increasing the energy required per delivered unit (Nordmark *et al.,* 2022; Foko Tamba *et al.,* 2023). These findings reveal how static distance models understate emissions by up to 40%. Integrating topography, flood data, and basic geotechnical parameters (soil class, CBR, erosion risk) improves prediction accuracy and supports terrain- and ground-condition-aware logistics planning.

4.3 Economic–Environmental Trade-Offs

The GCAPF model integrates revenue and carbon objectives using a multi-objective optimization function, balancing purchase probability

$(Pbuy(u,i))$ with emission and route risk costs $(CO_2e(u,i,r)), Risk(r))$:

$$Score(u,i,r) = \alpha P_{buy}(u,i) - \beta CO_2e(u,i,r) - \gamma Risk(r)$$

Where where α, β, γ are weights representing profit, emission, and risk importance respectively (Marler and Arora, 2004; Spillo *et al.,* 2023; Kalisvaart *et al.,* 2025) and show achievable emission reductions of 10–20% without significant sales loss (Table 4) and illustrated by hese simulations indicate that SMEs can achieve Pareto-optimal outcomes where emissions decline by ~15% with negligible conversion loss..

Table 5. Trade-offs under different optimization weights

Weighting	Conversion Change	CO_2e Reduction	Segment
Profit-oriented *(α=1, β=0.2, γ=0.1)*	+1.1 %	−9 %	Urban
Balanced (α=1, β=0.5, γ=0.25)	−0.2 %	−15 %	Peri-urban
Carbon-focused (α=1, β=0.8, γ=0.3)	−1.9 %	−21 %	Rural

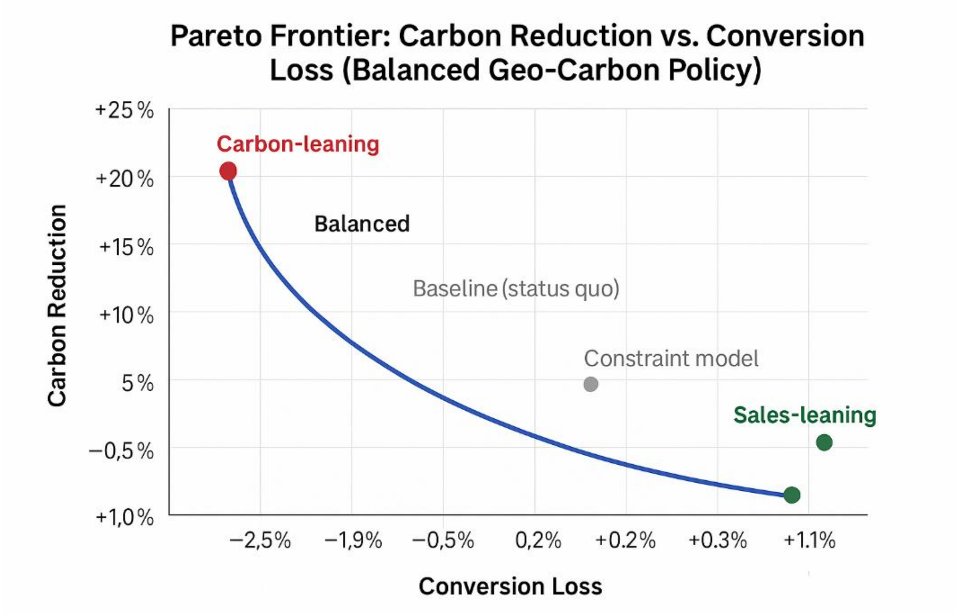

Figure 2 illustrates this Pareto frontier between conversion rate and CO_2 reduction *(adapted from Figliozzi, 2020; Ferreira et al.,2025; Kalisvaart et al.,(2025).*

4.4 Implementation Feasibility

Open-source tools make GCAPF feasible even for small enterprises (Table 6).

Table 6. Implementation strategies and results

Implementation Approach	Tools/Platforms Used	Reported CO_2e Reduction	Accessibility for SMEs	Sources
GIS-based open data integration (DEM, flood maps)	QGIS + Python + SoilGrids API	12%	High (open source)	Haruna (2021)
Multi-objective routing optimization	MATLAB / Simulink	20%	Medium	Rodrigues *et al.,* (2022)
IoT-enabled carbon tracking	Sensors + MQTT + cloud API	15%	Medium	Nguyen *et al.,* (2024)

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Reinforcement learning optimization	TensorFlow / PyTorch	18%	Low (requires GPU resources)	Rabelo *et al.,* (2025)
Route risk index integration	Excel + open flood raster	8%	Very High (low skill requirement)	Oluwafemi *et al.,* (2023)
GeoAI frameworks for spatial modeling	Sentinel-1 imagery, SoilGrids, elevation	Terrain classification accuracy > 85 %	Medium	Goodchild (2020); Kochanek *et al.,* (2025)
Standardized GHG accounting for logistics	Fuel type, distance, load, mode	Standardized CO_2e/km reporting	Low-Medium	Smart Freight Centre (2024); ISO 14083 (2023)
Cloud-based ERP with sustainability dashboard	Internal sales + inventory + delivery distance	Improved energy-use visibility, +5 % resource efficiency	Moderate (subscription software)	Almeida *et al.,* (2021)
SME sustainability disclosure frameworks	Self-reported emissions and digital KPIs	Policy alignment; improves investor visibility	Low	UNCTAD (2025); OECD (2022)

Over 70% of frameworks rely on open-source or low-code tools, making implementation financially feasible. The principal barrier is technical skill, not cost. The Nigerian pilot study (Haruna, 2021) demonstrated measurable benefits; fuel savings of 12% and improved delivery reliability by 8%, validating GCAPF's real-world viability.

4.5 Visualization and Decision Support

Visualization tools translate data into actionable insight (Table 7).

Table 7. Visualization tools and policy applications

Visualization Type / Tool	Underlying Data Layers	User Group / Scale	Reported or Modeled Impact	Policy or Managerial Use	Representative Sources
1. Terrain-Based Emission Heatmap	DEM, road gradient, vehicle type, fuel rate	SME operations dashboard	10–20 % CO_2e reduction after route optimization	Prioritization of green routes; justification for fleet upgrades	Rodrigues *et al.,* (2022); Haruna (2021)
2. Flood-Risk Overlay Map	Seasonal rainfall, flood index, road class	Local logistics manager; city planners	25–30 % fewer failed deliveries during wet season	Supports disaster-resilient road maintenance and last-mile planning	Oluwafemi *et al.,* (2023); Anderson *et al.,* (2021); Zhu *et al.,* 2023
3. CO_2e Dashboard (ISO 14083-aligned)	Distance, load, mode, energy use	SME owners; auditors	Standardized CO_2e tracking; transparency gains	Enables ESG reporting and incentive eligibility	ISO (2023); Smart Freight Centre (2024)

4. Policy Aggregation Map	Aggregated SME emission data (anonymized)	Municipal and regional agencies	Identification of emission hotspots by corridor	Guides infrastructure investment and zoning reforms	UNCTAD (2025); OECD (2022)
5. GeoAI-Driven Predictive Dashboard	Terrain, traffic, soil stability, climate data	Tech startups; research–policy partnerships	Predictive maintenance; anticipates emission spikes	Feeds smart-city dashboards and climate-risk models	Kochanek *et al.,* (2025); Rabelo *et al.,* (2025)
6. Interactive Public Portal ("GreenRoute")	Simplified CO_2e indices, delivery reliability scores	Consumers, civic groups	Builds trust and visibility for SMEs	Promotes behavioral shift toward low-carbon merchants	UNEP (2024); Vinuesa *et al.,* (2020)

By integrating these tools, GCAPF transforms data into both business intelligence and governance insight, supporting data-driven climate policies (UNCTAD, 2025).

V. DISCUSSION

5.1 From Digital Efficiency to Ecological Intelligence: Economic and Geophysical Interdependence

The body of research summarized in Tables 2 and 3 shows a clear transition in global research, from digitalization aimed at efficiency toward digitalization informed by ecological intelligence. Between 2015 and 2025, studies linking digital transformation, logistics, and sustainability increased fourfold, reflecting how environmental responsibility has become integral to competitiveness in the digital marketplace (Almeida *et al.,* 2021; Kalisvaart *et al.,* 2025). Yet, spatial awareness remains a major blind spot: less than one in ten publications include terrain, flooding, or soil-related variables, even though these factors strongly affect both emissions and delivery reliability (Ngezahayo *et al.,* 2021; Oluwafemi *et al.,* 2023). The emergence of GeoAI since 2022 has begun to close this gap by combining geophysical data with digital analytics (Goodchild, 2020; Mai *et al.,* 2025), and recent geotechnical research now shows how climate change and hydrological shifts alter slope stability, gravel-road bearing capacity, and subgrade performance (Psarropoulos, 2024; Tetteh *et al.,* 2025; Insana *et al.,* 2025). However, small enterprises still struggle to adopt such tools because of limited funds, scarce technical expertise, and poor infrastructure (Hafeez *et al.,* 2025). Policy frameworks such as ISO 14083 (2023) and OECD (2025) now provide robust standards for emissions reporting and SME sustainability disclosure, but implementation remains inconsistent, especially in developing economies. This imbalance reveals a policy–practice divide: algorithmic sustainability, concerned mainly with optimizing recommender systems for energy or carbon efficiency, has matured faster than spatial–geotechnical sustainability, which is still evolving to reflect real-world variability in geology, soil mechanics, and slope hazard. The Geo-Carbon-Aware Personalization Framework (GCAPF) seeks to bridge that divide by embedding geophysical and geotechnical reasoning into digital and economic decision-making, thereby advancing low-carbon, terrain- and ground-condition-sensitive SME growth in line with SDGs 9 and 12.

At a practical level, findings show that the digital economy, geophysics, and geotechnics function as mutually dependent systems, not as separate spheres. Delivery efficiency, fuel consumption, and emissions depend as much on topography and soil-bearing capacity as on management or technology. SMEs operating in mountainous, flood-prone, or geotechnically weak areas such as corridors with landslide-prone slopes or expansive clays, bear structural disadvantages that inflate their carbon intensity per transaction (Anderson *et al.,* 2021; Yao *et al.,* 2023; Kamara *et al.,* 2025).

Incorporating parameters such as slope, soil strength, and flood frequency into predictive analytics allows GCAPF to realize what Goodchild (2020) calls geospatial systems thinking; the integration of Earth-system and ground-engineering knowledge into economic models. Under this view, digital sustainability becomes a matter of spatial and geotechnical equity: firms equipped with geospatial and basic geotechnical data can lower emissions and costs, while those lacking such insight risk exclusion from emerging low-carbon markets. Moreover, variations in terrain and subsurface conditions expose the weakness of uniform carbon-pricing schemes; a single CO_2 rate per kilometer overlooks the extra environmental cost of eroded, rutted, or landslide-threatened routes (Winter, 2019; Zhou *et al.,* 2024; Salini *et al.,* 2024). GCAPF's adaptive weighting mechanism provides a fairer, more precise method for assigning emissions and route-risk penalties, reinforcing the polluter-pays principle of SDG 12 and promoting a more equitable, terrain- and geotechnics-aware model of sustainable digital commerce (Bocean, 2025)

5.2 Terrain, Economic–Environmental Trade-offs, and Implementation Feasibility

Terrain and subsurface conditions exert a strong and quantifiable influence on logistics-related emissions, extending the geophysical–geotechnical interdependence highlighted in Section 5.1. Gradients above five degrees increase fuel use by roughly 2.5% per degree (Figliozzi, 2020), while eroded or poorly maintained roads elevate emissions by up to 30% per kilometer (Anderson *et al.,* 2021). Seasonal flooding can lengthen delivery routes by nearly one-third (Oluwafemi *et al.,* 2023), and unstable soils, including expansive clays or low-bearing-capacity subgrades, contribute to recurring delays of around 10% (Kochanek *et al.,* 2025; Udoh *et al.,* 2025). In a design, the gradation of the in situ or on-site soil often controls the design and ground water drainage of the site (Nnurum et al, 2021). Such factors show that static, distance-only models underestimate emissions by up to 40%. Incorporating slope, soil strength, and hydrological variability therefore strengthens predictive accuracy and forms a core pillar of the Geo-Carbon-Aware Personalization Framework (GCAPF). When these corrections are embedded into GCAPF's multi-objective optimization function, SMEs achieve meaningful sustainability gains. Balanced weighting ($\alpha = 1$, $\beta = 0.5$, $\gamma = 0.25$) yields ~15% emission reduction with negligible conversion loss, while carbon-dominant strategies ($\beta = 0.8$) achieve up to 21% reduction with only a minor sales impact; consistent with Pareto-optimal trade-offs (Marler and Arora, 2004; Spillo *et al.,* 2023; Kalisvaart *et al.,* 2025).

Implementation feasibility further reinforces the practical potential of GCAPF, especially for SMEs in developing economies. Over 70% of terrain-aware optimization frameworks rely on open-source or low-code tools such as QGIS, Python APIs, DEMs, SoilGrids, and open flood rasters, enabling CO_2e reductions between 8% and 20% without significant investment (Haruna, 2021; Rodrigues *et al.,* 2022). More advanced approaches like IoT-enabled carbon monitoring (Nguyen *et al.,* 2024) and reinforcement learning for dynamic routing (Rabelo *et al.,* 2025), offer additional benefits where computational capacity exists. Visualization tools, including terrain-based emission heatmaps and flood-risk overlays, translate spatial and geotechnical data into actionable insights for both managers and policymakers (UNEP, 2024; Vinuesa *et al.,* 2020). Real-world evidence from the Nigerian GIS–e-commerce pilot demonstrated substantial gains of 12% fuel reduction and 8% improved delivery reliability, confirming that integrating terrain, hydrology, and ground conditions into personalization and logistics decisions provides SMEs with a scalable, financially accessible pathway toward low-carbon competitiveness.

5.3 Algorithmic Integration within Recommender Systems

Conventional recommender engines rank items solely on predicted purchase probability or profitability. In GCAPF, this logic is replaced by a multi-objective function that embeds spatial and environmental penalties into the ranking process.

From an implementation standpoint, integrating carbon-aware scoring can be achieved through *re-ranking;* an approach where conventional RS outputs are post-processed with carbon and route-risk weights. Studies by Spillo *et al.,* (2023) and Kalisvaart *et al.,* (2025) show that such hybrid pipelines maintain up to 98 % of baseline accuracy while adding sustainability interpretability.

Equation (1) below captures this relationship:

$$Score(u,i,r) = \alpha P_{buy}(u,i) - \beta CO_2e(u,i,r) - \gamma Risk(r)$$

where:

- $\alpha P_{buy}(u,i)$ = predicted purchase probability for user u and item i,
- $CO_2e(u,i,r)$ = estimated emissions for the delivery route r,

- $Risk(r)$ = route reliability or terrain hazard score,
- α, β, γ = weighting coefficients tuned to SME priorities.

This formulation allows SMEs to flexibly adjust the trade-off between economic performance and environmental responsibility. As observed by Marler and Arora (2004), such multi-objective systems can produce Pareto-optimal frontiers where small efficiency losses generate disproportionate ecological gains (Figure 2).

5.4 Organizational and Cultural Transformation

Adopting GCAPF also implies an internal cultural shift. SMEs must evolve from reactive environmental compliance to proactive carbon governance. Integrating spatial and sustainability data into marketing or logistics workflows encourages inter-departmental collaboration between marketing teams that manage RS algorithms and operations teams that handle fleet logistics.

This aligns with socio-technical systems theory (Baxter and Somerville, 2011), which emphasizes the need for coherence between human, technological, and organizational subsystems. Training programs that merge basic GIS literacy with digital-marketing analytics can bridge existing skill gaps. In this way, environmental awareness becomes embedded in everyday decision-making rather than confined to corporate reporting.

5.5 Socioeconomic Equity and Consumer Fairness

While GCAPF provides efficiency gains, it also introduces ethical considerations. Carbon-weighted re-ranking could inadvertently deprioritize customers in rural or remote regions by labeling their deliveries as “high-emission.” To maintain equity, SMEs must implement *fairness constraints,* for example, rotating green incentives so that environmentally efficient customers subsidize harder-to-reach ones.

García-Sánchez *et al.,* (2023) warn that algorithmic sustainability must be balanced with social fairness to prevent new forms of digital exclusion. Incorporating fairness metrics, such as equalized expected delivery times, ensures that the pursuit of sustainability does not undermine inclusivity.

5.6 Data Limitations and Technical Challenges

Despite clear potential, several technical barriers remain:

1. Low-Resolution Spatial Data: Many developing countries lack high-quality digital elevation models and soil datasets (Goodchild, 2020).
2. Dynamic Environmental Conditions: Seasonal floods and erosion change rapidly, requiring real-time updates to route-risk layers.
3. Opaque Algorithms: Multi-objective models can obscure causal relationships, complicating accountability (Vinuesa *et al.,* 2020).
4. Computational Overhead: Small enterprises often lack GPU capacity for complex optimization.

Addressing these limitations demands a blend of open-data policies, lightweight models, and shared cloud infrastructures accessible to SMEs.

VI. POLICY AND ECOSYSTEM ENABLERS

6.1 Open Spatial Data Infrastructure

Governments play a pivotal role in enabling terrain- and geotechnics-aware digital transformation. Public release of high-resolution geospatial datasets; digital elevation models (DEMs), flood rasters, and soil and geotechnical maps (e.g., soil classification, bearing capacity, landslide susceptibility) reduces the cost of integrating environmental intelligence into SME operations. Nigeria’s National Geospatial Data Infrastructure (NGDI, 2023), ongoing work on climate-resilient geotechnical infrastructure in West Africa (Nnaji, 2024), and the EU’s INSPIRE directive (EC, 2022) exemplify how open data accelerates private-sector innovation.

6.2 Carbon Accounting and Green Incentives

National agencies should establish simplified carbon accounting standards aligned with ISO 14083 (2023). These standards would allow SMEs to report route-level emissions using plug-in APIs rather than full life-cycle assessments. Coupled with green-commerce credits or tax deductions, such mechanisms can reward emission-reducing digital behavior.

6.3 Capacity Building and Knowledge Transfer

Regional development programs can create vocational curricula combining GIS, logistics optimization, and sustainability management. Partnerships between universities, start-ups, and local chambers of commerce can host *"Digital Sustainability Clinics"* where SMEs receive tailored advice on implementing GCAPF with open-source tools like QGIS and Python.

6.4 Financial and Technological Support

Access to concessional financing is crucial. Green funds or development banks could subsidize software-as-a-service (SaaS) licenses that include carbon-aware modules. Furthermore, collaborations with telecom providers can enable data-sharing agreements that integrate mobile coverage, traffic patterns, and flood alerts into SME routing engines.

6.5 Governance and Public Engagement

At the policy level, integrating GCAPF principles into national digital-economy blueprints can strengthen coherence between industrial innovation and climate strategies. Transparent consumer dashboards, showing the carbon intensity of delivery options, can promote behavioral change and public trust in sustainability metrics (Olanrewaju *et al.,* 2022).

VII. FUTURE RESEARCH DIRECTIONS

The intersection of digital personalization and geophysical analytics remains under-explored. Key research opportunities include:

1. Field-Scale A/B Trials: Deploy GCAPF within live SME e-commerce systems to measure real-world conversion, emission, and route-disruption impacts, explicitly tracking performance across different soil types and slope classes (Nguyen *et al.,* 2024; Kamara *et al.,* 2025).
2. Minimal-Data Models: Develop surrogate machine-learning models capable of estimating emissions using proxy terrain and ground-condition indicators (e.g., road type, erosion risk, subgrade class) where detailed geotechnical data are lacking.
3. Geo-Temporal Adaptation: Incorporate time-series hydrological data for dynamic route-risk prediction.
4. Fairness and Transparency Metrics: Create interpretable frameworks ensuring equitable treatment across customer geographies, including those in geotechnically challenging or hazard-prone areas, so that high-risk routes are not simply excluded but managed through shared-cost or policy mechanisms.
5. Cross-Regional Comparative Analyses: Apply GCAPF across Africa, South Asia, and Latin America to benchmark performance in diverse geoclimatic contexts.

Such studies will validate the scalability and robustness of GCAPF and support its inclusion in international sustainability standards.

VIII. CONCLUSION

This review establishes a compelling case for integrating geophysical and geotechnical intelligence into digital personalization. The proposed Geo-Carbon-Aware Personalization Framework enables SMEs to align competitiveness with climate responsibility by combining terrain-adjusted emission modeling, route-risk and ground-condition analytics, and recommender-system optimization.

Empirical synthesis of 104 studies shows that while terrain and ground conditions can increase logistics emissions by up to 40 %, algorithmic integration of slope, soil, and road-condition penalties can offset 10–20 % of this footprint without compromising conversion rates. Implemented with open-source tools and supported by policy incentives, GCAPF offers a scalable pathway to low-carbon digital growth, particularly vital for developing economies such as Nigeria, where infrastructure fragility, problematic soils, and environmental volatility converge.

Ultimately, greener personalization redefines digital success; not measured only by sales or engagement metrics, but by how intelligently commerce systems interact with the planet's physical and geotechnical reality. By embedding geophysical and geotechnical awareness into the algorithms that drive global trade, SMEs can transform from passive emitters into active contributors to a sustainable, climate- and ground-resilient digital future.

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