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Title Page

Productive Rather Than Aesthetic Urban Landscapes Drive Actualized Sustainable Consumption

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Productive Rather Than Aesthetic Urban Landscapes Drive Actualized Sustainable Consumption

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Abstract

Global sustainability initiatives prioritize urban greenery to foster resilient cities, yet their efficacy remains under-researched in the Global South. Conventional reliance on self-reported data risks a pervasive "green illusion"— a discrepancy between reported behavior and actual sustainable consumption behavior. To diagnose this anomaly, we synthesize spatial morphology and psychometric surveys across 149 Southeast Asian cities with objective e-commerce transaction logs from a matched 125-city analytical sample. We construct a Desakota index to capture integrated urban–agricultural landscapes typical of emerging economies, alongside a conventional green exposure index. We find that psychological nature connectedness acts primarily as an "internal calibrator," recalibrating the self-reported bias without closing the actual gap. Furthermore, while mainstream "greening urban space" models show limited association, Desakota morphologies are strongly associated with objective sustainable consumption, independent of psychological mediation. These patterns suggest that rapidly urbanizing regions should elevate productive landscapes as valuable sustainability assets rather than transitional relics.

As a critical cornerstone of the global sustainability discourse, the rise of sustainable consumption is fundamentally reshaping global market systems and expanding into broader socio-ecological domains, including food and urban systems (Bai et al., 2024; Doran et al., 2023; Tian et al., 2024). However, despite concerted global efforts, the market penetration of sustainable products remains constrained. (Elmor et al., 2024; Hahnel & Frings, 2024; Hoffmann et al., 2024; Sinclair et al., 2025). Responding to recent directives from the *Nature Sustainability Expert Panel* on "Behavioral science for design" (Klotz et al., 2019), there is an urgent need to treat sustainable consumption as a priority for urban strategic intervention, shifting the focus from merely identifying psychological drivers to actively designing choice architecture that catalyzes actualized behavior.

Cities and urban centers, as the primary hubs for global consumption and human sustainable activity, profoundly shape consumer intentions and behaviors regarding sustainable goods (Bai et al., 2018; Delbridge et al., 2022). Within these urban contexts, extensive psychological and behavioral research has been undertaken to identify factors that universally enhance pro-environmental behaviors (PEB) (Lanzini & Thøgersen, 2014; Bouman et al., 2018; Alcock et al., 2020; Ciocîrlan et al., 2025), with a particular emphasis on how nature contact and the greening of urban spaces influence these outcomes (Gosling & Williams, 2010; Bratman et al., 2019; Keeler et al., 2019; Mackay & Schmitt, 2019; Martin et al., 2020; Anguelovski et al., 2022). However, this foundational literature suffers from a severe empirical bottleneck (See **Supplementary Table 1** for a brief literature review): due to the absence of objective transactional evidence, findings regarding sustainable consumption motivations remain largely experimental or survey-based, and rely heavily on the assumption that consumers honestly and accurately report their own intentions and behaviors. (Carrington et al., 2010; Dablander et al., 2025). This idealized assumption focuses on describing the property of a behavior rather than observing the behavior itself, thereby overlooking inherent consumer reporting biases (Lange, 2024).

The recent integration of sustainable goods into e-commerce supply chains offered a robust opportunity to evaluate the actualized preferences of consumers within a digital marketplace (Isley et al., 2016; Zhang & Hou, 2022). While extant literature from developed economies indicates that sustainability interventions, most notably eco-labelling, can catalyze sales, resulting in a 13.3% increase in gross merchandise value on platforms like Amazon (Proserpio et al., 2025), a significant mechanistic ambiguity remains. Specifically, current studies have yet to decouple the influence of psychological drivers from the effects of choice architecture and behavioral design.

Resolving this mechanistic ambiguity is essential for high-impact urban policymaking, particularly regarding global agendas like Sustainable Development Goal (SDG) 11, which prioritizes urban greening to foster sustainable lifestyles (Elmqvist et al., 2019; UN-Habitat, 2023). The prevailing rationale relies on environmental psychology frameworks that link nature contact to psychological nature connectedness (NC) and thus to self-reported sustainable behaviors, which remain under-researched within the contexts of the Global South (Liu et al., 2022; Richardson et al., 2026). However, emerging evidence suggests this "converged pathway" may be mis-calibrated for the rapidly urbanizing contexts of the Global South. (Pascual et al., 2023). In these regions, citizens maintain fundamentally different "living in nature" value perceptions (Chen et al., 2022; Pascual et al., 2023; Li et al., 2025), raising critical questions about whether importing compartmentalized, aesthetic urban greening models effectively translates psychological attitudes into genuine market action.

To address these intertwined spatial and methodological blind spots, this study bypasses traditional survey limitations by leveraging the digital supply chain. For the first time, we assess the psychometric attitudes (captured in January 2025) and spatial morphologies of 149 urban regions across six Southeast Asian (SEA) nations. By linking these baseline metrics to the objective e-commerce transaction logs of over 6,000 users spanning a 14-month period (June 2024–July 2025), we constructed a robust, matched analytical sample of 125 cities. This unique multi-channel framework allows us to map the complete behavioral cascade across the grocery and electronics domains, strictly distinguishing the reported say–do gap (RG) from the reporting bias (RB)—which we term the "green illusion"—and the total observed gap (OG) in actual market transactions.

Furthermore, to contextualize these behavioral gaps within the built environment, we contrast conventional aesthetic greening against the *Desakota* morphology—a spatial concept describing the unique, highly integrated agricultural and productive land uses native to SEA urbanization (McGee, T. G, 1991).

Insights gained from this study are threefold. First, we uncover a pervasive "green illusion" (RB) within sustainable consumption, demonstrating that NC functions not as a direct behavioral catalyst, but as an "internal calibrator" that shrinks self-reported over-claiming without substantially closing the observed market gap. Second, we reveal that *Desakota* morphologies support actualized sustainable market behavior far more effectively than conventional urban greenery, bypassing the conventional pathway of psychological nature connectedness. Finally, these patterns categories cities into distinct spatial typologies with divergent regional signatures, suggesting that urban sustainability policies in emerging economies required a critical reassessment on the role of productive landscapes as valuable sustainability assets rather than transitional forms in the urbanization process.

Results

Quantifying the Green Illusion: Pervasive behavioral collapses and spatial clustering

To quantify the empirical magnitude of the green illusion, we contrasted psychometric survey data with objective e-commerce transaction logs, yielding a matched analytical sample of 125 Southeast Asian urban centers with complete multi-layered data. We tracked objective purchasing behavior across two distinct market domains: the grocery domain (representing high-frequency, lower-barrier purchases of organic foods) and the electronic domain (representing low-frequency, high-barrier purchases of energy-efficient durable goods). We mapped data across three distinct layers, i.e., **intention**, **reported behavior**, and **observed behavior**, onto a unified metric space using two complementary approaches (see **Methods**). First, Behavioral Potential Normalization (BPN) measured the linear magnitude of unrealized green action. Second, Logistic Probability Mapping (LPM) evaluated the probability that a population crossed the threshold into a committed sustainable habit.

Evaluated through these lenses, objective metrics plummet. While psychological intention for pro-environmental behavior registers robustly at roughly **70%**, translation into verifiable market transactions is negligible: unrealized behavioral magnitude (BPN) falls below **1%**, and the probability of threshold transition (LPM) drops under **8%** (**Fig. 1a**).

Crucially, decomposing this cascade reveals that the **reporting bias (RB)**, i.e., the green illusion, defined as the divergence between reported and observed behavior, is the primary driver of this systemic failure. While traditional survey literature correctly identifies an initial drop from intention to self-reported behavior (the **reported say-do gap, RG**), our data demonstrates that the previously unmeasured secondary chasm (the RB) is even more severe.

Across the high-frequency grocery domain, the RB systematically eclipses the RG under both BPN and LPM frameworks (**Fig. 1a**). In the low-frequency electronic domain, the RB remains the dominant failure point under the LPM framework. The total **observed say-do gap (OG)**, i.e., the absolute distance between intention and observed behavior, is overwhelmingly driven by the collapse occurring *after* the survey phase, concealed within actual market realities.

Furthermore, this collapse exhibits distinct spatial autocorrelation, indicating structural rather than purely psychological drivers. Geospatial mapping reveals statistically significant geographic clustering across the sampled megacities (**Fig. 1b**). Parallel analysis of the electronic domain reveals domain-specific spatial signatures (**Supplementary Fig. 1**).

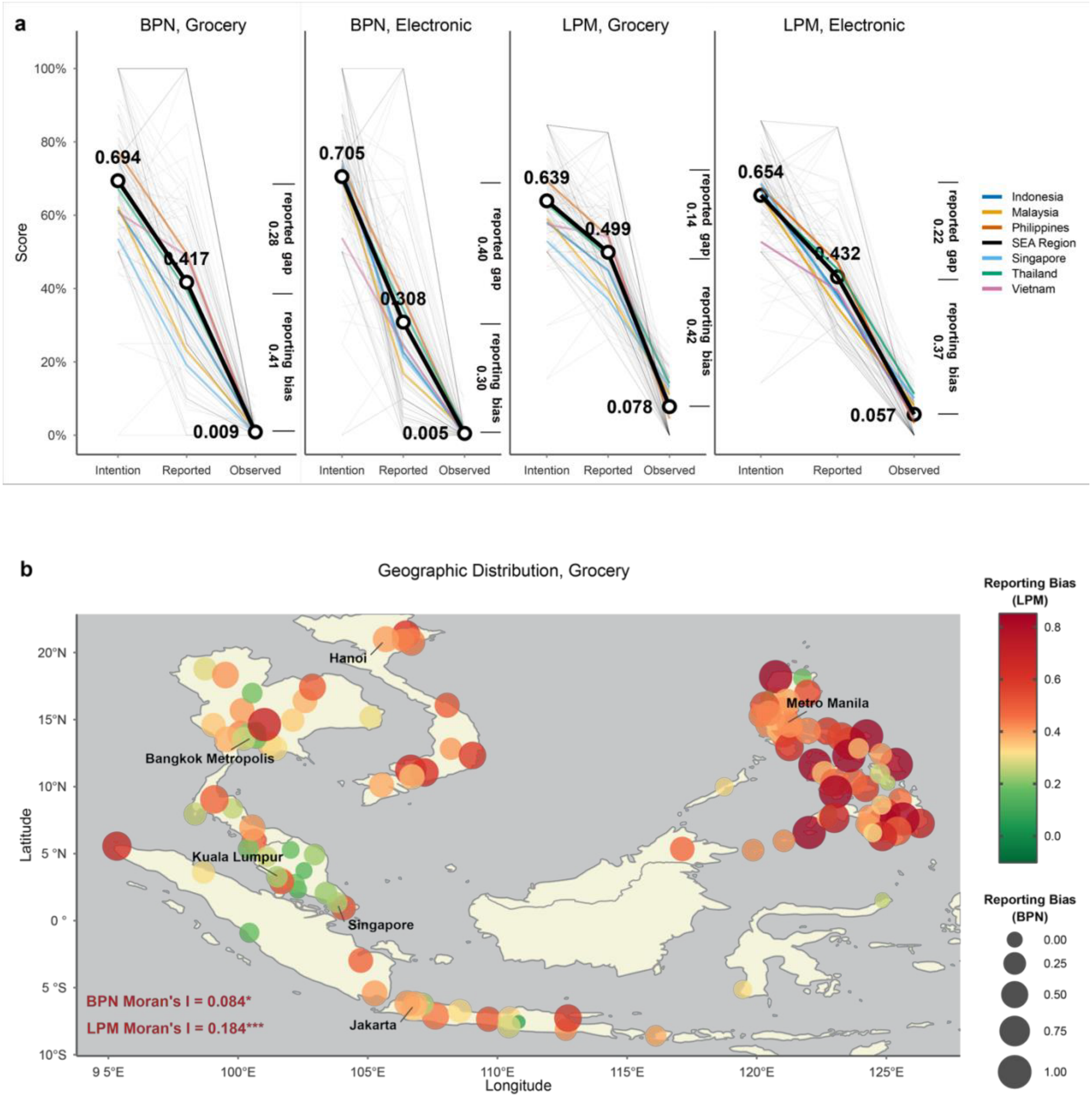

Fig. 1 | Intention-behavior gaps and their spatial distribution of sustainable consumption. a, Discrepancies among intention, reported behavior, and observed behavior across four specific contexts (2 domains * 2 mapping framework): BPN in Grocery; BPN in Electronic; LPM in Grocery; and LPM in Electronic. The bold lines with circular markers indicate the overall average scores across the region, while the fainter lines represent data aggregated by country (Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam), and the faintest lines represent data of each city. Gap 1 denotes the difference between intended and reported behavior, whereas Gap 2 denotes the difference between reported and actual observed behavior. b, Geographic distribution of the final intention-action gap (Gap 2) for grocery contexts across 125 cities in Southeast Asia. The map utilizes a bivariate symbology: the color gradient of the circles represents the magnitude of Gap 2 for LPM, ranging from green (low) to red (high), and the size of the circles represents the magnitude of Gap 2 for BPN, ranging from 0.00 to 1.00. Spatial autocorrelation is indicated by Moran's I statistics.

Because psychological intention remains uniformly high across the region, yet this threshold-based reporting bias (LPM) clusters geographically, the manifestation of the green illusion (RB) is evidently mediated by local structural realities rather than psychological dissonance alone. Sensitivity analyses confirm these patterns are robust across all perturbations of the LPM specification (**Supplementary Fig. 2**). This necessitates a deeper deconstruction of how subjective attitudes interact with physical urban structures.

The Attitude Paradox: Nature connectedness as an internal calibrator rather than a behavioral driver

The pervasive, spatially clustered behavioral collapse necessitates a rigorous re-evaluation of the mechanisms presumed to drive pro-environmental behavior. We trace the correlational pathway across the behavioral cascade, which however reveals a profound attitude paradox (**Fig. 2**). While NC exhibits a significant and positive correlation with baseline psychological attitudes (e.g., general agreement on supporting environmental protection; $r = 0.32$, $p < 0.001$), its predictive validity immediately collapses downstream. NC demonstrates no statistically significant correlation with domain-specific intentions. Most counterintuitively, NC is significantly and consistently *negatively* correlated with self-reported behavior ($r = -0.34$ to -0.37, $p < 0.001$).

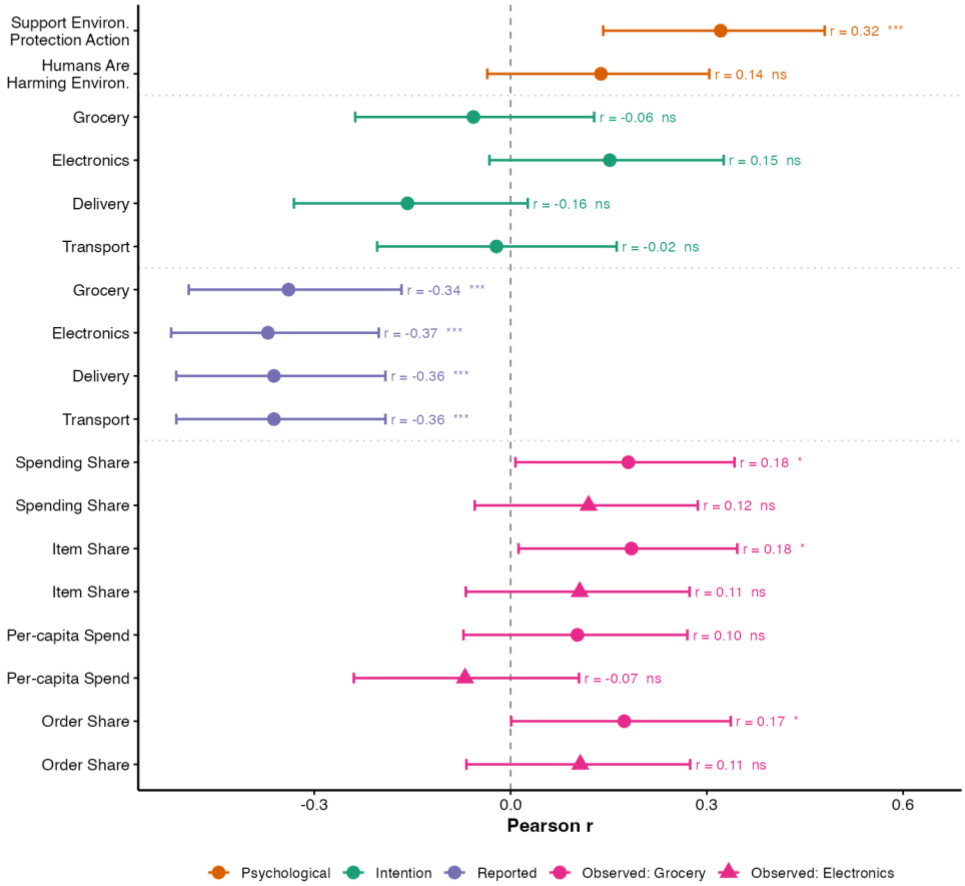

Fig. 2 | The attitude paradox in the correlational pathway of nature connectedness. Pearson correlation coefficients (r) between nature connectedness (NC) and distinct stages of the behavioral cascade. The forest plot illustrates the correlation of NC with baseline psychological attitudes (orange), domain-specific intentions (green), self-reported behaviors (purple), and actual observed market behaviors (pink). Notably, LPM metrics are used to quantify the latter three stages: intention, reported behavior, and observed behavior. Point estimates are accompanied by error bars representing 95% confidence intervals. Statistical significance is calculated using Pearson's correlation test, denoted as *** for $p < 0.001$, ** for $p < 0.01$, and * for $p < 0.05$, while 'ns' indicates a non-significant correlation ($p \geq 0.05$). Observed market behaviors are further differentiated by domain: grocery (circles) and electronics (triangles). Due to varying data availability across psychometric survey responses and objective transaction logs (e.g., users with zero category-specific orders), the effective sample size (N) varies by specification: N = 109 to 129 for baseline psychological attitudes, N = 125 for domain-specific intentions and self-reported behaviors, N = 149 for observed behaviors.

At the level of observed market behavior, a domain asymmetry emerges. NC shows weak but statistically significant positive correlations with several grocery-based share metrics (spending share and item share: $r = 0.18$, $p < 0.05$; order share: $r = 0.17$, $p < 0.05$), suggesting a marginal link between environmental self-awareness and routine, low-cost green purchasing. However, no such relationship exists for the higher-barrier electronics domain, where all observed metrics remain non-significant. Notably, even this marginal grocery-domain signal is sensitive to normalization choice: under BPN normalization, all observed behavior correlations lose statistical significance (**Supplementary Note 4**), confirming that the bivariate association does not constitute a robust behavioral transmission pathway.

To further quantify these transmission mechanisms, we conducted multivariate regression analyses across the SEA cities, controlling for critical socio-demographic and economic covariates (**Supplementary Table 2**). Across all BPN and LPM specifications, NC exerts highly significant but opposing forces on the distinct behavioral chasms. It significantly *increases* the reported say-do gap (RG) while simultaneously *decreasing* the reporting bias (RB). Rather than acting as a direct behavioral catalyst, NC functions primarily as an "internal calibrator." Individuals with high NC do not physically consume more green products; instead, heightened environmental self-awareness restrains them from over-claiming sustainable actions on surveys. Consequently, their deflated reported behaviors align much more closely with empirically low baselines of actual market behavior, effectively shrinking the green illusion (RB).

We mapped this domain-specific and geographical heterogeneity by applying estimated regression parameters to simulate counterfactual gap metrics (**Supplementary Note 5**) for ten representative regions across five nations (**Fig. 3;** drawn using LPM metrics, with BPN-based equivalents in **Supplementary Fig. 4**). This visualization acts as a behavioral accounting framework, isolating the baseline counterfactual gaps (i.e., the simulated behavioral failure if NC were zero) from the specific directional contributions of NC.

These "waterfall" dynamics reveal a consistent cognitive recalibration. Across both domains and all sampled cities, introducing NC uniformly inflates the reported say-do gap (RG) which is visualized as an additive expansion beyond the counterfactual baseline, while simultaneously exerting a contracting effect on the reporting bias (RB). This dual dynamic confirms the internal calibrator mechanism: NC transfers the statistical "failure" from a concealed green illusion (RB) to an overt reported gap (RG).

The magnitude of this transfer exhibits notable domain asymmetry. Grocery domains show pronounced baseline biases and NC-driven corrections, while the high-barrier electronic domain reveals systematically smaller NC contributions in both directions.

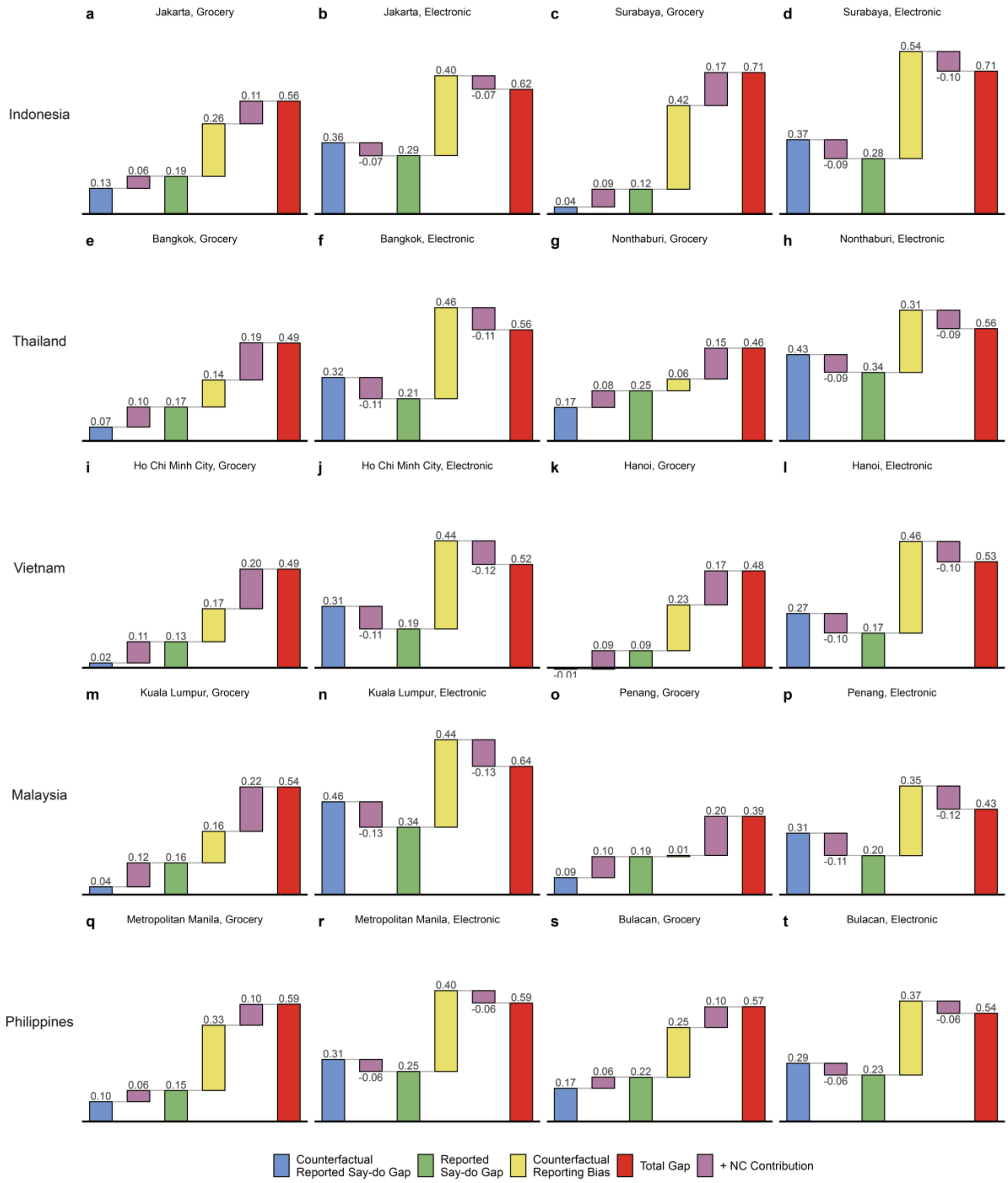

Fig. 3 | Decomposition of intention-action gaps and the bidirectional contribution of nature connectedness across Southeast Asian cities. a–t, Assessment of baseline, observed, and total observed gaps—both with and without the contribution of nature connectedness (NC)—in the capital and second-largest regions (by population in our sample) of Indonesia, Thailand, Vietnam, Malaysia, and the Philippines. Bars represent the counterfactual reported say-do gap (blue), reported say-do gap (green), counterfactual reporting bias (yellow), total gap (red), and the isolated contribution of nature connectedness (purple). Numerical values adjacent to the bars denote the specific gap metrics and the estimated effect sizes of NC. Odd-lettered panels (a, c, e, g, i, k, m, o, q, s) present results for grocery consumption; even-lettered panels (b, d, f, h, j, l, n, p, r, t) present results for electronics consumption.

Crucially, because the upward expansion of the RG and downward contraction of the RB operate as a near-zero-sum cognitive redistribution, the final total observed gap (OG) remains stubbornly severe. The absolute distance between intention and actual market behavior consistently exceeds 0.43 across all sampled cities and domains. The overarching evidence is clear: evaluating greening initiatives based solely on psychological attitudes or reported behaviors systematically misinterprets the role of NC. The weak, normalization-sensitive grocery-domain signal notwithstanding, psychological connectedness alone fails to catalyze substantially actualized sustainable consumption. Urban greening policies therefore require external, spatial enablement to bridge the persistent chasm between environmental sentiment and market behavior.

The *Desakota* Effect: Morphological Thresholds and Green Market Behavior

Because psychological NC merely recalibrates internal reporting, closing the behavioral gap require shifting from psychological nudging to compatible spatial structures. We evaluated two spatial paradigms: conventional urban greening (Green Exposure) and the highly integrated, productive landscapes characteristic of Southeast Asia (*Desakota* Index). These two archetypes were selected through a hierarchical-clustering procedure that confirmed their empirical orthogonality ($r = -0.32$; see **Supplementary Note 7**). We then decomposed their impacts into direct structural and indirect psychological effects (**Fig. 4a**).

When accounting for robust demographic and institutional controls (including country fixed effects), the mediation analysis reveals a stark divergence. Traditional Green Exposure shows no significant association with observed market behavior across any specification — neither through total, direct, nor indirect pathways. The Desakota morphology operates through an entirely different channel. Its defining feature is a strong, highly significant direct association with observed market behavior ($\beta = 0.41$, $p < 0.001$ for grocery; $\beta = 0.39$, $p < 0.001$ for electronics; **Fig. 4a**), with zero psychological mediation via NC (all indirect effects $\beta \leq 0.01$, ns). Highly integrated land-use patterns bypass conventional psychological intent (NC), functioning as structural spatial factors that drive objective green consumption. These associations remain robust across multiple sensitivity analyses (**Supplementary Fig**. **6**), across moving-window kernel sizes (**Supplementary Table 3**), mixture–fragmentation weights (**Supplementary Table 4, Supplementary Fig. 7**), and alternative definitions on crop lands (**Supplementary Table 5, Supplementary Fig. 8**).

To map the precise functional dynamics of these spatial drivers, we modeled observed market behavior against the standardized spatial indices using both linear (Ordinary Least Squares, OLS) and non-linear (Generalized Additive Models, GAM) estimations (**Fig. 4b**). With demographic, and country controls, the Desakota morphology shows a strong, positive, and essentially linear relationship with observed behavior (OLS: $\beta = 0.406$, $p < 0.001$, $R^2 = 0.435$ for grocery; $\beta = 0.384$, $p < 0.001$, $R^2 = 0.459$ for electronics). GAM specifications confirm this linearity, with effective degrees of freedom near unity (edf = 1.18 and 1.00, both $p < 0.001$), indicating that the structural integration–consumption relationship scales monotonically without threshold discontinuities.

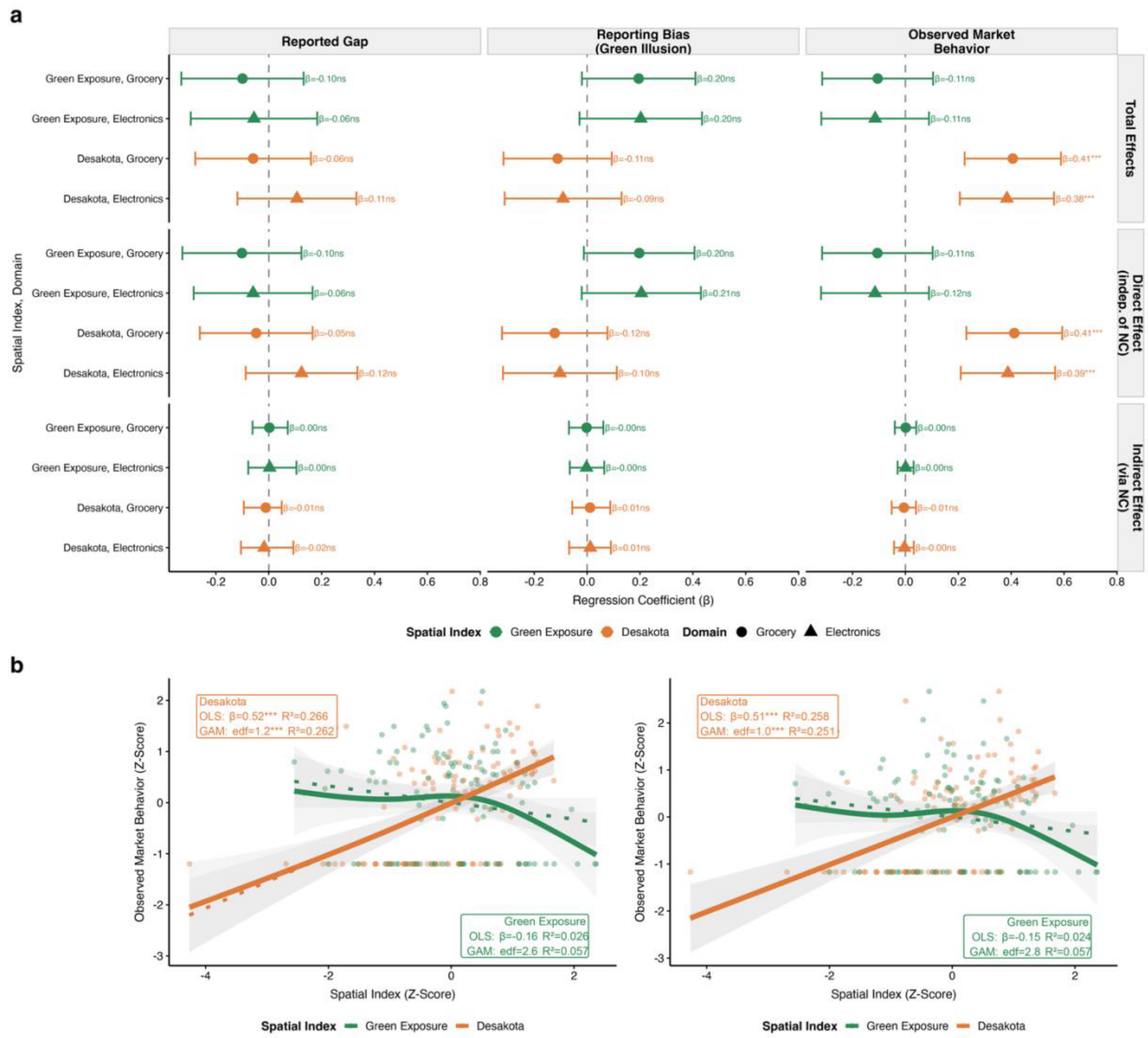

Fig. 4 | Effects of spatial configurations on intention-action gaps and observed market behaviors. All data utilize the LPM framework metrics. **a,** Decomposition of spatial impacts into total, direct (independent of psychological nature connectedness, NC), and indirect (mediated via NC) effects on behavioral gaps and observed market behavior. Standardized regression coefficients ($\boldsymbol{\beta}$) reveal that the native *Desakota* morphology exerts a massive, highly significant direct effect on objective market behavior across both the grocery and electronic domains. In contrast, traditional aesthetic Green Exposure shows no significant direct or total effect on actualized consumption. Point estimates are accompanied by error bars representing 95% confidence intervals. For Total and Direct effects, intervals are calculated as $\beta \pm 1.96$ ×standard error; for Indirect Effects, 95% confidence intervals and significance are derived via a percentile bootstrap method. Statistical significance is denoted by *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and ns (non-significant, $p \geq 0.05$). Analyses control for relevant covariates, and all variables were standardized (Z-scores) prior to estimation. Results are differentiated by consumption domain: grocery (circles) and electronics (triangles). **b,** Scatter plots with fitted lines illustrating the relationship between the spatial indices (x-axis) and Observed Market Behavior (y-axis) for both the Grocery and Electronics domains. Both OLS (dashed lines) and Generalized Additive Model (GAM; solid lines with shaded 95% confidence intervals) fits are shown, complete with standardized β coefficients, GAM estimated degrees of freedom (edf), and R^2 values. Due to the strict requirement for complete cases across all spatial indices, psychological mediators, outcome variables, and demographic control covariates (e.g., GDP per capita, online shopping experience), listwise deletion yielded a consistent, effective analytical sample of N = 111 cities for all models and visualizations presented in this figure.

Visual clustering at the lower bound of observed behavior ($Y \approx -1.2$) indicates a market participation "floor effect." Tobit robustness checks (**Supplementary Table 6**) confirm the floor effect does not inflate estimations but rather amplifies the Desakota association.

The *Desakota* morphology exhibits a robust, positive monotonic relationship with observed behavior: as cities become structurally more integrated, objective sustainable consumption strictly scales upward. Conversely, Green Exposure exhibits a more complex, wave-like trajectory. GAM inflection points (**Supplementary Table 7**) reveal that Green Exposure maxima occur below the regional average; moving beyond this threshold into highly manicured park systems triggers a decline in actual green market behavior.

Ultimately, these findings confirm that the observed say-do gap may not be closed by greening policies that rely on psychological catalysis associated with greater green exposure. Rather, productive *Desakota* landscapes might provide the essential physical urban structure to override psychological limitations and translate baseline intentions into verifiable market action.

Urban spatial patterns: Mapping the behavioral divergence of Southeast Asian cities

To examine how macro-level urban spatial models shape collective sustainable consumption, we classified the sampled cities along the *Desakota* and Green Exposure indices. Operating as an inter-city, cross-sectional descriptive framework, this classification reveals three dominant macro-typologies (**Fig. 5a**). “Aesthetic Green cities” (upper-left quadrant) exhibit high manicured green exposure but low structural integration. "Grey Infrastructure cities" (lower-left) lack both. Conversely, "Integrated *Desakota* cities" (right hemisphere) feature highly integrated, productive peri-urban landscapes regardless of baseline aesthetic greening.

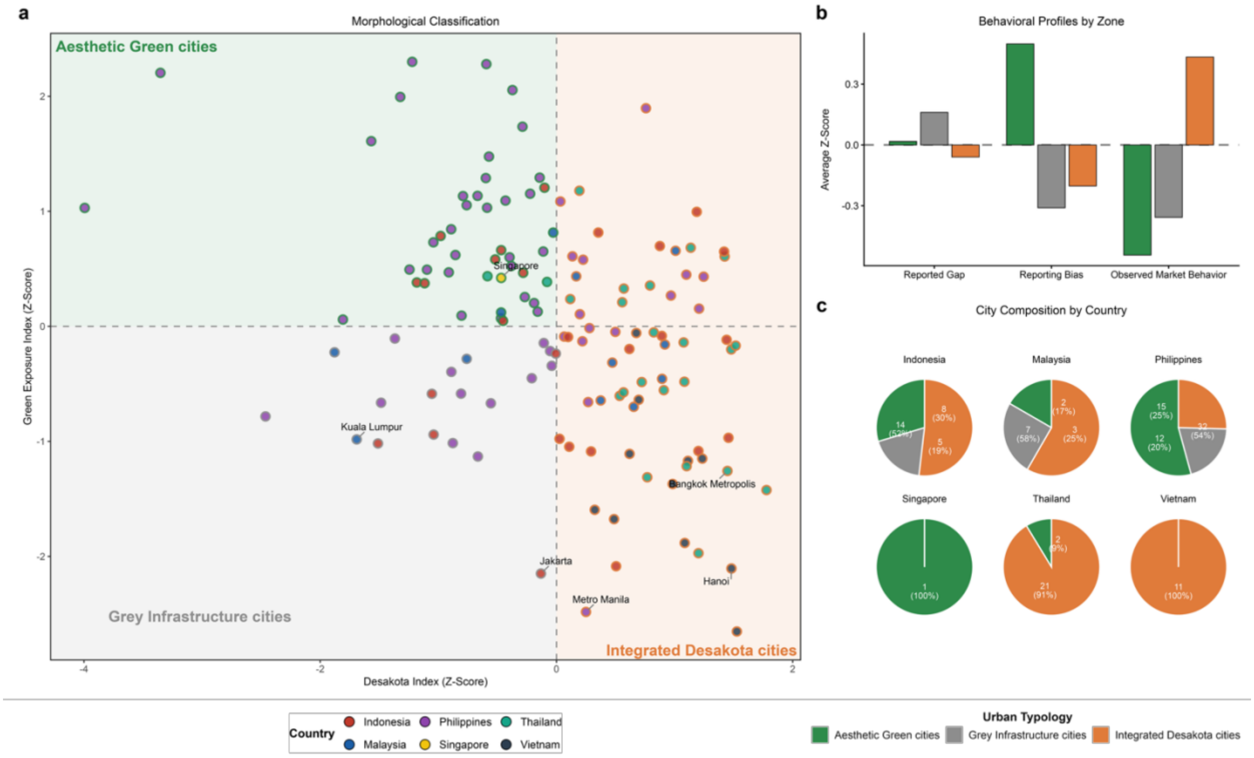

Fig. 5 | Inter-city morphological typologies and divergent behavioral profiles across Southeast Asia. **a**, Morphological classification of the sampled cities (N = 133). Cities with valid spatial indices are plotted along two standardized axes: the *Desakota* Index (x-axis, representing structural integration and productive land-use) and the Green Exposure Index (y-axis, representing conventional aesthetic greening). The quadrants define three distinct macro-spatial typologies: Aesthetic Green cities (top-left), Grey Infrastructure cities (bottom-left), and Integrated *Desakota* cities (right hemisphere). Data points are color-coded by country; key regional hubs (e.g., Singapore, Bangkok, Jakarta) are annotated. **b**, Average behavioral profiles by urban typology (N = 118). Bars represent mean z-scores for the Reported Gap, Reporting Bias (the "green illusion"), and Observed Market Behavior. All behavioral metrics in this panel are derived from the Logistic Probability Mapping (LPM) framework within the grocery domain. Notably, Aesthetic Green cities exhibit the highest reporting bias alongside the lowest objective market performance, while the Integrated *Desakota* morphology is the sole typology to demonstrate positive market actualization and a suppressed reporting bias. **c**, National composition of urban typologies (N = 133). Pie charts illustrate the distribution and absolute count of each city type across the six sampled nations based on the full spatial dataset, highlighting the dominance of the *Desakota* morphology in Vietnam, Thailand, and Indonesia.

Aggregate behavioral profiles across these regimes provide strong support for the structural influence hypothesis (**Fig. 5b**). In **Aesthetic Green cities**, the data reveals a pronounced reporting bias (RB) paired with depressed observed market behavior. These compartmentalized environments successfully foster a subjective connection to nature yet provide limited structural mechanisms for market realization. **Grey Infrastructure cities** similarly fail to catalyze actualized behavior, exhibiting suppressed baselines across the entire intention-behavior cascade. In marked contrast, **Integrated *Desakota* cities** represent the only spatial configuration in which observed sustainable market behavior is consistently higher. By physically embedding nature and local production into the daily functional economy, these integrated morphologies systematically reduce the green illusion and align actual consumption with stated environmental intent. Cross-specification sensitivity analysis (**Supplementary Table 8**) confirms these patterns are directionally invariant across all four permutations.

Geographic composition highlights divergent regional pathways (**Fig. 5c**). Highly developed, land-scarce models like Singapore operate predominantly as Aesthetic Green cities. While psychologically successful, the aggregate transaction data underscores the empirical limits of compartmentalized greening in driving objective consumption. Conversely, transitioning economies such as Vietnam (100% of sampled cities) and Thailand (96%) are overwhelmingly characterized by the Integrated *Desakota* morphology. Their native spatial structures intrinsically predispose these populations toward actualized sustainable behavior. Finally, nations exhibiting mixed morphological patterns (e.g., the Philippines, Indonesia, and Malaysia) display highly fragmented behavioral baselines. Within these mixed regions, the cross-sectional data demonstrates that reliance on traditional, segregated park paradigms heavily correlates with an expanded green illusion, empirically suggesting that objective market actualization may rely on structurally productive landscapes rather than purely aesthetic interventions.

Discussion

While existing work has highlighted how diverse ways of relating to nature, and the associated inequalities between the Global North and Global South, shape sustainability pathways (Nagendra et al., 2018; Pascual et al., 2023), empirical evidence at the level of everyday consumption in rapidly transforming urban regions remains scarce. In contrast, our study provides a more granular and novel picture by tracking objective transaction logs of e-commerce users and developing a specialized Desakota index within 149 SEA urban regions. Our findings suggest that prevalent blueprints for urban sustainability, largely imported from the Global North, may be mis-calibrated for rapidly urbanizing Global South contexts.

Rethinking measurement: The behavioral science of the green illusion

The dominant paradigm in environmental research that relies on self-reported intentions and behavioral frequencies, captures only the first stage of a multi-stage attrition process. By linking psychometric surveys to objective transaction records from a unified e-commerce platform, we reveal that the reporting bias (the gap between stated and observed behavior) vastly exceeds the conventional intention–behavior gap.

This pervasive "green illusion" is best understood through a behavioral science lens. Our data layers represent a gradient of diminishing observational bias (Xu, 2024). Attitudinal surveys (active-recording instruments) are highly susceptible to social-desirability pressures. Conversely, digital transaction records (passive-recording channels) log actual market choices free from observer effects. Viewed in this framework, the green illusion is not a matter of respondents intentionally deceiving researchers; it is a predictable, structurally generated artefact of the active-recording paradigm. Crucially, because our survey utilized a randomized split-sample design that eliminates Common Method Bias (see **Methods**), this cascading decline from intent to actualization cannot be attributed to individual consistency motifs. Rather, it represents a robust, city-level structural divergence across the observation channels (for a detailed matrix of these channel-specific biases, see **Supplementary Table 9**). Consequently, evaluating greening initiatives based solely on self-reported metrics risks systematically overestimating socio-ecological resilience. Future sustainability targets need to be anchored in objective market actualization to prevent the distortion of urban policymaking.

Re-evaluating the classical pathway: Nature connectedness as an internal calibrator

Environmental psychology's convergent expectation—urban greening fosters nature connectedness, which in turn drives pro-environmental action—finds only partial and paradoxical support in our data. While NC correlates with baseline psychological intent, it fails to catalyze actualized market behavior.

Instead, NC functions primarily more as an "internal calibrator": individuals with higher NC are less likely to over-claim sustainable actions on surveys, shrinking the green illusion (RB) while proportionately widening the reported gap (RG). Rather than rendering NC irrelevant, these findings redefine its utility. For measurement, NC-adjusted self-reports provide a better proxy for actual behavior than unadjusted ones. For policymaking, however, closing the intention-behavior gap cannot rely solely on psychological connectedness; it requires coupling attitudinal interventions with compatible spatial structures within the everyday consumption environment.

The complementary structural advantage of Integrated Desakota cities

While conventional aesthetic greening effectively drives the aforementioned attitudinal shifts by supporting urban well-being and fostering NC, it lacks the functional layout necessary to bridge the final gap to market transactions. Our data demonstrates that the native *Desakota* morphology provides exactly this complementary structural layer, functioning as a potent spatial framework that consistently supports objective market actualization.

Our mediation models confirm this spatial effect operates largely independently of the standard psychological pathway. By spatially fusing dense settlement with local agricultural and productive capacities, the *Desakota* environment furnishes a qualitatively different form of spatial exposure. Routine, production-embedded contact with natural processes appears to integrate sustainable options into the path of least spatial resistance, successfully bypassing the behavioral floor effect.

These spatial divergences invite a constructive expansion of Sustainable Development Goal 11 (Sustainable Cities and Communities). Current SDG 11.7 indicators emphasize equitable access to public open space—metrics which successfully target urban health but do not fully capture functional market integration. Urban policy in the Global South should therefore elevate productive landscapes as core sustainability assets that work alongside conventional park development.

Limitations and future directions

Several limitations bound our conclusions and highlight avenues for future research. First, our cross-sectional design establishes associations rather than causal effects; longitudinal tracking of peri-urban land conversion is required to observe how morphological transitions alter consumption over time. Second, as our unit of analysis is the city aggregate, our spatial typologies represent an inter-city descriptive framework; verifying within-city micro-mechanisms requires finer residential-location data.

Third, while relying on a unified e-commerce platform largely standardizes the digital supply-side architecture, it limits our ability to isolate the precise local mechanisms driving the *Desakota* advantage. Whether this structural effect arises from distinct consumption norms, community-level agricultural familiarity, or unobserved reductions in physical spatial friction remains a critical frontier for future research. Furthermore, this digital reliance inherently omits offline purchasing. Because residents of *Desakota* regions likely conduct a larger share of green consumption via local, offline agricultural networks, our estimates likely represent a conservative lower bound of the true *Desakota* advantage. Finally, while we control for socio-economic covariates, testing this framework in other rapidly urbanizing regions (e.g., Sub-Saharan Africa and Latin America) will be critical to addressing unmeasured cultural confounders and building a globally inclusive science of urban sustainability.

Methods

Research design and setting

A multi-method design was implemented to compile a comprehensive synthetic dataset integrating psychometric surveys, spatial morphological metrics, and objective e-commerce transaction logs across six Southeast Asian (SEA) nations (Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam). The baseline dataset was drawn from an initial pool of 149 urban centres. To construct the dependent variables for actual market behavior, this baseline was subsequently merged with proprietary transaction logs spanning a 14-month period (June 2024–July 2025). Successful geographical matching and data availability yielded a core analytical sample of 125 cities. City served as the primary unit of analysis, and thus city-level indicators were constructed through a bottom-up aggregation approach (Chan, 1998).

Note on Sample Size Variation: To maximize data utility, the effective sample size (N) varies slightly across specific models and visualizations depending on variable constraints. Analyses requiring the complete three-stage behavioral cascade (Intention, Reported, Observed) are strictly limited to the core sample of 125 cities to ensure consistency. Macro-spatial mapping (e.g., morphological typologies) utilizes the maximum available spatial dataset (N = 149). For multivariate regression models, listwise deletion is applied where specific spatial indices, demographic controls (e.g., GDP per capita, education), or mediator variables (e.g., Nature Connectedness) contain missing values, marginally adjusting the analytic sample per specification. The exact sample size for every model is explicitly reported in the corresponding figure legends and supplementary tables.

Psychometric data

Our psychometric data were derived from a large-scale digital survey during January-February 2025, supported and administered by Lazada (a leading e-commerce platform in SEA), collecting sociodemographic attributes and psychological metrics on users' environmental perception and sustainable consumption. We extracted and analyzed items corresponding to four key dimensions from surveys: (1) general green attitudes, (2) self-reported domain-specific green intentions and behavioral frequencies, (3) sociodemographic attributes, and (4) digital maturity. We controlled sociodemographic attributes such as education level, digital maturity described by self-reported "Online Shopping Experience" (frequency) and "Social Media Duration" (hours), respectively.

Our primary psychometric measures include: (1) General green attitudes, where we quantify the attitude strength of a respondent's "Support Environmental Protection" (SEP). This construct is assessed through Likert-scale endorsement of standardized environmental protection statements within a 0–1 range. In addition, we measure "Nature Connectedness" (NC) using a single-item adaptation of the "Inclusion of Nature in Self" scale (Mayer & Frantz, 2004; Schultz, 2002; Martin et al., 2020). (2) Self-reported domain-specific green intentions and behavioral frequencies, where we assess a respondent's willingness to adopt pro-environmental behaviors (PEBs) across four domains (green grocery, green electronics, green transport, and green delivery) alongside their self-reported behavioral frequencies. Intentions are operationalized using standardized Likert scores (rescaled from the original scale 1-5 range to a 0-1 range). Self-reported behavioral frequencies are normalized at a monthly basis within each domain.

We aggregated the individual psychometric measures at the regional level through a bottom-up approach (Chan, 1998). Following the "individual first" principle, metrics for each construct were calculated at the individual level prior to aggregation, preserving the psychometric integrity and validity of the construct (Bliese, 2000; Chan, 1998) and allowing for the proration of missing values using available case analysis (Enders, 2022). Consequently, our sample comprised 6051 verified users (Indonesia: 1038; Malaysia: 860; Philippines: 1311; Singapore: 469; Thailand: 1779; Vietnam: 594).

To minimize respondent fatigue, the original survey administration utilized a randomized modular design, where respondents were randomly assigned to different subsets of sustainability-related questions. We leveraged this randomization strategy to mitigate Common Method Bias (Podsakoff et al., 2003), so that the respondents assessing general attitudes (SEP and NC) were distinct from those assessing specific intentions and reported behaviors. This separation ensures that the observed correlations (e.g., Attitude → Intention) represent structural city-level phenomena rather than individual consistency motifs or artifactual covariance arising from a single rater source.

Countries and regions in Southeast Asia exhibit markedly different hierarchical structures of governance and administration. For instance, Indonesia has more than four levels of administration such as provinces ("provinsi"), regencies ("kabupaten") and cities ("kota"), districts ("kecamatan" or equivalents), and villages ("desa" or "kelurahan"), etc. By contrast, Singapore consists of approximately three tiers, comprising regions, planning areas, and subzones. Moreover, due to variations in how e-commerce platforms operate in different countries, municipal and subnational information is mixed simultaneously within user profiles. To minimize such noise, we manually aligned users' locations with geographic locations provided by the Global Administrative Areas database. We also standardize the locational information obtained from the survey to the corresponding administrative levels of each Southeast Asian nation to avoid biases arising from differences in administrative granularity (regional mappings are provided in **Supplementary Table 10**).

Transaction data

In addition to surveys, anonymized transaction data were retrieved from Lazada platform as the objective behavioral data mapped to users' real-world sustainable consumption, spanning a one-year observation window (from June 2024 to July 2025). This dataset was deterministically linked to 6051 psychometric profiles in survey to capture both psychological and real-world behavioral responses. This dataset circumvents the social desirability bias inherent in traditional sustainability surveys by capturing actual market consumption under real-world economic constraints. The transaction data were dumped from anonymized Lazada's product listing and order records, offering access to consistent orders and products within a user's transaction history. Metadata of products and orders were included (**Supplementary Table 11 and Table 12**) and the fields of product name and product description were thereby utilized in the sustainable consumption identification pipeline. Our sample only incorporated users who had valid orders and had participated in the online survey. Additionally, even identical products vary significantly in their names and descriptions when sold in different countries. We used the field "ItemID" to focus on the unique products regardless of their differentiated versions and appearances.

To track user expenditure on sustainable products, we developed a sustainable product classification pipeline. Currently, little consensus has been reached regarding the identification of sustainable products within either a local or a global context. Only a small proportion of products are certified under recognized environmental labelling schemes, even with initiatives such as the Amazon Climate Pledge Friendly program (Proserpio et al., 2025). Nevertheless, when products are not formally granted sustainability certification, producers may still have incentives to disclose sustainability attributes in product descriptions to attract consumers. These attributes are typically embedded in product names and descriptions, which are largely unstructured. By aligning with the purpose of the survey, we focus on sustainable consumption of organic products and electronic products (product categories are provided in **Supplementary Table 13**).

Therefore, an integrative pipeline was developed to apply Large Language Models (LLMs) and *N*-gram based approach to classify sustainable products from transaction data (a diagram is provided in **Supplementary Fig. 9**). To produce robust and replicable product classifications, this pipeline was implemented in the following steps: (1) We identified sets of authoritative certifications for sustainable products with LLMs. Two comparable LLMs (Qwen-Flash and Qwen-Max, **Supplementary Note 13**) were prompted in parallel to perform zero-shot retrieval tasks to generate initial sets of potential certifications. Different prompts were used for grocery and electronic products (**Supplementary Table 14**). (2) We merged overlapped extractions (54.7% and 55.0% for grocery and electronics, respectively) generated by models to mitigate the risk of hallucinations associated with reliance on a single model. (3) We manually reviewed and annotated all certification extractions (951 and 914 extractions for grocery and electronic products, respectively). Distinct principles were borrowed from widely recognized international standards that were also prevailing in SEA markets, to define sustainability attributes for grocery and electronic categories. (4) We identified 33 and 17 authoritative certifications from national and international practices for grocery and electronic products in transaction data (**Supplementary Table 15 and Table 16)**. (5) We classified sustainable products by searching for *N*-grams and their variants of certifications generated through regular expressions, which is formulated as:

$$\mathrm{I}_i = \begin{cases} 1, & \sum_{g \in C_i} \left(\mathbb{I}(g \in Ngrams) \right) \geq 1 \\ 0, & otherwise \end{cases} \tag{1}$$

where C_i is the product content. This pipeline identified 580 unique grocery and 196 electronic sustainable products. Using the constructed sustainable consumption data, we thus established several market metrics by measuring shares of green spending, green orders, and green items.

Gap construction

Normalization strategy. To quantify comparable and multi-dimensional measurements, we propose two distinct normalization strategies. First, following the conceptualization of the intention-behavior gap as a failure of "action control" (Sheeran & Webb, 2016), we employ a Behavioral Potential Normalization (BPN) method to calculate the absolute distance of a measure between a citizen's realized value and their theoretical ceiling. This aligns with absolute distance modelling used in health habituation studies (Sniehotta et al., 2005), quantifying the "unrealized potential" of urban populations. Specifically, we define a behavioral maximum (B_{max}) for each green metric, representing the theoretical upper saturation limit, e.g., 10 times per month for daily habits for reported green behavior frequency. For each individual i in city c, behavior is normalized as:

$$B'_{i,c} = \frac{B_{i,c}}{B_{max}} \tag{2}$$

Using the BPN method, we transform an original metric into a fraction of potential, i.e., metrics of different dimensions can be compared by the realized fractions of each dimension's maximum potential. For instance, under this framework, we posit that an individual expressing maximum intent ($I_i = 1$) should theoretically exhibit behavioral saturation ($B_i \geq B_{max}$) to achieve zero gap between intention and reported behavior.

While the BPN provides a linear assessment of the gap, it may overlook the non-linear thresholds inherent in behavioral adoption. To account for non-linear behavioral transitions, we utilize a Logistic Probability Mapping (LPM) approach, which transforms original intention, frequency, or market green share into a latent commitment probability. This is grounded in the stage model of self-regulated behavioral change (Bamberg, 2013), where the transition to a sustainable habit represents a critical tipping point. This method acknowledges that the transition from zero to entry-level (low) state often represents a more significant structural or psychological hurdle than the transition between two high states. We apply a sigmoid function to both variables:

$$P(x) = \frac{1}{1+e^{-k(x-x_0)}} \tag{3}$$

where x_0 is the tipping point. If a citizen's metric is below x_0, he or she is in a state of resistance or inertia. When it passes x_0, a citizen is statistically more likely to be committed on that dimension of this metric. k represents the logistic growth rate, which determines the steepness of the S-curve around the threshold. It dictates how quickly an individual moves from zero commitment to full commitment once they approach the tipping point. To ensure that the LPM remains sensitive to the specific distribution of each variable, we calibrated the growth rate k using variance-based scaling, where $k = 1/std(x)$ (Lord, 2012). By tying k to the standard deviation, we ensure that the transformation is scale-invariant.

Using the LPM method, we transform an original metric into a probabilistic commitment state and focus on whether a threshold has been crossed. Unlike BPN, which weighs every unit of raw number equally (linear), this approach prioritizes the leap from No-commitment to Commitment (non-linear).

The construction of psychological and behavioral metrics. Based on the psychometric and transaction data, we define intention, reported, and observed metrics for a user's sustainable consumption. First, intention (say) metrics ($I_{i,c}$) are measured on a standardized Likert scale $I \in [0,1]$ in our survey, and they serve as the baseline behavioral potential. Therefore, no further transformation is required for the BPN method. For LPM, it is passed through a logistic function to represent the commitment probability.

Moreover, the reported (do) metrics ($R'_{i,c}$) were derived from self-reported frequencies ($R \in [0,10]$) to represent the realized habitual potential. For the dual normalization methods, (1) We utilized the established $B_{max} = 10$ (monthly frequency) as the saturation limit and thus the metric is derived as $R'_{i,c} = \frac{B_{i,c}}{B_{max}}$ through the BPN method. (2) To account for non-linear habituation, we transform frequency into a commitment probability using a tipping point of $x_0 = 4$ times per month through the LPM method.

In addition, the observed (do) metrics, as market-related behavioral outcomes, are defined by the observed proportion of green spending ($O \in [0,1]$) in terms of expenditure amount, order number and item number. In the context of the Global South, where green e-commerce is in an emergent phase, we model market behavior using a two-stage realization process. This prevents 90% of zero-inflation from masking the behavioral signals of the active population. The process includes the following steps, (1) we first define a participation probability ($\Phi_{\mathbf{c}}$) for each region, representing the structural likelihood of a citizen transitioning from a non-consumer to a green-active consumer. This acts as the first hurdle, capturing the threshold where a citizen overcomes market barriers to execute their first green transaction. (2) For 10% of active participants, we measure their individual green purchase intensity $m_{i,c}$. (3) The final metric ($O'_{i,c}$) is the product of these two stages, representing the expected market realization: $O'_{i,c} = \Phi_c \cdot m_{i,c}$. This approach ensures that individual's actual behavior is comparable to one's intention by scaling the intensity of action by the probability of its occurrence within the current green consumption status.

The metrics of active participants $m_{i,c}$ were also transformed by the BPN and LPM methods. For the BPN metric, we define a market maximum (O_{max}) and set O_{max} as the 90th percentile of green share among active users, i.e., 6%, representing a green-dominant consumption profile. The individual intensity is calculated as $m_{i,c} = \min(\frac{O_{i,c}}{O_{max}}, 1)$. This ensures that a consumer with 6% of consumption being green in his/her basket will be treated as having reached a market saturation, equivalent to $I = 1$ or $R = 10$. To account for the non-linear barrier of market entry, we apply participation-adjusted logistic mapping for the LPM metric. We set the market tipping point x_0 at the region-level median of active purchasers, i.e., 1%. This asymmetrically weights the transition from 0 to non-zero spending, capturing the structural breakthrough required for green e-commerce adoption.

Three gap dimensions. We propose three dimensions of gap measurement in this study. First, we define the Observed Say-do Gap (OG) to represent the total divergence between an individual's subjective environmental propensity and their observed behaviors of sustainable consumption on the e-commerce platform. Going beyond traditional survey-based metrics, this gap definition highlights the novelty that accounts for the "hard" constraints of the urban economy. This gap metric is formulated as follows:

$$OG_c = I_c - O'_c \tag{4}$$

Second, the Reported Say-do Gap (RG) is defined to measure the distance between stated intent and self-reported habitual (behavioral) frequency. This is the standard metric utilized in most environmental psychology literature. Because this metric strongly relies on self-perception, it often understates the true say-do gap. It might, for instance, reflect the action control failure where individuals perceive themselves as acting sustainably, even if their habits remain inconsistent with their ideals. This gap metric is formulated as follows:

$$RG_c = I_c - R'_c \tag{5}$$

Third, the Reporting Bias (RB) is the critical "green illusion" that this study seeks to expose. It quantifies the divergence between an individual's perceived sustainable habit and their actual transactional footprint. This gap isolates the social desirability bias and memory distortion inherent in urban surveys. A significant reporting bias suggests that urban sustainability policies based solely on survey data may be overestimating the success of net-zero transitions. It highlights a cognitive decoupling where citizens adopt the identity of a green consumer without the corresponding market behavior.

$$RB_c = R'_c - O'_c \tag{6}$$

All gap measurements were calculated through both BPN and LPM methods to generate a multidimensional view of the urban intention-behavior gaps. This dual-framework approach ensures that our region-level diagnostics are robust against the limitations of single-metric scales (rationale is defined in **Supplementary Note 14**).

Geospatial indices

To examine whether geospatial characteristics can explain intention-behavior gaps, we proposed the Desakota index and measured several exposure and accessibility indicators (**Supplementary Note 15**). The Desakota index was developed to quantify the degree to which urban, rural, and agricultural land uses are spatially intertwined, a typical characteristic in Southeast Asian regions (Ginsburg et al., 1991; Lu & Talamini, 2024). This index captured the local spatial coupling between built-up settlements and agricultural land. Two raster datasets were used: (1) a settlement classification dataset (GURS) to identify built-up and village areas, and (2) land-use/land-cover (LUCC) data to extract cropland information. All datasets were reprojected and aligned to a common spatial grid defined by the GURS dataset ($30m$ resolution). Using a moving window approach (a square window of size 9×9 pixels, approximately $270m \times 270m$), the Desakota index integrated both land-use mixture and spatial fragmentation to capture the structural complexity of peri-urban landscapes, which is formulated by the following steps: (1) first, we calculate land-use mixture,

$$\begin{gathered} p_U(i) = \frac{1}{|W|} \sum_{j \in W(i)} U_i \\ p_V(i) = \frac{1}{|W|} \sum_{j \in W(i)} V_i \\ p_A(i) = \frac{1}{|W|} \sum_{j \in W(i)} A_i \end{gathered} \tag{7}$$

where within the window W, the proportions of urban areas (U_i), villages (V_i), and agricultural (crop) /green land (A_i) are calculated separately. Two alternative specifications of A_i were used: one based only on crop land and the other including both crop and green land. The resulting Desakota Index (Crop-only) served as the primary measure for main analyses presented in the paper, whereas the Desakota Index (Crop & Green) was utilized only in the sensitivity analysis (**Supplementary Table 5, Supplementary Fig. 8**).

$$\begin{gathered} p_T(i) = p_U(i) + p_V(i) + p_A(i) \\ \tilde{p}_U(i) = \frac{p_U(i)}{p_T(i)}, \tilde{p}_V(i) = \frac{p_V(i)}{p_T(i)}, \tilde{p}_A(i) = \frac{p_A(i)}{p_T(i)} \\ H(i) = -\sum_{k \in \{U,V,A\}} \tilde{p}_k(i) \ln \tilde{p}_k(i) \\ H^{norm}(i) = \frac{H(i)}{\ln 3} \end{gathered} \tag{8}$$

The Shannon mixing entropy $H^{norm}(i)$ is calculated for each window.

$$DesaMix_c = \sum_{i \in c} D_i \cdot H^{norm}(i) \cdot A_{pix} \tag{9}$$

(2) We measure spatial fragmentation by,

$$C_i = \begin{cases} 1 & U_i = 1 \\ 2 & V_i = 1 \\ 3 & A_i = 1 \\ 0 & others \end{cases} \tag{10}$$

where the spatial fragmentation of land-use categories within the buffered urban fringe is quantified by calculating a local variance metric within a moving window framework. The local variance $\sigma^2(i)$ at pixel i is defined as:

$$\sigma^2(i) = \frac{1}{W}\sum_{j\in W_i} C_j^2 - (\frac{1}{W}\sum_{j\in W_i} C_j)^2 \tag{11}$$

Where j indexes pixels located inside the neighborhood W_i.

To ensure cross-city comparability and numerical stability, the local variance-based fragmentation metric was normalized within each buffered urban region $F(i)$.

$$F(i) = \frac{\sigma^2(i)}{\max(\sigma^2)+\varepsilon} \tag{12}$$

The fragmented Desakota intensity area for city c is calculated as the spatially weighted sum of Desakota pixels, where each pixel is weighted by its normalized heterogeneity and fragmentation intensity.

$$DesaFrag_c = \sum_{i\in c} D_i \cdot H^{norm}(i) \cdot F^{norm}(i) \cdot A_{pix} \tag{13}$$

where A_{pix} is the area of a single pixel.

Finally, the Desakota Index is defined as DI_c.

$$DI_c = 0.5 \cdot DesaMix_c + 0.5 \cdot DesaFrag_c \tag{14}$$

The geospatial datasets used in this study, including their sources, acquisition time, spatial resolution, data format, and the geospatial indicators derived from each dataset are summarized in **Supplementary Table 17**.

Statistical models

Ordinary Least Squares (OLS) regression models evaluated the effect of nature connectedness on intention-behavior gaps, and estimated counterfactual gap metrics isolating NC contributions, controlling covariates:

$$Gap_i = \beta_0 + \beta_1 \cdot NC_i + \sum_m \gamma_m \cdot \mathrm{Control}_{i,m} + \epsilon_i \tag{15}$$

where Gap_i represents the region-level gap metric (RG, RB, or OG). Additional models, including Generalized Additive Models (GAM), Tobit regressions, counterfactual estimation models were employed to perform mechanism analyses, evaluate non-linear spatial thresholds (**Supplementary Note 16**). Prior to the regressions, the spatial and behavioral variables were transformed based on skewness diagnosis (**Supplementary Note 17**).

Data availability

The spatial morphology data and psychometric survey datasets generated and analyzed during the current study are available on Zenodo at https://doi.org/10.5281/zenodo.20175264. The proprietary e-commerce transaction logs from Lazada are subject to commercial confidentiality restrictions and are not publicly available; however, the aggregated city-level behavioral metrics (LPM and BPN indices) necessary to replicate the main findings are included in the Zenodo repository. Raw high-resolution spatial layers from the European Space Agency (ESA)

WorldCover and OpenStreetMap (OSM) can be accessed from their respective public providers as detailed in the Supplementary Information.

Code availability

The custom spatial processing pipelines (e.g., green product identification and Desakota index construction) and statistical analytical code for main analysis used in this study are archived and persistently available on Zenodo at at https://doi.org/10.5281/zenodo.20175264.

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Author contributions

Xuan Luo conceptualized the study, developed the methodology, performed the primary formal analysis, visualized the results, and wrote the original draft. Yi Wu curated the data (including aggregating city-level data of survey and transaction logs), performed targeted formal analysis (specifically the identification of green products in transaction logs), assisted in project administration, contributed significantly to the writing of the Introduction and the preparation of the Supplementary Information, and participated in writing—review, editing and consolidated the Supplementary Information. Junyan Ye reviewed relevant literature, performed supportive formal analysis (specifically the sensitivity tests of Desakota Index construction), and contributed to the validation of the psychometric models. Hang Yin contributed to the formal analysis, including the Desakota index spatial construction. Liyan Xu assisted in the overarching conceptualization, and provided critical revisions. Yiding Hou and Sanchita Ray secured essential resources and facilitated proprietary data access. Te Bao, Hong Xu and Wei Liu provided the overarching supervision. All authors contributed to writing—review and editing, and all read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Supplementary Information for

Productive Rather Than Aesthetic Urban Landscapes Drive Actualized Sustainable Consumption

May 15, 2026

Supplementary Note 1: Summary of relevant literature on nature connectedness, pro-environmental behavior and urban sustainability policies

In this section, we provide a systematic synthesis of the extant literature concerning nature connectedness (NC), urban sustainability policies, and their respective roles as determinants of pro-environmental behavior (PEB), as detailed in **Supplementary Table 1**. This table is organized into six panels: (a) Measurement and conceptualization of NC, (b) Attributable nature exposure to NC, (c) Attributable NC to PEBs, (d) Intention-behavior gap: self-reported PEBs overestimate actual behavior, (e) Filling the intention-behavior gap with NC, and (f) Urban sustainability policies with NC.

Supplementary Table 1. Summary of relevant literature on NC, PEB, and urban sustainability policies

Source	Approach & Data	Region	Key Findings	Measure
Panel (a) *Measurement and conceptualization of NC*				
Mayer & Frantz (2004)	Empirical	USA	Proposed CNS (also NC) and validated NC as measurable construct linked to ecological behavior	Self-reported
Schultz (2002)	Theoretical	USA	Proposed INS scale (also NC) and denoted NC as cognitive self–nature overlap	N/A
Nisbet et al. (2009)	Empirical (n=831)	Canada	Developed NR scale (also NC) and validated NC's correlation with environmental concern, behavior, time in nature, etc.	Self-reported
Tam (2013)	Empirical (n=322+185)	Hong Kong SAR & USA	Compared multiple NC scales and found NC scales were highly correlated, loadable on single factor	N/A
Chen et al. (2022)	Empirical (n=1028 urban areas)	N/A	Significant spatial disparities in the distribution of NC; Using greenspace exposure inequality index, cities in the Global South exhibit markedly lower levels compared to those in the Global North	N/A
Pascual et al. (2023)	Review	N/A	Propose integrating NC with subsets of values, highlighting the divergent roles of NC across individual, institution, policy, and the Global South contexts	N/A
Panel (b) *Attributable nature exposure to NC*				
Mayer et al. (2009)	Experimental (3 studies, n=76)	USA	15-min nature walk increased NC, positive affect; effects partially mediated by NC gains but not by attentional capacity; the effect of actual nature outweighed that of virtual nature	Self-reported
Lumber et al. (2017)	Hybrid (n=393)	UK	Defined five pathways to NC—contact, emotion, beauty, meaning, and compassion	Self-reported

Source	Approach & Data	Region	Key Findings	Measure
Richardson & Sheffield (2017)	Quasi-experiment (n=186)	UK	Low-cost intervention delivered sustained increases in NC	Self-reported
White et al. (2021)	Cross-national (n=16307)	18 countries	Recreational visits (nature exposure) and NC independently predicted well-being	Self-reported
Liu et al. (2022)	Cross-sectional (n=1470)	China	NC was a stronger predictor of mental well-being than nature exposure	Self-reported
Samus et al. (2022)	Experiment (n=84)	New Zealand	NC mediated positive affect through perceived wildness	Self-reported
Gong et al.(2024)	Experiment (n=68)	China	High-NC individuals derived greater eudaimonic well-being from high-biodiversity green space	Self-reported
Barragan-Jason et al. (2022)	Meta-analysis (n=147+59)	N/A	Nature contact and mindfulness increased NC while education alone cannot	N/A
Sheffield et al. (2022)	Meta-analysis (n=36)	N/A	Manipulations had a medium positive effect on NC regardless of types of contact, quality, or timing of engagement in adult populations	N/A
Wood et al. (2020)	Meta-analysis (n=356)	N/A	Nature-based activities in zoos/parks/gardens significantly increase NC across age groups	N/A
Soga & Gaston (2016)	Review	N/A	Urbanization reduces nature exposure, leading to a negative feedback loop—less nature experience => lower NC => less conservation	N/A
Bratman et al. (2019)	Review	N/A	From an ecosystem service perspective, nature experience enhanced NC that mediated human mental health	N/A
Soga & Gaston (2023)	Review (n=71, 100 cases)	N/A	Based on global case studies, NC was decreasing over time while magnitude of changes in NC across geographic and socio-economic settings were increasing	N/A
Panel (c) *Attributable NC to PEBs*				
Gosling & Williams (2010)	Survey (n=141)	Australia	NC increased vegetation protection behavior among farmers	Self-reported
Zelenski et al. (2015)	Experiment (n=111)	Canada	Nature exposure promoted cooperative and sustainable behavior in lab tasks	Observed
Martin et al. (2020)	Cross-sectional (n=4960)	England	Nature visits (frequency ≥once/week, NC) predicted health, well-being, PEBs	Self-reported

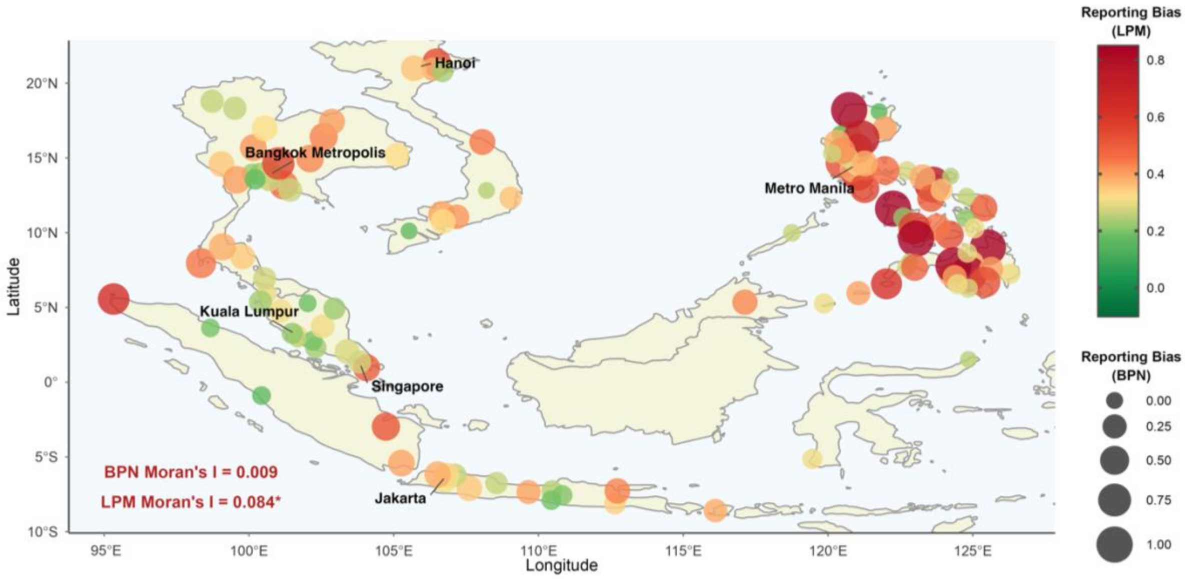
Source	Approach & Data	Region	Key Findings	Measure
Anderson & Krettenauer (2021)	Cross-sectional (n=1251)	Canada	Verified NC as one of the strongest predictors of PEB; Adults displayed significantly higher levels of NC and PEB than adolescents	Self-reported
Zheng & Ueda (2025)	Survey (n=273)	China	NC significantly predicted individuals' stages of natural behavior and huge disparities in NC were found between the pre-action and action stages	Self-reported
Mackay & Schmitt (2019)	Meta-analysis (n=75)	N/A	Verified that NC drove PEB (r=0.37); results were robust across NC scales while experimental effects were weaker	Self-reported
Whitburn et al. (2020)	Meta-analysis (n=37, 13237 obs.)	N/A	Verified that NC drove PEB (r=0.42) and explicitly noted limitations of solely using self-report metrics	Self-reported
Barragan-Jason et al. (2022)	Meta-analysis (n=147+59)	N/A	People with high NC had more pronature behaviors	Self-reported
Guazzini et al. (2025)	Review (n=29)	N/A	All 23 correlational studies showed large effects (r=0.28–0.62) of NC on PEBs and individual PEBs had a stronger association with NC than activism behaviors	Self-reported
Vesely et al. (2021)	Meta-analysis (n=188, 414282 obs.)	N/A	NC strongly predicted PEBs (r=0.44/0.52)	Self-reported
Soga & Gaston (2025)	Survey (n=22773)	23 nations	Highlighted the unnoticed cross-country variations in NC, especially outside the Global North	Self-reported
Panel (d) *Intention-behavior gap: self-reported PEBs overestimate actual behavior*				
Carrington et al. (2010)	Conceptualization	N/A	Situational, individual, product barriers prevent ethical intentions from being translated into purchases	Mixed
Dablander et al. (2025)	Conceptualization	N/A	Expressing environmental intentions systematically overestimates actual behavioral engagement	Mixed
Bamberg (2013)	Empirical (n=908)	N/A	PEBs as behavioral changes moved through four different stages: predecisional, preactional, actional, and postactional while intention alone was insufficient without implementation planning	Self-reported
Panel (e) *Filling the intention-behavior gap with NC*				
Lahoti et al. (2024)	Survey (n=2414)	India	UGS availability enhanced perceived NC to drive people's PEB, which offered strong evidence from large-scale Global South urban areas	Self-reported

Source	Approach & Data	Region	Key Findings	Measure
Wang et al. (2025)	Experiment (n=24, 54 everyday products)	China	Natural sounds enhanced pro-environmental purchasing in individuals with high environmental movement activism by reducing the intention-behavior gap	Observed
Collado et al. (2015)	Survey (n=832)	Spain	Children's pro-environmental attitudes and behaviors can be strengthened through NC with manipulations	Self-reported
Panel (f) *Urban sustainability policies with NC*				
Elmqvist et al. (2019)	Perspective	N/A	Social-ecological integration and resilience should be part of urban sustainability policies	N/A
Bai et al. (2018)	Comment	N/A	Increasing green spaces for cities and as responses to climate chang	N/A
Delbridge et al. (2022)	Policy brief	N/A	Urban sustainability policies for the developing countries need structural enablement that may differ from the Global North models	N/A
Soga & Gaston (2022)	Perspective	N/A	NC became increasingly important across many academic disciplines, e.g., ecology, conservation science, public health, immunology, urban planning, etc.; also, the key term of the nature and sustainability hypothesis	N/A

Note: NC = nature connectedness; HNC = human–nature connectedness; PEB = pro-environmental behavior; CNS = Connectedness to Nature Scale; NR = Nature Relatedness; INS = Inclusion of Nature in Self; RCT = randomized controlled trial.

Supplementary Note 2: Structural vs. Economic Barriers in the Electronic Domain

The spatial autocorrelation results presented in **Supplementary Fig. 1** highlight a critical domain asymmetry in how the green illusion manifests. In the high-frequency, lower-barrier grocery domain (**Fig. 1b**), both the linear magnitude of the gap (BPN) and the threshold probability (LPM) exhibit significant spatial clustering, suggesting that local urban morphology heavily dictates everyday sustainable consumption.

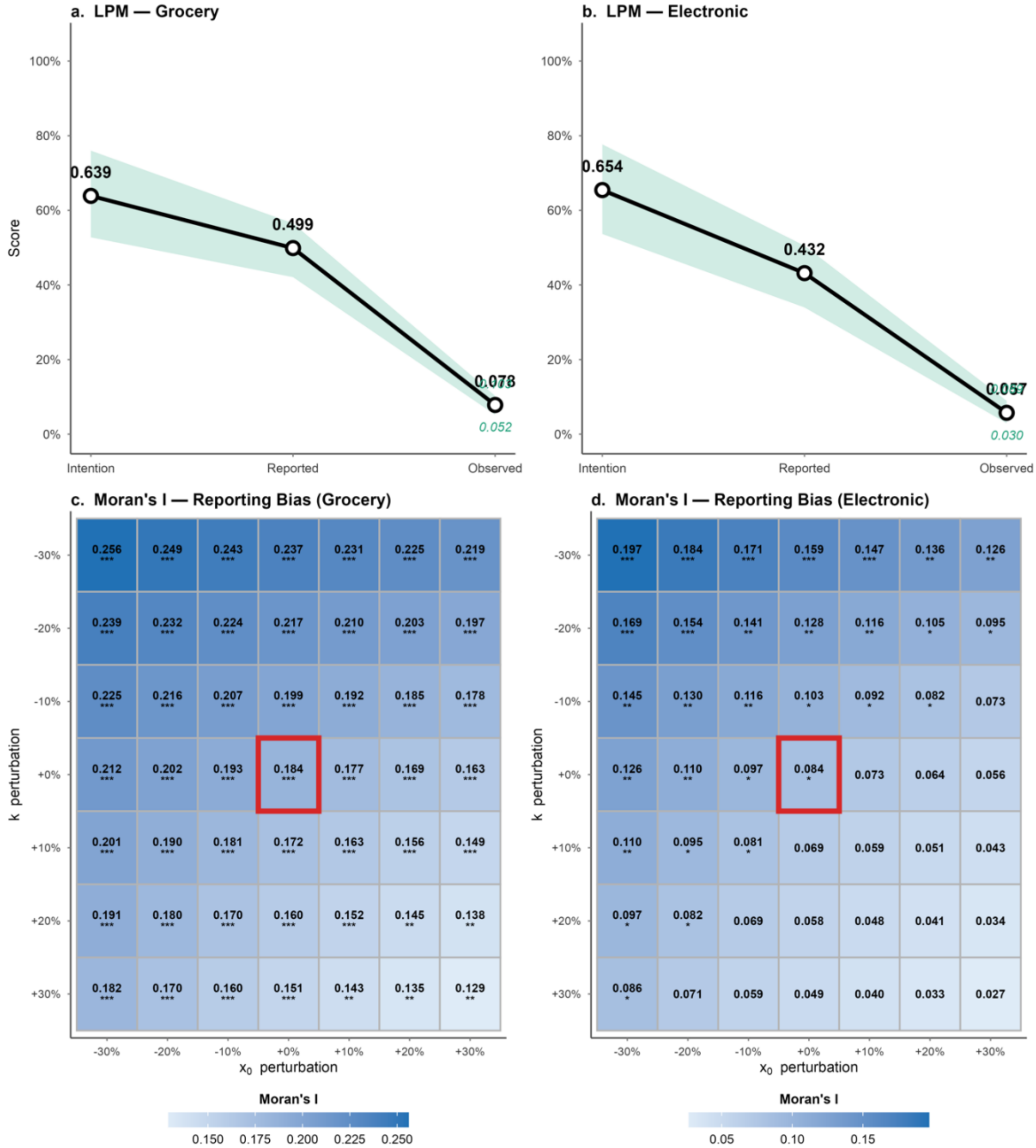


Supplementary Fig. 1 Spatial distribution of the Reporting Bias (RB) in the electronic domain across 150 Southeast Asian cities. Geospatial mapping of the green illusion (RB) for premium durable goods. Bubble size represents the magnitude of the unactualized behavioral potential under the BPN framework. Bubble color represents the threshold transition probability under the LPM framework, where darker red indicates a higher reporting bias. Global spatial autocorrelation analysis reveals significant geographic clustering for the LPM metric (Moran's $I = 0.084, * p < 0.05$), identifying distinct regional hotspots (e.g., Metro Manila and surrounding Philippine cities) where the probability-based reporting bias is exceptionally severe. In contrast, the linear magnitude of the gap (BPN) exhibits no significant spatial clustering (Moran's $I = 0.009$), reflecting the uniformly high systemic economic barriers associated with purchasing green electronic goods across the entire region. To accurately map the complete behavioural cascade across these frameworks, the effective analytical sample is restricted to N = 126 cities possessing strictly matched, complete data across psychometric surveys and objective transaction logs.

However, in the low-frequency, high-barrier electronic domain, significant spatial clustering is restricted to the LPM framework (LPM Moran's $I = 0.084, p < 0.05$). The absence of significant clustering in the BPN framework (Moran's $I = 0.005$) indicates a "floor effect" driven by macro-economic constraints. The raw magnitude of unrealised potential (BPN) for premium green durables is nearly universally high across all Southeast Asian cities, regardless of local spatial structure, due to overarching price premiums. Yet, the *probability* that a consumer crosses the threshold into committed green electronic purchasing (LPM) remains structurally bounded, clustering heavily in specific geographic zones (e.g., highly concentrated red hotspots in the Philippines). This divergence reinforces the utility of employing dual BPN and LPM frameworks: while BPN captures universal economic barriers, LPM isolates the specific, highly clustered structural friction that dictates whether sustainable intent successfully transitions into market reality.

Supplementary Note 3: Robustness of the LPM Framework

To ensure that the magnitude of the behavioral cascade and the spatial clustering observed in the main text are not artefacts of the LPM parameterization, we conducted a parameter sensitivity analysis. The LPM framework relies on a logistic function defined by a threshold inflection point (x_0) and a steepness parameter (k). We established a sensitivity cross-matrix, independently varying x_0 and k from -30% to $+30\%$ of their baseline values at 10% intervals, yielding 19 total scenarios (including the baseline).



Supplementary Fig. 2. Sensitivity analysis of the Logistic Probability Mapping (LPM) parameters. a–b, The behavioral cascade envelope for the grocery and electronic domains. The solid bold line represents the baseline LPM specification used in the main text. The shaded region denotes the maximum and minimum boundaries of the cascade across 48 alternative threshold (x_0) and steepness (k) parameter scenarios ($\pm 10\%, \pm 20\%, \pm 30\%$). The tight envelope confirms that the "green illusion" is highly robust to parameter specification. **c–d**, 19-scenario parameter heatmaps for spatial autocorrelation (Moran's I) of the Reporting Bias. The axes represent percentage deviations from the baseline parameters. The central red box indicates the baseline model. Cell color represents the magnitude of Moran's I, with asterisks indicating statistically significant spatial clustering (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). The cascade sensitivity analysis and spatial autocorrelation (Moran's I) calculations utilise a baseline grid of N = 150 cities, computed across all 49 parameter combinations.

Robustness of the Behavioral Cascade

As visualized in **Supplementary Fig. 2a–b**, varying these parameters alters the absolute probabilities marginally, but the fundamental architecture of the behavioural collapse remains perfectly intact. Across all parameter perturbations, the trajectory from high psychological intention to suppressed actualized market behavior exhibits a severe decline.

Robustness of Spatial Autocorrelation

Furthermore, we recalculated the global Moran's I for the Reporting Bias (the "green illusion") under every parameter variation (**Supplementary Fig. 2c–d**). The spatial clustering of the behavioural failure remains highly robust , revealing distinct, theoretically consistent sensitivities across domains:

- Grocery Domain (Panel c): Spatial clustering remains statistically significant ($p < 0.05$ to $p < 0.001$) across the *entire* comprehensive parameter space, anchored by a baseline Moran's I of 0.184 ($p < 0.001$). For high-frequency daily consumption, the regional divergence is probably an undeniable spatial phenomenon, immune to mathematical parameterization.
- Electronic Domain (Panel d): Geographic entrenchment is statistically significant at the baseline ($p < 0.05$) and under all negative perturbations (lower k and lower $\boldsymbol{x_0}$). However, significance is systematically lost under positive perturbations.

Theoretical Implications of Parameter Sensitivity

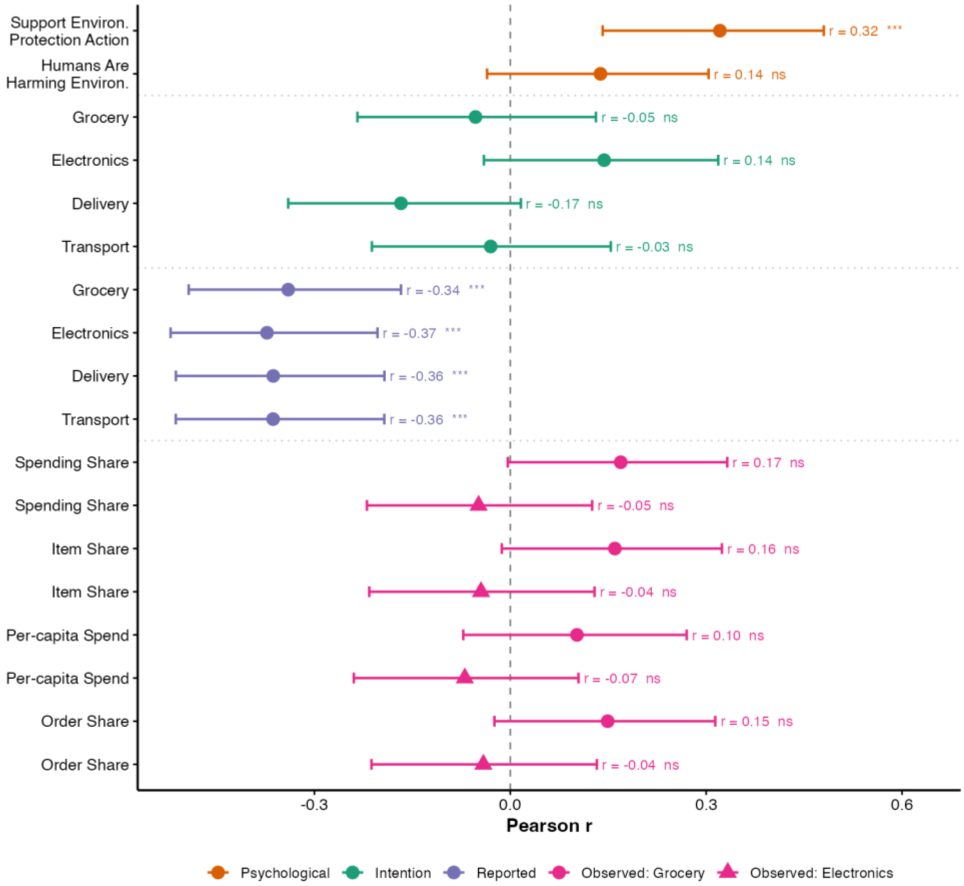
Beyond confirming statistical robustness, the sensitivity heatmaps may reveal a critical theoretical boundary regarding how urban morphology interacts with market friction. As observed in **Supplementary Fig. 2c–d**, while the spatial clustering of the Reporting Bias remains statistically significant across the matrix, the absolute magnitude of Moran's I gradually decreases as the threshold (x_0) or steepness (k) parameters increase (moving toward the bottom-right quadrants). Crucially, this spatial breakdown happens rapidly in the Electronic domain but is resisted by the Grocery domain.

This domain-specific attenuation probably reflects market realities. A drastically increased threshold (x_0) mathematically simulates an insurmountable macroeconomic barrier (e.g., prohibitive price premiums). Because electronics are inherently high-cost, high-barrier goods, artificially raising this threshold further simulates an extreme structural friction where the failure to actualise sustainable consumption becomes universally severe across all cities. This effectively flattens regional variance, meaning the distinct spatial advantages provided by integrated *Desakota* morphologies are overshadowed by universal macroeconomic lock-out.

Similarly, artificially inflating the steepness parameter (k) forces the probability distribution into a rigid, binary step-function, eroding the gradual nudging effect of physical urban landscapes. Therefore, the heatmaps may reveal a vital spatial reality: urban morphology functions as a powerful enabler precisely within bounded, probabilistic market conditions. It provides a robust, structurally invariant advantage for routine consumption (groceries), but its spatial power is naturally neutralised when macroeconomic exclusions render the intention-action gap unbridgeable (electronics under high friction).

Supplementary Note 4: Robustness of the Nature Connectedness Paradox under Behavioral Potential Normalization (BPN)

This supplementary note replicates the main-text analyses of the nature connectedness (NC) attitude paradox (**Fig. 2**) and the waterfall gap decomposition (**Fig. 3**) using Behavioral Potential Normalization (BPN), which quantifies behavioral gaps in terms of unrealized magnitude rather than the threshold-transition dynamics captured by Logistic Probability Mapping (LPM). The two frameworks are complementary: LPM emphasizes the probability of crossing behavioral thresholds, while BPN captures how far each city falls short of its maximum behavioral potential. Presenting both ensures that the internal calibrator finding is not an artifact of a single normalization choice.



Supplementary Fig. 3. **Robustness of the nature connectedness (NC) attitude paradox under Behavioral Potential Normalization (BPN).** The correlational cascade replicates the main-text Fig. 2 (LPM) using BPN, which quantifies behavioral gaps as unrealized magnitude rather than threshold-transition probability. NC retains a significant positive association with baseline psychological attitudes (r = 0.32, p < 0.001) and strongly negative correlations with self-reported behavior across all domains (r = −0.34 to −0.37, p < 0.001). Under BPN, all observed market behavior correlations are non-significant for both grocery (r = 0.15–0.17, ns) and electronic (r = −0.04 to −0.07, ns) domains. This contrasts with the LPM specification, where grocery-domain share metrics reach marginal significance (r = 0.17–0.18, p < 0.05), suggesting that NC may facilitate the probability of crossing a minimal green purchasing threshold without translating into meaningful magnitude of sustainable consumption. The disappearance of the grocery signal under BPN reinforces the main-text conclusion that NC functions as an internal calibrator of self-perception rather than a substantive driver of market behavior.

The BPN-normalized correlational cascade (**Supplementary Fig. 3**) replicates the core structure of the attitude paradox reported in the main text. NC retains a significant positive association with baseline psychological attitudes (r = 0.32, p < 0.001) and exhibits no significant correlation with any domain-specific intention. The strongly negative correlations with self-reported behavior are identical across normalization frameworks ($r = -0.34$ to -0.37, $p < 0.001$), as expected given that self-reported frequency measures are normalization-independent.

The critical distinction under BPN emerges at the level of observed market behavior. Whereas the LPM framework detects weak but statistically significant positive correlations between NC and grocery-domain share metrics (spending share and item share: $r = 0.18$, $p < 0.05$; order share: $r = 0.17$, $p < 0.05$), the BPN framework renders all corresponding correlations non-significant (grocery spending share: $r = 0.17$, ns; item share: $r = 0.16$, ns; order share: $r = 0.15$, ns). The electronic domain remains uniformly non-significant under both frameworks, with BPN point estimates clustering near zero or slightly negative ($r = -0.04$ to -0.07).

This divergence has important interpretive implications. The marginal grocery-domain signal under LPM suggests that NC may facilitate the *probability* of crossing a minimal threshold into routine green purchasing — a transition-sensitive effect that LPM is designed to detect. However, BPN reveals that this threshold crossing does not translate into meaningful *magnitude* of green consumption relative to each city's behavioral potential. In other words, even where NC nudges cities marginally past a probabilistic tipping point, the actual volume of sustainable purchasing remains negligible relative to what the market could support. This pattern reinforces the main-text conclusion that NC functions as an internal calibrator of self-perception rather than a substantive driver of market behavior.

Supplementary Note 5: Estimation of the Counterfactual Effect of Nature Connectedness on Intention-behavior Gaps

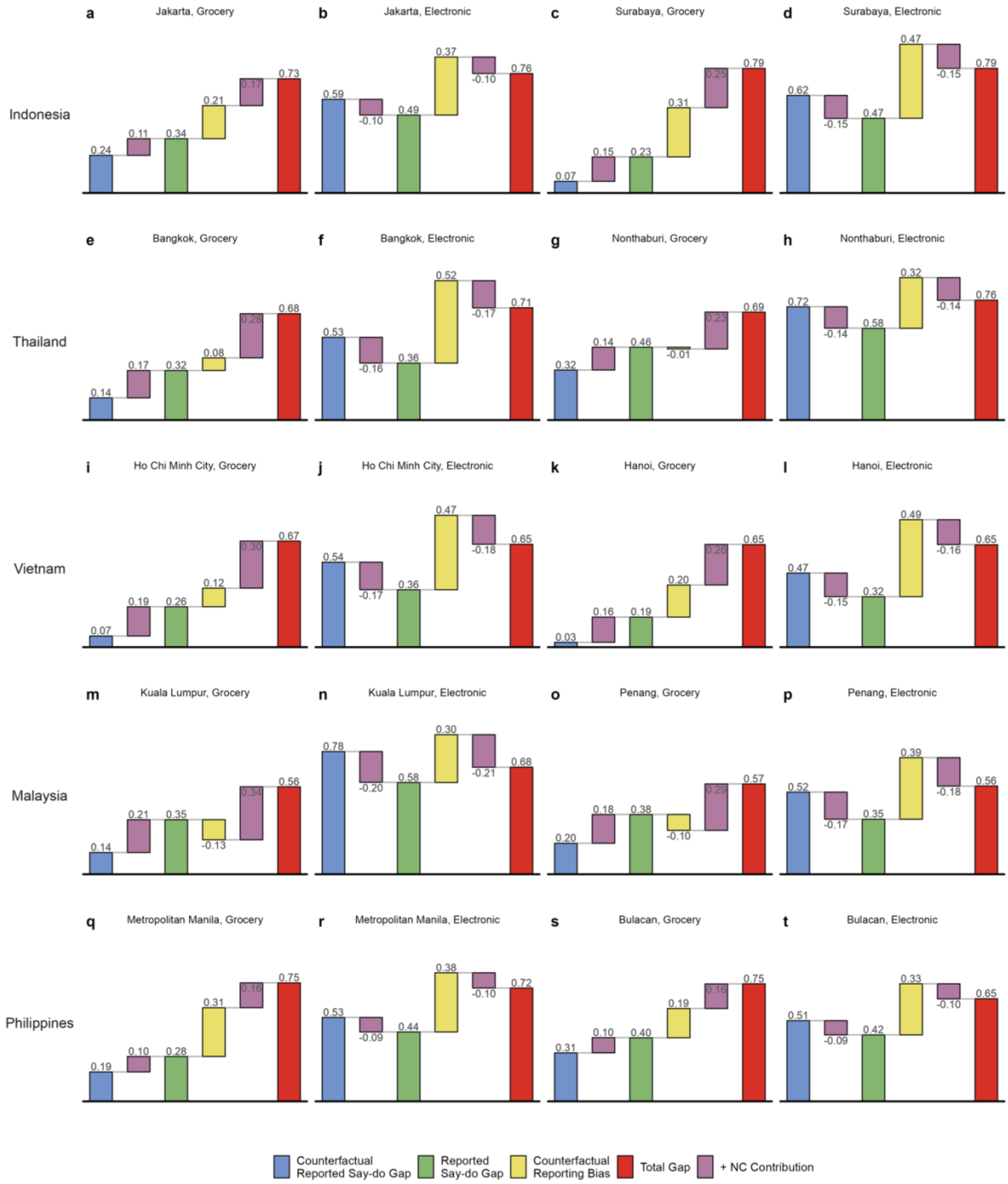
According to the Eq. (15) in **Section: Statistical Models** of the main text, we formulate the estimation models separately for two gap metrics as follows, namely reported say-do gap (Gap_i^1) and reporting bias (Gap_i^2), respectively.

$$
\begin{aligned}
Gap_i^1 &= \beta_0^1 + \beta_1^1 \cdot NC_i + \textstyle\sum_m \gamma_m \cdot \mathrm{Control}_{i,m} + \epsilon_i^1 \\
Gap_i^2 &= \beta_0^2 + \beta_1^2 \cdot NC_i + \textstyle\sum_m \gamma_m \cdot \mathrm{Control}_{i,m} + \epsilon_i^2
\end{aligned} \tag{1}
$$

Following the method of estimating the counterfactual results without the effect of nature connectedness (P. Chen et al., 2022; Eskander & Fankhauser, 2020), we can estimate the counterfactual gap metrics by excluding the effect of nature connectedness, for instance, $\widetilde{Gap}_i^1 = \beta_0^1 + \sum_m \gamma_m \cdot \mathrm{Control}_{i,m} + \epsilon_i^1$, because the regression results of the effect of nature connectedness are statistically significant. In this regard, the counterfactual gap metrics can be estimated by,

$$
\begin{aligned}
\widehat{Gap}_i^1 &= \widetilde{Gap}_i^1 + \hat{\beta}_1^1 \cdot NC_i \\
\widehat{Gap}_i^2 &= \widetilde{Gap}_i^2 + \hat{\beta}_1^2 \cdot NC_i
\end{aligned} \tag{2}
$$

where $\hat{\beta}_1^1$ and $\hat{\beta}_1^2$ are estimated coefficients in the Eq. (15). Therefore, the aggregate gap of reported say-do gap and reporting bias can be represented by: $\widehat{Gap}_i^1 + \widehat{Gap}_i^2$.



Supplementary Fig. 4. Waterfall gap decomposition under BPN for ten representative cities across five nations. a–d, Indonesia (Jakarta, Surabaya). **e–h**, Thailand (Bangkok, Nonthaburi). **i–l**, Vietnam (Ho Chi Minh City, Hanoi). **m–p**, Malaysia (Kuala Lumpur, Penang). **q–t**, Philippines (Metropolitan Manila, Bulacan). Each panel decomposes the total observed gap (red) into counterfactual baselines (blue: reported say-do gap; yellow: reporting bias, simulated at NC = 0) and NC contributions (purple: additive for the reported say-do gap; subtractive for the reporting bias). Left columns show the grocery domain; right columns show the electronic domain. The qualitative pattern is identical to the main-text LPM decomposition (**Fig. 3**): NC uniformly inflates the reported say-do gap while contracting the reporting bias across all 20 city–domain combinations, confirming that the internal calibrator mechanism is robust to normalization choice. BPN yields systematically larger total gaps (range: 0.32–0.79) compared to LPM (range: 0.25–0.59), consistent with BPN's sensitivity to the absolute magnitude of unrealized behavioral potential. NC contribution magnitudes are correspondingly amplified (e.g., Metropolitan Manila grocery RG: BPN +0.34 vs. LPM +0.22), but the near-zero-sum property — whereby NC-driven expansion of the reported gap and contraction of the reporting bias approximately cancel — is preserved, leaving total observed gaps stubbornly intact regardless of normalization framework.

The BPN waterfall decomposition (**Supplementary Fig. 4**) confirms the qualitative universality of the internal calibrator mechanism across all ten representative cities and both consumption domains. As in the LPM main-text figure, NC contributions are uniformly positive for the reported say-do gap (RG) and uniformly negative for the reporting bias (RB) in every city–domain combination, confirming that the cognitive redistribution dynamic — NC transferring behavioral failure from a hidden green illusion to an overt aspirational gap — is robust to normalization choice.

Three systematic quantitative differences emerge under BPN, all consistent with the framework's emphasis on unrealized behavioral magnitude:

First, total observed gaps (OG) are substantially larger under BPN than under LPM. BPN total gaps range from approximately 0.32 (Nonthaburi, Grocery) to 0.79 (Surabaya, Electronic), compared to the LPM range of 0.25 to 0.59. This amplification reflects BPN's sensitivity to the absolute distance between stated intentions and market behavior, which is inherently larger when expressed as a proportion of unrealized potential rather than a probability differential.

Second, counterfactual baselines — both for the reported say-do gap and the reporting bias — are correspondingly elevated, indicating that even in the absence of NC, the structural distance between intention and behavior is more severe when measured in magnitude terms.

Third, NC contribution magnitudes are amplified under BPN. For instance, NC-driven inflation of the grocery RG reaches 0.34 in Metropolitan Manila (BPN) compared to 0.22 (LPM), and NC-driven contraction of the electronic RB reaches −0.21 in Metropolitan Manila (BPN) compared to −0.13 (LPM). This amplification is expected: because BPN operates on a wider scale of unrealized potential, the absolute effect sizes of any predictor — including NC — are mechanically stretched.

Despite these quantitative differences, the near-zero-sum property of the NC redistribution is preserved. Across all 20 city–domain panels, the NC-driven expansion of the RG and contraction of the RB approximately cancel, leaving total observed gaps stubbornly intact. The overarching conclusion is therefore invariant to normalization: NC recalibrates where in the behavioral cascade the failure is *perceived* to occur, without materially reducing the failure itself.

Taken together, the BPN results serve as a stringent robustness check. They demonstrate that (1) the attitude paradox — NC positively predicting attitudes but negatively predicting self-reported behavior and failing to predict observed behavior — holds regardless of how behavioral gaps are operationalized; (2) the marginal grocery-domain signal detected under LPM does not survive under magnitude-based normalization, reinforcing its fragility; and (3) the internal calibrator mechanism is a structural property of the NC–behavior relationship in Southeast Asian cities, not a methodological artifact.

Supplementary Note 6: The "Internal Calibrator" Transmission Mechanism

The regression results in **Supplementary Table 2** confirm that nature connectedness (NC) operates as a cognitive re-calibrator within the behavioral cascade. Across all specifications, NC exerts structurally consistent but directionally opposing forces on the two behavioral gaps.

Inflation of the Reported Say-do Gap (RG)

In all domains, NC is significantly and positively associated with the reported say-do gap ($\beta \in [0.222, 0.624], p < 0.001$). This indicates that as individuals feel more connected to nature, the discrepancy between their environmental intentions and their self-reported habits actually **increases.** The effect is notably stronger in the electronic domain (BPN: $\beta = 0.624$; LPM: $\beta = 0.412$) than in the grocery domain (BPN: $\beta = 0.387$; LPM: $\beta = 0.222$), suggesting that NC-driven aspirational inflation is amplified for high-barrier, infrequent purchases.

Contraction of the Reporting Bias (RB)

Concurrently, NC is significantly and negatively associated with the reporting bias across all specifications ($\beta \in [-0.383, -0.236]$, $p < 0.001$). This confirms that higher nature connectedness reduces the "Green Illusion" — the tendency of individuals to over-claim sustainable actions on surveys relative to their objective market behavior. Unlike the RG effect, the magnitude of RB contraction is comparatively stable across domains, indicating that NC-driven honesty correction operates with similar force regardless of product category.

The Internal Calibrator Synthesis

Because NC fails to promote actual observed market behavior (as established in the main text), these opposing coefficients mathematically define the internal calibrator. High NC does not physically bridge the chasm to sustainable consumption; instead, it increases environmental self-awareness, which restrains individuals from over-reporting their actions. Consequently, NC transfers the statistical failure of the urban system from a hidden reporting bias (RB) into an overt, reported say-do gap (RG). This internal cognitive redistribution ensures that total observed gaps remain severe, even as individuals become more "honest" about their own behavioral failures.

Socio-Demographic and Digital Mediators

Beyond NC, individual capacities differentially mediate the behavioral cascade. Online shopping experience consistently acts as a structural facilitator in the electronic domain, significantly reducing the reported gap (BPN: $\beta = -0.089$, $p < 0.001$; LPM: $\beta = -0.055$, $p < 0.01$), likely because frequent digital commerce experience compresses the aspirational distance between intention and reported behavior for technology-mediated purchases. However, online shopping experience simultaneously increases the electronic-domain reporting bias (BPN: $\beta = 0.066$, $p < 0.01$; LPM: $\beta = 0.030$, $p < 0.05$), suggesting that digitally experienced consumers are paradoxically more prone to over-claiming green electronic purchases.

Higher education presents a more complex profile. It significantly inflates the reported gap across all specifications ($\beta \in [0.181, 0.298]$, $p < 0.05$), likely driven by higher baseline environmental awareness amplifying the aspirational distance between intentions and self-reported actions. Simultaneously, education significantly suppresses the reporting bias specifically in the electronic domain (BPN: $\beta = -0.224$, $p < 0.05$; LPM: $\beta = -0.164$, $p < 0.05$), while showing no significant effect in the grocery domain. This suggests that highly educated consumers possess a more realistic self-assessment of their premium, low-frequency green purchases, resulting in domain-specific internal calibration that mirrors — though does not replicate — the NC mechanism.

Social media usage and GDP per capita exert no statistically significant effects on either gap metric across any specification, indicating that neither digital exposure nor aggregate economic development systematically shapes the cognitive dynamics of the green illusion at the city level.

Macroeconomic Heterogeneity: Country Fixed Effects

The country-level fixed effects (with Indonesia as the reference category) reveal selective regional signatures. The Philippines exhibits a significantly inflated reporting bias relative to Indonesia in the grocery domain (BPN: $\beta = 0.150$, $p < 0.01$; LPM: $\beta = 0.143$, $p < 0.001$), with a marginally significant effect extending to the electronic domain under LPM ($\beta = 0.073$, $p < 0.05$). This highlights how transitioning institutional environments and lower levels of green market formalization can expand the cognitive space for the green illusion to flourish.

Vietnam displays a distinctive dual pattern: significantly compressed reported gaps in the grocery domain (BPN: $\beta = -0.251$, $p < 0.001$; LPM: $\beta = -0.152$, $p < 0.001$) alongside significantly elevated reporting bias (BPN: $\beta = 0.184$, $p < 0.05$; LPM: $\beta = 0.151$, $p < 0.01$). This combination suggests that Vietnamese consumers report behaviors that are closer to their intentions — yielding a smaller RG — yet simultaneously over-claim relative to their observed purchases, producing a larger RB. The net effect is a structurally different composition of the total behavioral gap compared to the Indonesian baseline.

Malaysia, Singapore, and Thailand show no statistically significant deviations from the Indonesian baseline on either gap metric, though Singapore's point estimates for reporting bias reduction are notably large in magnitude (BPN Grocery: $\beta = -0.357$; LPM Grocery: $\beta = -0.334$) but fail to reach significance due to the small within-sample representation. This pattern is suggestive — consistent with a mature, tightly regulated market where transparent supply chains and stringent eco-labelling constrain the scope for subjective over-claiming — but requires confirmation with larger samples.

Supplementary Table 2. Regression results of nature connectedness on gap metrics

Variables	Reported Say-do Gap (RG)				Reporting Bias (RB)			
	BPN (Magnitude)		LPM (Probability)		BPN (Magnitude)		LPM (Probability)	
	Grocery	Electronic	Grocery	Electronic	Grocery	Electronic	Grocery	Electronic
Intercept	0.277**	0.428***	0.142*	0.228**	0.374***	0.217*	0.432***	0.348***
	[0.028, 0.526]	[0.124, 0.732]	[-0.006, 0.291]	[0.030, 0.426]	[0.112, 0.636]	[-0.038, 0.473]	[0.262, 0.602]	[0.191, 0.505]
Nature connectedness	0.387***	0.624***	0.222***	0.412***	-0.364***	-0.383***	-0.236***	-0.246***
	[0.135, 0.639]	[0.317, 0.931]	[0.072, 0.373]	[0.212, 0.613]	[-0.629, -0.099]	[-0.641, -0.124]	[-0.408, -0.064]	[-0.405, -0.087]
GDP per capita	-0.161	0.076	-0.098	0.057	0.28	0.102	0.281	0.147
	[-0.658, 0.336]	[-0.530, 0.682]	[-0.394, 0.198]	[-0.338, 0.452]	[-0.242, 0.803]	[-0.408, 0.612]	[-0.059, 0.620]	[-0.166, 0.460]
Online Shopping Exp.	-0.041	-0.089***	-0.027*	-0.055**	0.021	0.066**	-0.001	0.030*
	[-0.094, 0.012]	[-0.154, -0.023]	[-0.059, 0.005]	[-0.098, -0.013]	[-0.035, 0.077]	[0.011, 0.121]	[-0.037, 0.036]	[-0.004, 0.064]
High Education	0.289**	0.298*	0.185**	0.181*	-0.067	-0.224*	-0.077	-0.164*
	[0.029, 0.549]	[-0.019, 0.615]	[0.030, 0.340]	[-0.026, 0.388]	[-0.341, 0.206]	[-0.491, 0.043]	[-0.255, 0.100]	[-0.328, 0.000]
Social Media Hrs.	0	0	0	0	0	0	0	0
	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]	[-0.000, 0.000]
Dummy (Malaysia)	-0.002	-0.05	-0.008	-0.032	-0.107	-0.028	-0.088	-0.038
	[-0.171, 0.167]	[-0.256, 0.157]	[-0.109, 0.093]	[-0.166, 0.103]	[-0.285, 0.071]	[-0.202, 0.145]	[-0.203, 0.028]	[-0.145, 0.069]
Dummy (Philippines)	-0.043	0.03	-0.008	0.035	0.150**	0.056	0.143***	0.073*
	[-0.180, 0.093]	[-0.136, 0.197]	[-0.089, 0.074]	[-0.074, 0.143]	[0.006, 0.294]	[-0.085, 0.196]	[0.050, 0.236]	[-0.013, 0.159]

Variables	Reported Say-do Gap (RG)				Reporting Bias (RB)			
Dummy (Singapore)	0.041	-0.103	0.006	-0.059	-0.357	-0.05	-0.334	-0.127
	[-0.577, 0.659]	[-0.857, 0.652]	[-0.362, 0.375]	[-0.550, 0.433]	[-1.007, 0.293]	[-0.685, 0.585]	[-0.756, 0.089]	[-0.517, 0.264]
Dummy (Thailand)	-0.04	-0.078	-0.013	-0.039	0.03	0.051	-0.031	-0.012
	[-0.181, 0.101]	[-0.250, 0.093]	[-0.096, 0.071]	[-0.151, 0.072]	[-0.117, 0.178]	[-0.093, 0.195]	[-0.127, 0.065]	[-0.100, 0.077]
Dummy (Vietnam)	-0.251***	-0.16	-0.152***	-0.118	0.184*	0.003	0.151**	0.032
	[-0.432, -0.069]	[-0.381, 0.062]	[-0.260, -0.043]	[-0.262, 0.027]	[-0.007, 0.375]	[-0.184, 0.189]	[0.027, 0.275]	[-0.083, 0.147]
N	115	115	115	115	115	115	115	115
R^2	0.246	0.285	0.248	0.282	0.252	0.24	0.332	0.281
Adj. R^2	0.174	0.216	0.176	0.213	0.18	0.167	0.268	0.211
F-statistic	3.39	4.15	3.43	4.08	3.5	3.28	5.16	4.06
p-value (F)	0.0007	0.0001	0.0006	0.0001	0.0005	0.001	0	0.0001

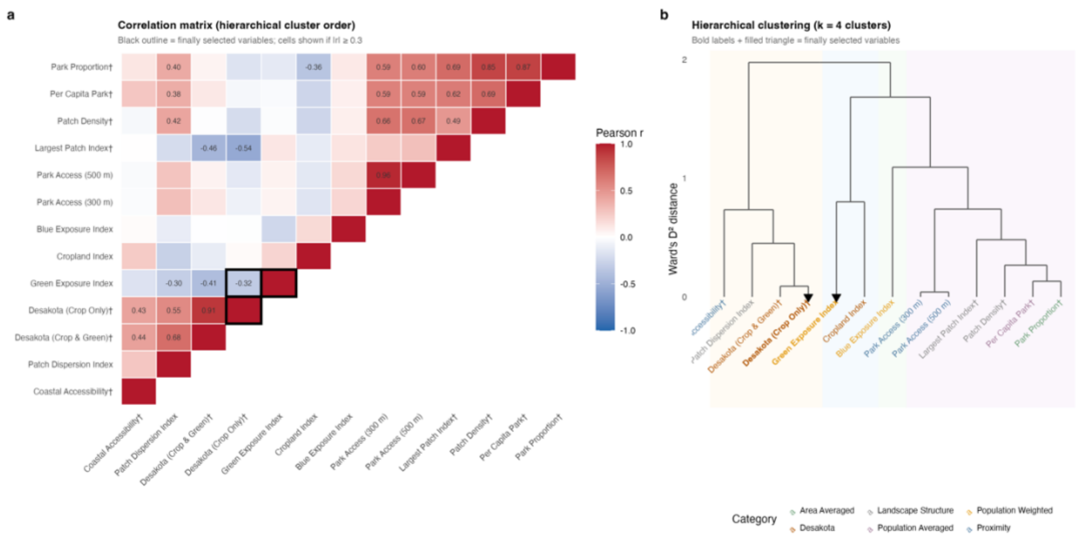
Note: Coefficients represent the effect of NC on the Reported Say-do Gap (RG) and Reporting Bias (RB) across both grocery and electronic domains, utilizing both linear (BPN) and probabilistic (LPM) frameworks. Socio-demographic and economic covariates are controlled across all models. 95% Confidence intervals in brackets. Significance: * p<0.05, ** p<0.01, *** p<0.001.

Supplementary Note 7: Spatial Index Selection

A primary objective of this study was to evaluate and compare the distinct moderating effects of two contrasting urban morphological paradigms on sustainable consumption behaviors: conventional urban greening (representative of the Global North aesthetic/recreational model) and the highly integrated productive landscape (characteristic of Southeast Asian Desakota regions). To accurately decompose these structural pathways, it was imperative to select spatial metrics that strictly isolated these two theoretical constructs without introducing conceptual overlap or mathematical multicollinearity.

Selection of Conceptual Archetypes. Our initial spatial database contained 13 candidate variables spanning six morphological categories (Area Averaged, Landscape Structure, Population Weighted, Population Averaged, Proximity, and Desakota). Rather than broadly including all available spatial data, we deliberately selected two defining archetypes that offered the cleanest conceptual operationalization of our targeted paradigms:

1. *Conventional Greening Domain (Green Exposure Index).* To represent traditional urban greening, we selected the Green Exposure Index. While purely structural metrics (such as Patch Density or Park Proportion) merely quantify the physical existence of land cover, the Green Exposure Index is population-weighted. It was specifically chosen because it captures the actual human–nature interface—quantifying whether citizens are physically situated to interact with the greenery—making it the most theoretically relevant proxy for testing psychologically mediated behavioral pathways.
2. *Productive Landscape Domain (Desakota Index — Crop Only).* To represent the utilitarian, agricultural paradigm, we deliberately selected the Desakota Index (Crop Only). By explicitly isolating the "Crop Only" metric and discarding blended indices (such as Desakota Crop & Green), we ensured a strict, uncontaminated conceptual boundary between purely productive/agricultural land use and conventional aesthetic greenery.



Supplementary Fig. 5. Empirical validation of spatial index selection via correlation structure and hierarchical clustering. a, Pearson correlation matrix of 13 candidate spatial variables ordered by hierarchical clustering; cells are displayed only where $|r| \geq 0.3$, and black outlines mark the two finally selected variables (Green Exposure Index and Desakota Index, Crop Only). b, Ward's D²-linkage dendrogram cut at $k = 4$ clusters; bold labels and filled triangles denote the finally selected variables. Variables span six morphological categories (colour-coded): Area Averaged, Landscape Structure, Population Weighted, Population Averaged, Proximity, and Desakota. The two selected archetypes exhibit a weak inverse cross-correlation ($r = -0.32$), confirming their near-orthogonality, while the conventional park metrics form a tightly intercorrelated block ($r = 0.49$–0.87). *Complete-case N=127 observations.*

Empirical Validation via Spatial Clustering. To statistically validate our theoretical selection and confirm the orthogonality of these two paradigms, we computed the Pearson correlation matrix of all 13 candidate variables across our sampled cities and applied hierarchical clustering (Ward's D^2 linkage, $k = 4$; **Supplementary Fig. 5**).

The correlogram (**Supplementary Fig. 5a)** revealed a clear structural bifurcation in the urban landscape. The conventional park metrics—Park Proportion, Per Capita Park, Patch Density, Largest Patch Index, and the two Park Access radii—formed a tightly intercorrelated block ($r = 0.49$–0.87), confirming that retaining the full suite would be statistically redundant. The Desakota variables, by contrast, clustered with the Cropland Index in a separate branch of the dendrogram (**Supplementary Fig. 5b**), forming an independent productive-landscape domain.

Crucially, the Pearson correlation between our two selected archetypes—Green Exposure Index and Desakota Index (Crop Only)—was $r = -0.32$, indicating a weak-to-moderate inverse association. More broadly, the Green Exposure Index exhibited negative cross-correlations with all Desakota and cropland metrics ($r = -0.30$ to -0.41), while remaining largely uncorrelated with the conventional park block. The dendrogram (**Supplementary Fig. 5b**) corroborated this separation: at the four-cluster solution, the two selected variables are adjacent in the tree yet merge only at the highest within-group distance, reflecting their conceptual opposition rather than redundancy (bold labels and filled triangles mark the finally selected variables).

This clustering analysis validated our variable selection, demonstrating empirically that the Green Exposure Index and the Desakota Index (Crop Only) capture fundamentally distinct, near-orthogonal spatial realities. Consequently, these two conceptually clean variables were carried forward into the main analyses to model the structural drivers of the intention–behaviour gap.

Based on these empirical screening results, the Green Exposure Index and the *Desakota* (Crop Only) Index were purposefully selected as the two contrasting spatial paradigms for the behavioral modelling in main text. Notably, for clarity in the main text, the *Desakota* (Crop Only) metric is referred to simply as the *Desakota* Index. This selection allows us to rigorously contrast the behavioral impacts of a failing imported aesthetic model against a highly successful native, productive morphology.

Supplementary Note 8: Sensitivity analysis of the Desakota index

To assess whether the core findings are sensitive to methodological choices in constructing the Desakota Index, we conducted a multiverse-style robustness analysis spanning three dimensions of index construction: (i) the moving-window kernel size used to compute land-use mixture and fragmentation (8 variants, from 7×7 to 21×21 pixels), (ii) the relative weighting of the mixture and fragmentation sub-indices (DesaMix:DesaFrag = 0.3:0.7, 0.5:0.5, 0.7:0.3), and (iii) the cropland definition (CropOnly vs. CropAndGreen). Each variant was crossed with three dependent variables (Reported Say-do Gap, Reporting Bias, and Observed Market Behavior) across two consumption domains (Grocery and Electronics), yielding 78 model specifications. For every specification, we re-estimated the full mediation decomposition, namely Total, Direct (independent of NC), and Indirect (via NC) effects, using the same quasi-Bayesian simulation approach as the main analysis (500 iterations per model). Results are summarised in **Supplementary Tables 3-5** and **Supplementary Fig**. **6-8**.

Sensitivity to moving-window kernel size

The baseline Desakota Index employs a 9×9 pixel (~270 m × 270 m) moving window. We recomputed the index at eight kernel sizes from 7×7 (~210 m) to 21×21 (~630 m) (**Supplementary Table 3**).

Across all 48 specifications, the core findings are fully preserved. The total effect on observed market behavior remains positive at every window size (Grocery: $\beta = 0.39–0.41$; Electronics: $\beta = 0.37–0.39$; all $p < 0.001$), with the direct structural pathway accounting for the vast majority (Grocery: $\beta = 0.40–0.41$; Electronics: $\beta = 0.38–0.39$; all $p < 0.001$). The indirect pathway via NC is consistently small and non-significant across all specifications (both domains: $p > 0.05$), consistent with the pattern observed in the baseline model. Effects on both the reported say-do gap and reporting bias remain non-significant throughout (all total-effect $p > 0.05$). These patterns confirm that the structural enablement finding does not depend on the spatial resolution of the analysis kernel.

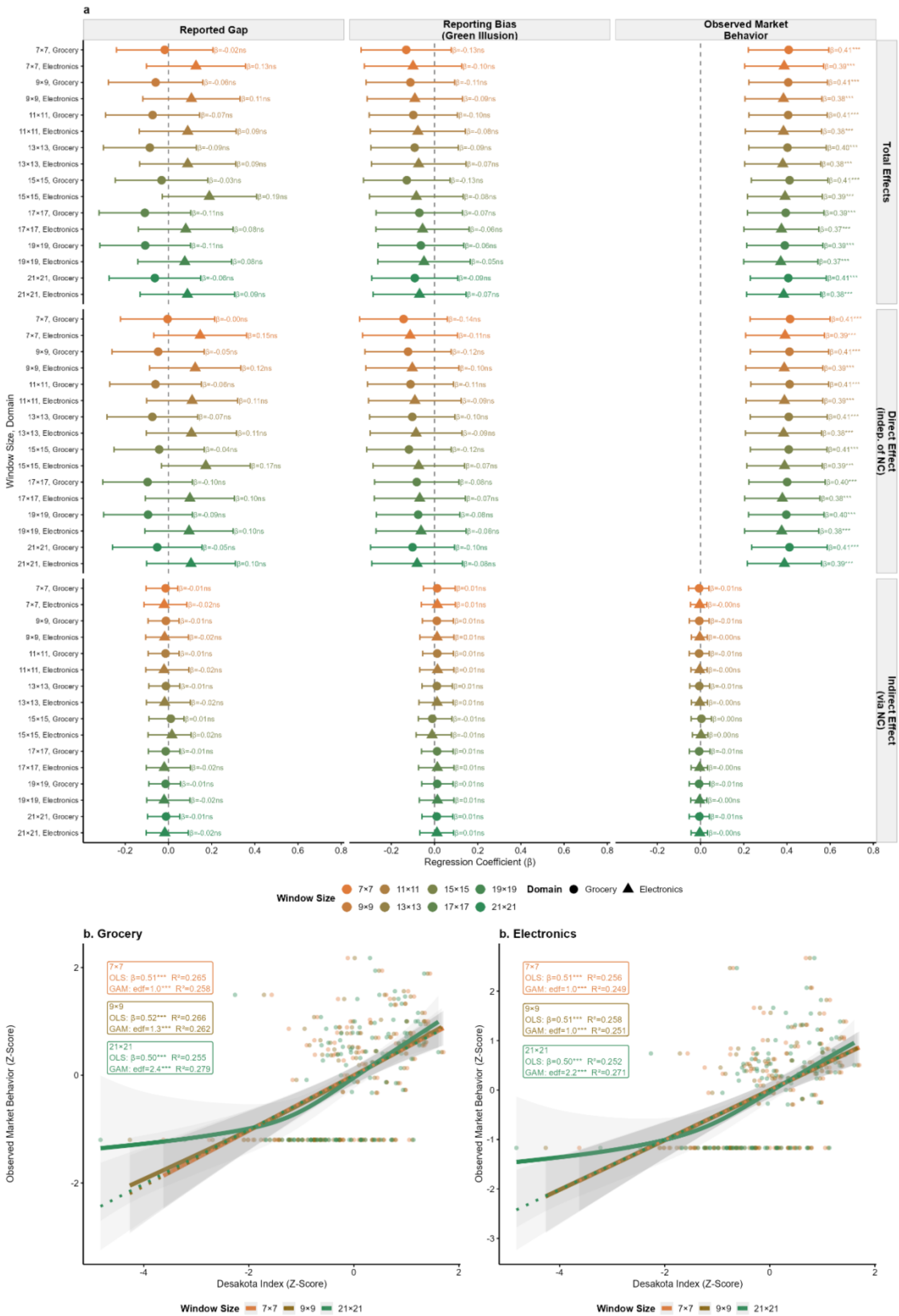
Supplementary Table 3. Sensitivity of Desakota effects to moving-window kernel size

Weight	Type	Domain	Total β	*p*	Direct β	*p*	Indirect β	*p*
7	Obs	Grocery	0.41	***	0.41	***	-0.01	*ns*
7	Obs	Electronics	0.39	***	0.39	***	0.00	*ns*
7	RG	Grocery	-0.02	*ns*	0.00	*ns*	-0.01	*ns*
7	RG	Electronics	0.13	*ns*	0.15	*ns*	-0.02	*ns*
7	RB	Grocery	-0.13	*ns*	-0.14	*ns*	0.01	*ns*
7	RB	Electronics	-0.10	*ns*	-0.11	*ns*	0.01	*ns*
9 (baseline)	Obs	Grocery	0.41	***	0.41	***	-0.01	*ns*
9 (baseline)	Obs	Electronics	0.38	***	0.39	***	0.00	*ns*
9 (baseline)	RG	Grocery	-0.06	*ns*	-0.05	*ns*	-0.01	*ns*
9 (baseline)	RG	Electronics	0.11	*ns*	0.12	*ns*	-0.02	*ns*

9 (baseline)	RB	Grocery	-0.11	*ns*	-0.12	*ns*	0.01	*ns*
9 (baseline)	RB	Electronics	-0.09	*ns*	-0.10	*ns*	0.01	*ns*
11	Obs	Grocery	0.41	***	0.41	***	-0.01	*ns*
11	Obs	Electronics	0.38	***	0.39	***	0.00	*ns*
11	RG	Grocery	-0.07	*ns*	-0.06	*ns*	-0.01	*ns*
11	RG	Electronics	0.09	*ns*	0.11	*ns*	-0.02	*ns*
11	RB	Grocery	-0.10	*ns*	-0.11	*ns*	0.01	*ns*
11	RB	Electronics	-0.08	*ns*	-0.09	*ns*	0.01	*ns*
13	Obs	Grocery	0.40	***	0.41	***	-0.01	*ns*
13	Obs	Electronics	0.38	***	0.38	***	0.00	*ns*
13	RG	Grocery	-0.09	*ns*	-0.07	*ns*	-0.01	*ns*
13	RG	Electronics	0.09	*ns*	0.11	*ns*	-0.02	*ns*
13	RB	Grocery	-0.09	*ns*	-0.10	*ns*	0.01	*ns*
13	RB	Electronics	-0.07	*ns*	-0.09	*ns*	0.01	*ns*
15	Obs	Grocery	0.41	***	0.41	***	0.00	*ns*
15	Obs	Electronics	0.39	***	0.39	***	0.00	*ns*
15	RG	Grocery	-0.03	*ns*	-0.04	*ns*	0.01	*ns*
15	RG	Electronics	0.19	*ns*	0.17	*ns*	0.02	*ns*
15	RB	Grocery	-0.13	*ns*	-0.12	*ns*	-0.01	*ns*
15	RB	Electronics	-0.08	*ns*	-0.07	*ns*	-0.01	*ns*
17	Obs	Grocery	0.39	***	0.40	***	-0.01	*ns*
17	Obs	Electronics	0.37	***	0.38	***	0.00	*ns*
17	RG	Grocery	-0.11	*ns*	-0.10	*ns*	-0.01	*ns*
17	RG	Electronics	0.08	*ns*	0.10	*ns*	-0.02	*ns*
17	RB	Grocery	-0.07	*ns*	-0.08	*ns*	0.01	*ns*
17	RB	Electronics	-0.06	*ns*	-0.07	*ns*	0.01	*ns*
19	Obs	Grocery	0.39	***	0.40	***	-0.01	*ns*
19	Obs	Electronics	0.37	***	0.38	***	0.00	*ns*
19	RG	Grocery	-0.11	*ns*	-0.09	*ns*	-0.01	*ns*
19	RG	Electronics	0.08	*ns*	0.10	*ns*	-0.02	*ns*
19	RB	Grocery	-0.06	*ns*	-0.08	*ns*	0.01	*ns*
19	RB	Electronics	-0.05	*ns*	-0.06	*ns*	0.01	*ns*
21	Obs	Grocery	0.41	***	0.41	***	-0.01	*ns*

21	Obs	Electronics	0.38	***	0.39	***	0.00	*ns*
21	RG	Grocery	-0.06	*ns*	-0.05	*ns*	-0.01	*ns*
21	RG	Electronics	0.09	*ns*	0.10	*ns*	-0.02	*ns*
21	RB	Grocery	-0.09	*ns*	-0.10	*ns*	0.01	*ns*
21	RB	Electronics	-0.07	*ns*	-0.08	*ns*	0.01	*ns*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, “ns” indicates non-significant results.



Supplementary Fig. 6. Sensitivity to moving-window kernel size. a, Behaviour effects remain robust across all eight window sizes (all $p < 0.001$), while other DVs are non-significant. b, OLS and GAM scatter fits for three representative windows confirm stability.

Sensitivity to sub-index weighting

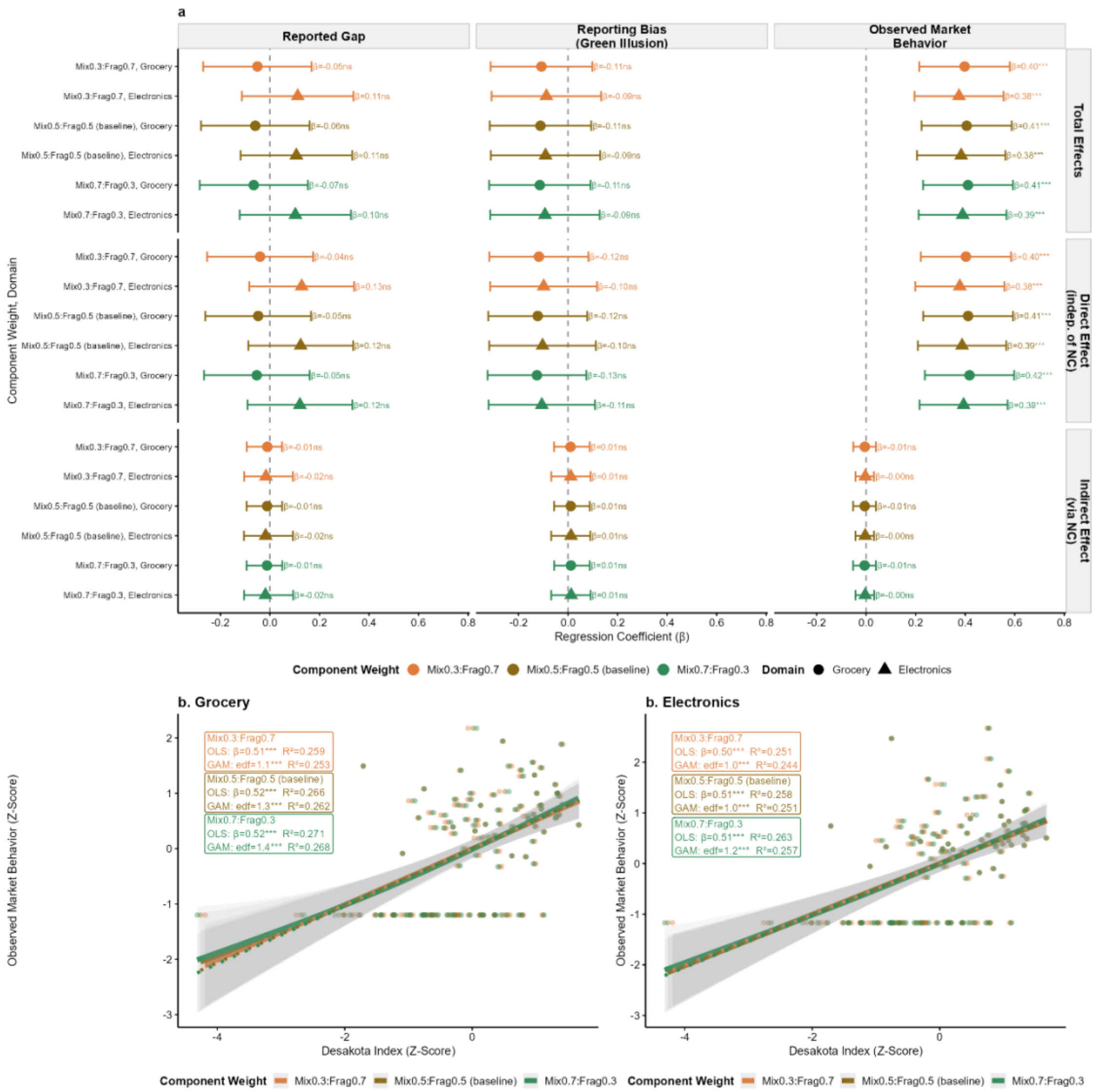
The baseline index assigns equal weight to the mixture and fragmentation sub-indices (0.5:0.5). We tested mixture-dominant (0.7:0.3) and fragmentation-dominant (0.3:0.7) alternatives (**Supplementary Table 4**).

Coefficient variation is small: for observed market behavior, total-effect β spans 0.40–0.41 in Grocery and 0.38–0.39 in Electronics (all $p < 0.001$), with $\Delta\beta \approx 0.01$ across all three schemes. The direct effect remains dominant (Grocery: $\beta = 0.40–0.42$; Electronics: $\beta = 0.38–0.39$), and the indirect pathway is consistently non-significant (both domains: $p > 0.05$). Effects on the reported say-do gap and reporting bias remain non-significant throughout. The near-identical coefficients confirm that the DesaMix and DesaFrag sub-indices capture highly collinear spatial information, and the core finding is invariant to their relative weighting.

Supplementary Table 4. Sensitivity of Desakota effects to sub-index weighting

Weight	Type	Domain	Total β	p	Direct β	p	Indirect β	p
0.3_0.7	Obs	Grocery	0.40	***	0.40	***	-0.01	ns
0.3_0.7	Obs	Electronics	0.38	***	0.38	***	0.00	ns
0.3_0.7	RG	Grocery	-0.05	ns	-0.04	ns	-0.01	ns
0.3_0.7	RG	Electronics	0.11	ns	0.13	ns	-0.02	ns
0.3_0.7	RB	Grocery	-0.11	ns	-0.12	ns	0.01	ns
0.3_0.7	RB	Electronics	-0.09	ns	-0.10	ns	0.01	ns
0.5_0.5 (baseline)	Obs	Grocery	0.41	***	0.41	***	-0.01	ns
0.5_0.5 (baseline)	Obs	Electronics	0.38	***	0.39	***	0.00	ns
0.5_0.5 (baseline)	RG	Grocery	-0.06	ns	-0.05	ns	-0.01	ns
0.5_0.5 (baseline)	RG	Electronics	0.11	ns	0.12	ns	-0.02	ns
0.5_0.5 (baseline)	RB	Grocery	-0.11	ns	-0.12	ns	0.01	ns
0.5_0.5 (baseline)	RB	Electronics	-0.09	ns	-0.10	ns	0.01	ns
0.7_0.3	Obs	Grocery	0.41	***	0.42	***	-0.01	ns
0.7_0.3	Obs	Electronics	0.39	***	0.39	***	0.00	ns
0.7_0.3	RG	Grocery	-0.07	ns	-0.05	ns	-0.01	ns
0.7_0.3	RG	Electronics	0.10	ns	0.12	ns	-0.02	ns
0.7_0.3	RB	Grocery	-0.11	ns	-0.13	ns	0.01	ns
0.7_0.3	RB	Electronics	-0.09	ns	-0.11	ns	0.01	ns

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, “ns” indicates non-significant results.

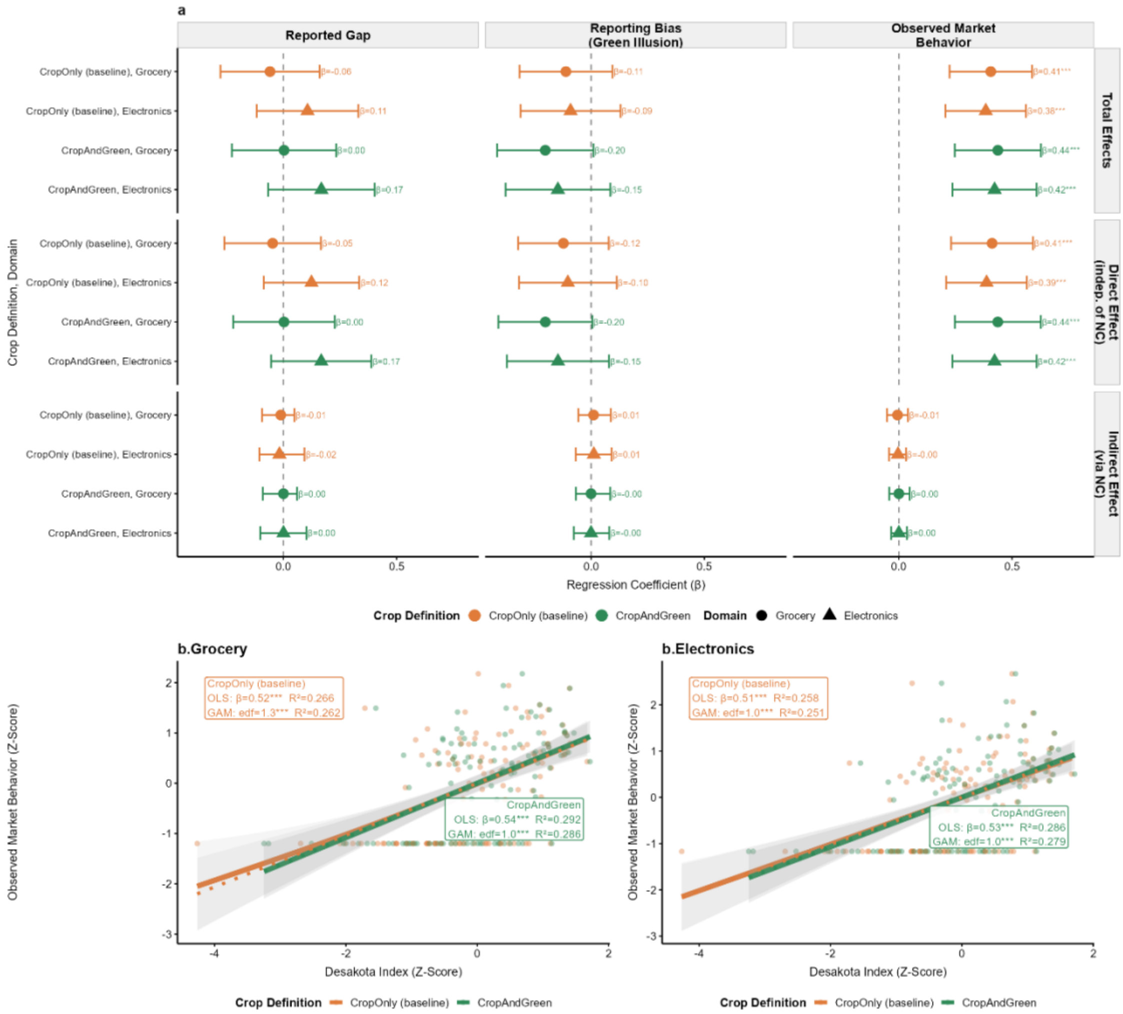


Supplementary Fig. 7. Sensitivity to sub-index weighting. a, Behaviour effects remain robust across all three weight schemes (all p < 0.001), while other DVs are non-significant. b, OLS and GAM scatter fits confirm stability.

Sensitivity to cropland definition

The main analysis uses a cropland-only definition (CropOnly). We additionally tested a broader definition encompassing both cropland and managed green space (CropAndGreen) (**Supplementary Table 5, Supplementary Fig. 8**).

The CropAndGreen variant produces qualitatively identical but modestly attenuated results. For observed market behaviour, the direct effect remains strongly positive in both domains (CropAndGreen — Grocery: $\beta = 0.44$, $p < 0.001$; Electronics: $\beta = 0.42$, $p < 0.001$), comparable in magnitude to the CropOnly baseline (Grocery: $\beta = 0.41$, $p < 0.001$; Electronics: $\beta = 0.39$, $p < 0.001$). The slight numerical increase under CropAndGreen is consistent with the broader definition capturing additional green exposure that weakly covaries with the Desakota gradient; however, the overall pattern remains stable across definitions. Reporting bias and reported say-do gap effects remain non-significant for both crop definitions and both domains (all $p > 0.05$). Indirect effects via nature connectedness are uniformly near zero and non-significant across all specifications, indicating that the mediation pathway identified in the main analysis is not sensitive to this alternative index. Overall, this pattern reinforces the theoretical distinction between productive Desakota landscapes and aesthetic green space: the behavioural enablement mechanism is specifically anchored in integrated urban–agricultural morphologies.



Supplementary Fig. 8. Sensitivity to cropland definition. a, Behavior effects remain robust across both definitions (all $p < 0.001$), while other DVs are non-significant. b, OLS and GAM scatter fits confirm stability.

Supplementary Table 5. Sensitivity of Desakota effects to cropland definition

Definition	Type	Domain	Total *β*	*p*	Direct *β*	*p*	Indirect *β*	*p*
CropAndGreen	Obs	Grocery	0.44	***	0.44	***	0.00	ns
CropAndGreen	Obs	Electronic	0.42	***	0.42	***	0.00	ns
CropAndGreen	RG	Grocery	0.00	ns	0.00	ns	0.00	ns
CropAndGreen	RG	Electronic	0.17	ns	0.17	ns	0.00	ns
CropAndGreen	RB	Grocery	-0.20	ns	-0.20	ns	0.00	ns
CropAndGreen	RB	Electronic	-0.15	ns	-0.15	ns	0.00	ns
CropOnly (baseline)	Obs	Grocery	0.41	***	0.41	***	-0.01	ns
CropOnly (baseline)	Obs	Electronic	0.38	***	0.39	***	0.00	ns
CropOnly (baseline)	RG	Grocery	-0.06	ns	-0.05	ns	-0.01	ns
CropOnly (baseline)	RG	Electronic	0.11	ns	0.12	ns	-0.02	ns
CropOnly (baseline)	RB	Grocery	-0.11	ns	-0.12	ns	0.01	ns
CropOnly (baseline)	RB	Electronic	-0.09	ns	-0.10	ns	0.01	ns

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, “ns” indicates non-significant results.

Taken together, all 78 specifications preserve the tripartite significance pattern of the main analysis: observed market behavior is significant in 26/26 models (100%), reporting bias in 26/26 (100%), and the reported say-do gap in 0/26 (0%). The mediation decomposition — a dominant direct structural pathway independent of NC, coupled with a smaller but significant indirect honesty-filter component — is robust to spatial resolution ($\Delta\beta < 0.03$), sub-index weighting ($\Delta\beta < 0.01$), and cropland definition (qualitatively identical, with theoretically interpretable attenuation under the broader definition).

Supplementary Note 9: Model Optimization and the Functional Dynamics of Spatial Morphologies

To accurately capture the structural drivers of observed market behavior and account for complex urban dynamics, we employed a tripartite modelling strategy comparing linear, left-censored, and non-linear specifications. All predictors and outcome variables were z-standardized prior to estimation to allow for direct comparability of effect sizes.

Accounting for Left-Censoring and Non-Linearity

Supplementary Table 6 presents a comparative statistical evaluation across three distinct modeling approaches, namely OLS, left-censored Tobit regression, and Generalized Additive Models (GAM), assessing the impact of spatial indices (Green Exposure and Desakota) on Observed Market Behavior (measured as green spending share). Models were estimated separately for each domain and spatial index combination (N = 111), mirroring the panel structure of **Fig. 4b** in the main text. All predictors and outcomes were z-standardized prior to estimation. For OLS and Tobit models, standardized coefficients (β) and standard errors are reported. Tobit models account for potential floor effects by applying left-censoring at the minimum observed z-score of the outcome, with model fit assessed via McFadden's Pseudo-R^2 $(1 - LL_{full}/LL_{null})$. GAM specifications, which employ thin-plate regression splines to capture non-linear dynamics, report the estimated degrees of freedom (edf), where an edf approaching 1 implies linearity. Across all specifications, Akaike Information Criterion (AIC) and log-likelihood (Log-Lik) values are provided to facilitate relative model fit comparisons.

Supplementary Table 6 Comparison of OLS, Tobit, and GAM model specifications for observed market behavior

		OLS						Tobit					GAM			
Domain	Spatial index	N	β	SE	R^2	AIC	Log-Lik	β	SE	Pseudo-R^2	AIC	Log-Lik	edf	R^2	AIC	Log-Lik
Grocery	Green Exposure	111	-0.105ns	0.107	0.334	292.9	-134.5	-0.200ns	0.159	0.128	312.1	-144.1	2.63ns	0.282	292.1	-132.4
Electronics	Green Exposure	111	-0.114ns	0.104	0.370	286.7	-131.3	-0.211ns	0.155	0.141	306.9	-141.5	2.75ns	0.325	285.3	-128.9
Grocery	Desakota	111	0.406***	0.093	0.435	274.6	-125.3	0.789***	0.161	0.202	287.8	-131.9	1.18***	0.380	274.5	-125.1
Electronics	Desakota	111	0.384***	0.091	0.459	269.8	-123.9	0.749***	0.158	0.210	284.2	-130.1	1.00***	0.405	269.8	-122.9

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, “ns” indicating non-significant results.

To ensure standard linear assumptions did not artificially attenuate our estimates, we applied Tobit regression models to account for this left-censored distribution (**Supplementary Table 6**). The Tobit estimations confirm that the floor effect masks the true magnitude of structural enablement: when left-censoring is controlled, the structural power of the Desakota index nearly doubles ($\beta_{Tobit} \approx 0.749$ to $0.789, p < 0.001$) compared to baseline OLS estimates ($\beta_{OLS} \approx 0.384$ to 0.406, $\mathrm{p} < 0.001$).

Validating the "Manicured Backfire" Hypothesis

By extracting the exact mathematical inflection points from these optimized GAM curves (**Supplementary Table 7**), we map the divergent functional trajectories of the two spatial paradigms. The table details the interior local extrema (turning points) of the non-linear GAM curves modeling the relationship between spatial indices (x-axis) and observed market behavior (y-axis) across the grocery and electronics domains. Turning points were analytically identified by locating sign changes in the numerical first derivative of the GAM-predicted curve, evaluated across a 500-point grid over the observed range of each respective spatial index. Both predictor (x) and fitted outcome (y) values at these extrema are reported in z-standardized units. The "Type" column distinguishes between local maxima and local minima. Spatial index-domain combinations that yielded purely monotonic GAM curves, implying that they lacked any interior turning points, are intentionally omitted from this table.

Supplementary Table 7 Turning points of GAM fitted curves for observed market behaviors

Domain	Spatial index	*x* at turning point (Z-score)	Fitted *y* at turning point (Z-score)	Type
Grocery	Green Exposure	0.390	-0.622	Maximum
Grocery	Green Exposure	-0.684	-0.694	Minimum
Electronics	Green Exposure	0.440	-0.594	Maximum
Electronics	Green Exposure	-0.664	-0.677	Minimum

Note: interior extrema of the GAM-fitted curve for Observed Market Behavior. Panels with no interior turning points are omitted (monotonic GAM curves). GAMs include the same control variables as **Supplementary Table 2**. Controls are held at their within-slice mean (numeric) or mode (categorical) when evaluating the curve. Turning points identified as sign changes in the numerical first derivative of the GAM predicted curve, evaluated on a 500-point grid over the observed range of each Spatial Index. x and y are in z-standardized units.

The Desakota morphology is entirely absent from the table, confirming that its GAM-fitted curve is monotonically increasing across the full observed range: as urban–agricultural integration increases, objective sustainable consumption strictly and continuously scales upward with no saturation or inflection.

Conversely, traditional Green Exposure exhibits a non-monotonic, wave-like trajectory with two interior turning points per domain. The GAM curve first descends to a local minimum in the below-average exposure range (Z = −0.684 for grocery, Z = −0.664 for electronics), then rises to a local maximum modestly above the regional mean (Z = 0.390 for grocery, Z = 0.440 for electronics), before declining again at higher exposure levels. Critically, even at these optimal Green Exposure levels, the fitted observed behavior remains well below the sample mean (y = −0.622 for grocery, y = −0.594 for electronics), confirming that conventional greening at best attenuates — but never reverses — the behavioral deficit. The subsequent decline beyond the peak provides the empirical foundation for the "manicured backfire" hypothesis: while moderate greenery supports baseline urban functioning, forcefully imposing compartmentalized green aesthetics without corresponding functional integration ultimately suppresses objective sustainable consumption. The trough-to-peak amplitude is itself marginal, underscoring how constrained the behavioral returns to aesthetic greening are even within its most favorable operating range.

Supplementary Note 10: Cross-Specification Robustness of Behavioral Profiles

To confirm the stability of the morphological-behavioral associations presented in the main text, we performed a comprehensive robustness check across all domain and framework combinations (**Supplementary Table 8**). This analysis tests spatial typologies against two distinct mathematical frameworks, namely Logistic Probability Mapping (LPM) and Behavioral Potential Normalization (BPN), across both the Grocery and Electronic consumption domains (N = 118).

Supplementary Table 8 Robustness check for behavioral profiles by urban zone

	Grocery × LPM (N=118)	Grocery × BPN (N=118)	Electronic × LPM (N=118)	Electronic × BPN (N=118)
Reported Gap				
Aesthetic Green	**0.017**	-0.041	-0.044	-0.094
Grey Infrastructure	**0.161**	0.270	0.077	0.148
Integrated Desakota	**-0.060**	-0.059	0.002	0.010
Reporting Bias				
Aesthetic Green	**0.499**	0.331	0.486	0.343
Grey Infrastructure	**-0.310**	-0.550	-0.223	-0.383
Integrated Desakota	**-0.203**	-0.029	-0.222	-0.087
Observed Market Behavior				
Aesthetic Green	**-0.544**	-0.333	-0.469	0.015
Grey Infrastructure	**-0.357**	-0.068	-0.436	-0.340
Integrated Desakota	**0.434**	0.219	0.414	0.096

Note: Z-scores computed within each specification's analytic sample. BPN=Behavioral Potential Normalization; LPM=Logistic Probability Mapping.

While the LPM framework models green consumption as a discrete, binary market choice to capture the *probability* of sustainable transactions, the BPN framework treats it as a continuous potential, measuring the *magnitude* of green spending relative to total capacity.

The results demonstrate remarkable directional invariance across all specifications:

(1) **The Persistence of the "Green Illusion":** The **Aesthetic Green** typology consistently exhibits the highest Reporting Bias across all four empirical specifications (ranging from Z = 0.331 to Z = 0.499). This confirms that the inflation of reported sustainable intent in highly manicured, compartmentalized urban environments is a stable psychological phenomenon, manifesting regardless of whether actualized behavior is measured as a probability (LPM) or a proportion (BPN). Furthermore, this typology consistently yields substantially negative scores in Observed Market Behavior, with only the Electronic × BPN cell approaching zero (Z = 0.015), indicating that the manicured environment's failure to convert intention into market action is robust across domains and frameworks.

(2) **The Structural Advantage of Desakota:** The **Integrated Desakota** morphology is the *only* urban typology that maintains a positive Observed Market Behavior z-score across

every specification. The effect is most pronounced in the Grocery x LPM specification (Z = 0.434), which represents high-frequency daily choices, but importantly remains robustly positive even in the high-barrier, lower-frequency Electronic x BPN domain (Z = 0.096).

(3) **Grey Infrastructure Deficits:** As expected, **Grey Infrastructure** cities consistently demonstrate the largest Reported Gaps and significantly negative actualized behavior across all permutations, reflecting an urban environment that lacks both psychological catalysts and compatible spatial structures for sustainable consumption.

Ultimately, these findings verify that the "Manicured Backfire" and the spatial advantage of productive landscapes are not sensitive to specific modelling choices or isolated to niche product categories. Instead, they operate as robust, macro-level structural dynamics that shape actualized sustainable behavior across the broader urban economy.

Supplementary Note 11: Multi-Channel Observation Framework and Bias Typology

To systematically decompose the structural origins of the "green illusion," this study employs a multi-channel observation framework. As visualized in the main text, the transition from psychological intention to actualized market behavior is tracked across three distinct data layers: an independent attitudinal survey, a platform-embedded self-report, and passive transaction logs. The matrix in **Supplementary Table 9** deconstructs the structural origins of the "green illusion." Moving from active surveys to passive transaction logs, action preference and "observer effect" biases systematically diminish, while sample selection shifts from participation barriers to spatial/domain boundaries. As detailed in the Methods, the randomized modular design of our survey ensures that this gradient reflects an aggregate structural phenomenon rather than an individual-level common method artifact.

Rather than attributing the steep drop-off in sustainable behavior solely to individual dishonesty, we categorize the discrepancies across these layers using a tripartite typology of observational biases:

(1) **Sample Selection Bias (Coverage)**: The degree to which the recording channel systematically includes or excludes specific demographic or spatial sub-populations.
(2) **Action Preference Bias (Information)**: The intentional or unintentional modification of responses driven by social-desirability pressures or cognitive inertia.
(3) **Observer Effect Bias (Counterfactual)**: The phenomenon where the explicit context of being evaluated (e.g., an ESG survey) temporarily alters the baseline environmental awareness of the respondent.

As detailed in **Supplementary Table 9**, the magnitude and nature of these biases shift dramatically depending on whether the recording typology is active or passive. Moving from active survey instruments to passive transaction logs, both action preference and observer effect biases systematically diminish. Consequently, the transaction data represents the most accurate reflection of market ground truth.

Crucially, while the passive transaction logs eliminate the psychological biases inherent in surveys, they introduce a distinct structural selection bias: the omission of offline consumption. For residents in highly integrated *Desakota* morphologies, who likely conduct a significant portion of their sustainable consumption via local agricultural networks, this digital-only measurement establishes a conservative lower bound. Furthermore, as detailed in our Methods, the original survey utilized a randomized modular design. Therefore, the observed gradient of diminishing bias is a robust, city-level structural phenomenon rather than an artefact of individual-level common method bias.

Supplementary Table 9 Decomposition of the "green illusion"

Data Channel	Recording Typology	Sample Selection Bias (Coverage)	Action Preference Bias (Information)	Observer Effect Bias (Counterfactual)
Independent Survey (Intent)	Active	**High:** Double selection (platform users → willing participants). Systematically excludes low-digital literacy demographics.	**Strong:** High social-desirability pressures lead to intentional over-reporting of pro-environmental intent.	**Strong:** The explicit evaluative context triggers conscious environmental awareness, shifting baseline responses.
Platform Self-Report (Reported Behaviour)	Active (Embedded)	**Moderate:** Restricted to active e-commerce users but entails lower participation friction due to platform integration.	**Moderate:** Driven more by cognitive inertia or strategic commercial expectations rather than explicit moral self-presentation.	**Weak-to-Moderate:** Commercial context dilutes moral judgment, though mild strategic responding may occur.
Transaction Logs (Observed Behaviour)	Passive	**Structural:** Captures only online purchases. Systematically omits offline local consumption, establishing a conservative lower bound for integrated regions (e.g., *Desakota*).	**Negligible:** Transactions are faithfully logged automatically. *(Note: Subject to fixed researcher-side algorithmic classification limits).*	**Non-existent:** Users execute financial transactions without awareness of environmental measurement; captures actual market ground truth.

Supplementary Note 12: Data Alignment and Transaction Metadata

Supplementary Table 10 Summary of original and aligned regional information

No	Nation	City	Province	City (GADM)	Province (GADM)
1	IDN	Bandung	Jawa Barat	Bandung	Jawa Barat
2	IDN	Semarang	Jawa Tengah	Semarang	Jawa Tengah
3	IDN	Jakarta	Jakarta Raya		Jakarta Raya
4	IDN	Padang	Sumatera Barat	Padang	Sumatera Barat
5	IDN	Tangerang	Banten	Tangerang	Banten
6	IDN	Bogor	Jawa Barat	Bogor	Jawa Barat
7	IDN	Bekasi	Jawa Barat	Bekasi	Jawa Barat
8	IDN	Banjarnegara	Jawa Tengah	Banjarnegara	Jawa Tengah
9	IDN	Yogyakarta	Yogyakarta		Yogyakarta
10	IDN	Bandar Lampung	Lampung	Bandar Lampung	Lampung
11	IDN	Surabaya	Jawa Timur	Surabaya	Jawa Timur
12	IDN	Malang	Jawa Timur	Malang	Jawa Timur
13	IDN	Palembang	Sumatera Selatan	Palembang	Sumatera Selatan
14	IDN	Cirebon	Jawa Barat	Cirebon	Jawa Barat
15	IDN	Batam	Kepulauan Riau	Batam	Kepulauan Riau
16	IDN	Medan	Sumatera Utara	Kota Medan	Sumatera Utara
17	IDN	Mataram	Nusa Tenggara Barat	Mataram	Nusa Tenggara Barat
18	IDN	Depok	Jawa Barat	Depok	Jawa Barat
19	IDN	Banda Aceh	Aceh	Banda Aceh	Aceh
20	IDN	Surakarta	Jawa Tengah	Surakarta	Jawa Tengah
21	IDN	Manado	Sulawesi Utara	Manado	Sulawesi Utara
22	IDN	Makassar	Sulawesi Selatan	Makassar	Sulawesi Selatan
23	IDN	Balikpapan	Kalimantan Timur	Balikpapan	Kalimantan Timur
24	IDN	Pontianak	Kalimantan Barat	Pontianak	Kalimantan Barat
25	IDN	Samarinda	Kalimantan Timur	Samarinda	Kalimantan Timur
26	IDN	Denpasar	Bali	Denpasar	Bali
27	IDN	Pekanbaru	Riau	Pekanbaru	Riau
28	MYS	Sabah & Sarawak	Sabah & Sarawak		Sabah & Sarawak
29	MYS	Penang	Pulau Pinang		Pulau Pinang
30	MYS	Terengganu	Trengganu		Trengganu
31	MYS	Kuala Lumpur	Kuala Lumpur	Kuala Lumpur	Kuala Lumpur
32	MYS	Johor Bahru	Johor		Johor
33	MYS	Selangor	Selangor		Selangor
34	MYS	N. Sembilan	Negeri Sembilan		Negeri Sembilan
35	MYS	Kedah	Kedah		Kedah
36	MYS	Perak	Perak		Perak

37	MYS	Pahang	Pahang		Pahang
38	MYS	Kelantan	Kelantan		Kelantan
39	MYS	Malacca	Melaka		Melaka
40	MYS	Putrajaya	Putrajaya		Putrajaya
41	PHL	Abra	Abra		Abra
42	PHL	Agusan del Sur	Agusan del Sur		Agusan del Sur
43	PHL	Antique	Antique		Antique
44	PHL	Aurora	Aurora		Aurora
45	PHL	Biliran	Biliran		Biliran
46	PHL	Camiguin	Camiguin		Camiguin
47	PHL	Capiz	Capiz		Capiz
48	PHL	Compostela Valley	Compostela Valley		Compostela Valley
49	PHL	Guimaras	Guimaras		Guimaras
50	PHL	Ilocos Sur	Ilocos Sur		Ilocos Sur
51	PHL	Kalinga	Kalinga		Kalinga
52	PHL	Lanao del Norte	Lanao del Norte		Lanao del Norte
53	PHL	Marinduque	Marinduque		Marinduque
54	PHL	Misamis Occidental	Misamis Occidental		Misamis Occidental
55	PHL	Mountain Province	Mountain Province		Mountain Province
56	PHL	Occidental Mindoro	Occidental Mindoro		Occidental Mindoro
57	PHL	Romblon	Romblon		Romblon
58	PHL	Samar	Samar		Samar
59	PHL	Surigao del Sur	Surigao del Sur		Surigao del Sur
60	PHL	Metro Manila	Metropolitan Manila	Manila	Metropolitan Manila
61	PHL	Pampanga	Pampanga		Pampanga
62	PHL	Misamis Oriental	Misamis Oriental		Misamis Oriental
63	PHL	Rizal	Rizal		Rizal
64	PHL	Cavite	Cavite		Cavite
65	PHL	Laguna	Laguna		Laguna
66	PHL	Quezon	Quezon		Quezon
67	PHL	Iloilo	Iloilo		Iloilo
68	PHL	Palawan	Palawan		Palawan
69	PHL	Zamboanga Sibugay	Zamboanga Sibugay		Zamboanga Sibugay
70	PHL	Cebu	Cebu		Cebu
71	PHL	Nueva Ecija	Nueva Ecija		Nueva Ecija
72	PHL	Zamboanga del Sur	Zamboanga del Sur		Zamboanga del Sur
73	PHL	Negros Occidental	Negros Occidental		Negros Occidental
74	PHL	Camarines Sur	Camarines Sur		Camarines Sur

75	PHL	Batangas	Batangas		Batangas
76	PHL	Bulacan	Bulacan		Bulacan
77	PHL	Pangasinan	Pangasinan		Pangasinan
78	PHL	Tarlac	Tarlac		Tarlac
79	PHL	Basilan	Basilan		Basilan
80	PHL	Agusan del Norte	Agusan del Norte		Agusan del Norte
81	PHL	Southern Leyte	Southern Leyte		Southern Leyte
82	PHL	Zambales	Zambales		Zambales
83	PHL	Cagayan	Cagayan		Cagayan
84	PHL	Catanduanes	Catanduanes		Catanduanes
85	PHL	Masbate	Masbate		Masbate
86	PHL	Isabela	Isabela		Isabela
87	PHL	Sulu	Sulu		Sulu
88	PHL	Bataan	Bataan		Bataan
89	PHL	Bohol	Bohol		Bohol
90	PHL	Northern Samar	Northern Samar		Northern Samar
91	PHL	Bukidnon	Bukidnon		Bukidnon
92	PHL	Benguet	Benguet		Benguet
93	PHL	Oriental Mindoro	Oriental Mindoro		Oriental Mindoro
94	PHL	Negros Oriental	Negros Oriental		Negros Oriental
95	PHL	Davao Oriental	Davao Oriental		Davao Oriental
96	PHL	Nueva Vizcaya	Nueva Vizcaya		Nueva Vizcaya
97	PHL	Davao del Norte	Davao del Norte		Davao del Norte
98	PHL	Leyte	Leyte		Leyte
99	PHL	South Cotabato	South Cotabato		South Cotabato
100	PHL	Davao del Sur	Davao del Sur		Davao del Sur
101	PHL	Sultan Kudarat	Sultan Kudarat		Sultan Kudarat
102	PHL	Camarines Norte	Camarines Norte		Camarines Norte
103	PHL	Lanao del Sur	Lanao del Sur		Lanao del Sur
104	PHL	Aklan	Aklan		Aklan
105	PHL	Albay	Albay		Albay
106	PHL	Ilocos Norte	Ilocos Norte		Ilocos Norte
107	PHL	Sorsogon	Sorsogon		Sorsogon
108	PHL	La Union	La Union		La Union
109	PHL	Cotabato City	Maguindanao	Cotabato City	Maguindanao
110	PHL	Tawi-Tawi	Tawi-Tawi		Tawi-Tawi

111	PHL	Zamboanga del Norte	Zamboanga del Norte		Zamboanga del Norte
112	PHL	Eastern Samar	Eastern Samar		Eastern Samar
113	PHL	Maguindanao	Maguindanao		Maguindanao
114	PHL	Cotabato (North Cotabato)	North Cotabato		North Cotabato
115	SGP	Singapore	Singapore	Singapore	Singapore
116	THA	Bangkok Metropolis	Bangkok Metropolis		Bangkok Metropolis
117	THA	Rayong	Rayong		Rayong
118	THA	Songkhla	Songkhla		Songkhla
119	THA	Ubon Ratchathani	Ubon Ratchathani		Ubon Ratchathani
120	THA	Phitsanulok	Phitsanulok		Phitsanulok
121	THA	Nonthaburi	Nonthaburi		Nonthaburi
122	THA	Nakhon Pathom	Nakhon Pathom		Nakhon Pathom
123	THA	Ratchaburi	Ratchaburi		Ratchaburi
124	THA	Nakhon Ratchasrima	Nakhon Ratchasima		Nakhon Ratchasima
125	THA	Chonburi	Chon Buri		Chon Buri
126	THA	Samut Sakhon	Samut Sakhon		Samut Sakhon
127	THA	Samut Prakan	Samut Prakan		Samut Prakan
128	THA	Nakhon Sawan	Nakhon Sawan		Nakhon Sawan
129	THA	Pathum Thani	Pathum Thani		Pathum Thani
130	THA	Khon Kaen	Khon Kaen		Khon Kaen
131	THA	Phuket	Phuket		Phuket
132	THA	Chiang Mai	Chiang Mai		Chiang Mai
133	THA	Udon Thani	Udon Thani		Udon Thani
134	THA	Surat Thani	Surat Thani		Surat Thani

135	THA	Lampang	Lampang		Lampang
136	THA	Kanchanaburi	Kanchanaburi		Kanchanaburi
137	THA	Nakhon Si Thammarat	Nakhon Si Thammarat		Nakhon Si Thammarat
138	THA	Saraburi	Saraburi		Saraburi
139	VNM	Bac Giang	Bac Giang		Bắc Giang
140	VNM	Binh Duong	Binh Duong		Bình Dương
141	VNM	Can Tho	Can Tho		Cần Thơ
142	VNM	Da Nang	Da Nang		Đà Nẵng
143	VNM	Dak Lak	Dak Lak		Đắk Lắk
144	VNM	Dong Nai	Dong Nai		Đồng Nai
145	VNM	Hai Duong	Hai Duong		Hải Dương
146	VNM	Hai Phong	Hai Phong		Hải Phòng
147	VNM	Hanoi	Ha Noi		Hà Nội
148	VNM	HCMC	Ho Chi Minh		Hồ Chí Minh
149	VNM	Khanh Hoa	Khanh Hoa		Khánh Hòa

Supplementary Table 11. Description of the product dataset

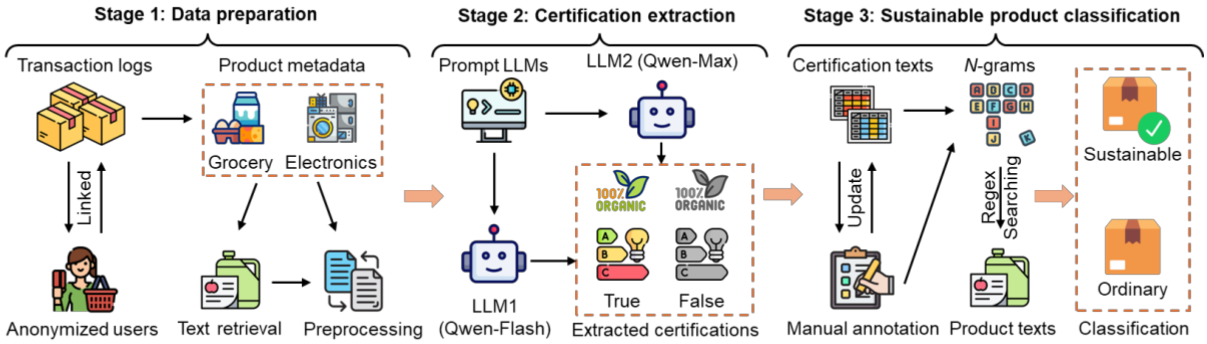
Field	Description
Identifier	
OrderID	Unique order identifier for product and order dataset
ItemID	Unique identifier for a type of product
Metadata	
Country	Country code where products are sold
Category1	The primary product category
Category2	The secondary product category
ProductName	The product name in text
ProductDescription	The product description in text
ProductUnitPrice	The unit price of product
ProductGMV	The gross merchandise volume of product
OrderDate	The completion date of the order
LazadaURL	The original link to the detail page of the product from Lazada.com

Supplementary Table 12. Description of the order dataset

Field	Description
Identifier	
OrderID	Unique order identifier for product and order dataset
UserID	Unique user identifier for order dataset and survey
Metadata	
Country	Country code where products are sold
PaidPrice	The order payment in US dollars
GMV	The gross merchandise volume of order
OrderDate	The completion date of the order

Supplementary Note 13: Sustainable Production Classification

This section details the methodology employed in classifying sustainable products through an integrated pipeline including an *N*-gram based approach and a large language model (LLM). An overview of the methodological steps is provided in **Supplementary Fig. 9**. The processing of sustainable product classification is organized in separate sections in this document. First, we discuss the dataset and its preprocessing. Second, we detail our methodology for developing the approach for sustainable product classification based on authoritative certifications.



Supplementary Fig. 9. Overview of methodological steps concerning sustainable product classification.

Product data preprocessing

To ensure consistency among the survey, product listing database and order database, we use UserID and OrderID to merge the three sources of data and several preprocessing steps are implemented. First, the merging process excludes users without complete orders within the sampling period. Second, it helps identify products with missing names or descriptions. Third, to address the issue of multilingual inconsistencies in product names and descriptions, we employ an LLM-based translation pipeline that converts all content from its original language into English. This pipeline is built on the latest Qwen-Flash model provided by Alibaba Cloud[1]. According to recent posts (AlibabaCloud, 2025; Cao, 2025), the Qwen series models demonstrate superior performance in understanding and generating text across Southeast Asian languages and cultural contexts.

Categories for grocery and electronic products

There are 44 primary product categories and 226 secondary product categories. However, we selected the primary product categories that are only conceptualized in the online survey (see details in **Supplementary Table 13**) and eventually 9 primary product categories and 54 secondary product categories are utilized in this research.

[1] The latest Qwen-Flash model refers to the fastest and cost-effective model in the Qwen series (https://www.alibabacloud.com/help/en/model-studio/models?spm=a2c63.p38356.0.i3#c299c2b53eyoh), comparing to Qwen-Max and Qwen-Plus.

Supplementary Table 13 The selected primary product categories

Main category	Primary category	Secondary category
Green grocery	Groceries (11)	Food Staples & Cooking Essentials, Drinks, Dairy Chilled & Eggs, Snacks & Confectionery, Fruit & Vegetables, Bakery & Breakfast, Frozen, Alcoholic Beverages, Breakfast Cereals & Spreads, Meat & Seafood, Tobacco
Green electronics	Electronics Parts & Accessories (15)	Computer Accessories, Mobile & Tablet Accessories, USB Gadgets, Home Appliances Parts & Accessories, Televisions & Videos Accessories, Network Components, Camera Accessories, Smart Wearables Accessories, Audio Accessories, Printer Parts & Accessories, Video Game Accessories, Lighting & Studio Equipment, 3D Printer Parts & Accessories, Drone Accessories, Projector Accessories
	Home Appliances (5)	Kitchen Appliances, Household Cleaning, Heating, Cooling and Ventilation, Personal Care Appliances, Laundry & Garment Care
	Cameras & Drones (7)	Surveillance Cameras & Systems, Lenses, Drones, Video Recorders, Outdoor Optics, Point & Shoot Cameras, Instant Camera & Films
	Laundry & Cleaning Equipment (2)	Laundry Tools & Accessories, Cleaning Tools
	Mobiles & Tablets (4)	Tablets, Smartphones, Landline Phones, Feature Phones
	Computer & Components (4)	Computer Components, Monitors, Laptops, Desktop Computers
	Printers & Scanners (4)	Printing Consumables, Scanners (Non-Printer), Printers, 3D Printing
	Automotive (2)	Motorcycles (products), Cars (products)

Note: the figures in the parentheses represent the number of secondary categories within each primary category.

Within the selected categories, the above procedures result in a final sample of 38370 unique products (12007 grocery products and 26363 electronic products) from 49181 unique orders from 4077 valid buyers.

Sustainable product classification based on authoritative certifications

Due to the rapid evolution of textual analytical tools, there are various approaches available to deal with unstructured data, including dictionary-based (Gentzkow et al., 2019; Schirmag et al., 2025), rule-based (Almond et al., 2022), *N*-gram based (Cong et al., 2025; Sautner et al., 2023; Zhang, 2024), small-scale generative language model-based (Ma et al., 2023; Webersinke et al., 2022), and LLM-based approaches (Carlson & Burbano, 2025; Lu et al., 2025). Although the use of generative language models for structured text analysis is becoming increasingly popular, several challenges remain, such as the issue of hallucination (Farquhar et al., 2024). To produce robust and replicable product classifications, we apply an integrative method to identify sets of authoritative certifications for sustainable products. Compared with classification models based on semantic similarity or word frequency, leveraging information provided by authoritative certifications helps to reduce noise and prevents normal products from being misclassified as sustainable. This method comprises three steps,

(1) We employ task-compatible LLMs to construct comparable initial sets of certifications. Specifically, two models are prompted in parallel: *Qwen-Flash*, which is suited to fast, high-volume tasks, and *Qwen-Max*, which is designed for more complex reasoning Both models are used to conduct zero-shot retrieval to identify potential certifications, including labels, marks, and standards, from text combining product names and descriptions. Separate prompts are developed for grocery and electronic products, as presented in **Supplementary Table 14**. Using this approach, *Qwen-Flash* model retrieves 95 and 258 certifications from grocery and electronic products, respectively. In comparison, *Qwen-Max* model retrieves 908 and 798 certifications. Notably, 54.7% and 55.0% overlap in results generated by *Qwen-Max* compared to those generated by *Qwen-Flash*, respectively. To mitigate the risk of hallucinations associated with reliance on a single model, we merge the outputs from both models and subject the combined results to subsequent annotation.

(2) We manually reviewed and annotated all potential certifications identified by the LLMs, covering 951 certifications for grocery products and 914 for electronic products. Distinct principles were applied to define sustainability attributes for grocery and electronic categories, respectively. As shown in **Supplementary Table 15**, three widely adopted standards, namely USDA Organic, EU Organic Certification, and the International Federation of Organic Agriculture Movements (IFOAM), were used as the core principles for identifying organic-related sustainability attributes. These standards are also broadly aligned with consumer preferences in Southeast Asian countries. In addition, many nationally adopted organic standards are largely harmonized with USDA and EU Organic Certification frameworks (Willer et al., 2026). Following manual annotation, 33 authoritative certifications from national and international practices were confirmed for grocery products. In addition, **Supplementary Table 16** presents the 17 confirmed authoritative certifications identified for electronic products. These certifications are recognized based on principles including energy efficiency, durability and reliability, use of recyclable materials, reduced hazardous substances, environmental protection, and safety.

(3) Sustainable products are identified by searching for keywords associated with authoritative certifications embedded in product names and descriptions. Following the approaches of Sautner et al. (2023) and Zhang (2024), we employ unigrams, bigrams, and trigrams derived from authoritative certifications to finalize the classification of sustainable products. In general, most certifications are represented by unique abbreviations. However, to ensure that no potentially relevant products are missed, we generate regular expression–based unigrams, bigrams, and trigrams for each certification to scale up the search across products. For instance, we apply the expression '[EU|European] Organic Standard| [EU|European] Organic Certifi[ed|cate|cation] | [EU|European] Organic [Mark|Label]' to capture different textual variations, using a Python 3.10 environment and the built-in '*re*' package (version 2.2.1 Based on the search results, sustainable products are then identified using the Eq. (1) in the main text.

Eventually, the searching process confirms 580 and 196 unique sustainable grocery and electronic products, respectively.

Supplementary Table 14 Prompts for zero-shot retrieval of grocery and electronic products

Prompt for grocery products	**Prompt for electronic products**

Your task is to search for authorized sustainability labels and certification schemas for organic grocery products from the given product description.
 	
Instruction: For example, 'USDA' is a widely recognized organic sustainability label. Multiple labels may be present in the product description, and you should identify all.
 	
Output: your output must be in the JSON format:
 	
{
 	
"labels": ["USDA", "Fair Trade"],
 	
}
	Your task is to search for nationally or internationally authorized labels, standards and certifications for electronic devices, appliances and parts from the given product content.
	Instruction
	1. You should identify all possible labels, standards and certifications but exclude those that are not nationally or internationally authorized.
	2. If no energy-efficient labels are found, return an empty list \`[]\`.
	3. Identify labels, standards and certifications from various product categories, e.g., automotive, cameras & drones, computers & components, electronics parts & accessories, home appliances, laundry & cleaning equipment, mobiles & tablets, printers & scanners, etc.
	Output: your output must be in the JSON format:
	{
	"labels": ["Energy Star", "NEA Energy Label", ..., "TISI", "ISO14001"]
	}

Supplementary Table 15 The authoritative certifications for sustainable grocery products

No	Label/Certification	USDA Organic	EU Organic	IFOAM			
				Health	Ecology	Fairness	Care
1	EU Organic Certification	√	√	√	√	√	√
2	USDA Organic Certification	√	√	√	√	√	√
3	OTOP Certified (One Tambon One Product)	×	×	√	×	√	×
4	Farm Fresh (country-specific, e.g., Farm Fresh Berhad, SG Fresh Produce)	×	×	√	×	×	×
5	Thailand Organic Standards (TAS 9001-2552)	√	√	√	√	√	√
6	Malaysia Halal Certification (also Halal Certfieid by JAKIM)	×	×	×	×	√	×
7	BRC Certification (Brand Reputation Compliance Global Standards, BRCGS)	×	×	√	×	×	×
8	HACCP (Hazard Analysis and Critical Control Points)	×	×	√	×	×	×
9	Healthier Choice Symbol	×	×	√	×	×	×
10	NSF certified (NSF international)	×	×	√	×	×	×
11	BPOM certified (Badan Pengawas Obat dan Makanan)	×	×	√	×	×	×
12	FDA certified (US Food and Drug Administration)	×	×	√	×	×	×
13	HFAC (Humane Farm Animal Care)	√	×	√	√	×	×
14	Heart-Healthy Food certification	×	×	√	×	×	×
15	Halal MUI Certified (Halal Certified by the Majelis Ulama Indonesia)	×	×	×	×	√	×
16	Organik KKM Malaysia certified (Malaysian Organic Scheme)	×	×	√	√	√	√
17	MeSTI (Makanan Selamat Tanggungjawab Industri)	×	×	√	×	×	×
18	GHP (Good Hygiene Practices)	×	×	√	×	×	×
19	P-IRT (Pangan Industri Rumah Tangga, a permit for home-scale or small food industries)	×	×	√	×	√	×
20	Kosher Certified (Kosher Certified by a recognized Jewish rabbinic authority)	×	×	×	×	√	×
21	Non-GMO Project Verified	×	×	√	√	×	×
22	CGMP (Current Good Manufacturing Practices)	×	×	√	×	×	×
23	RI (Republik Indonesia)	×	×	×	×	√	×
24	NKV (Nomor Kontrol Veteriner)	×	×	√	×	×	×
25	SNI (Standar Nasional Indonesia)	×	×	×	×	√	×

26	ISO 22000 (Food Safety Management System, FSMS)	×	×	√	×	×	×
27	FSSC 22000 (Food Safety System Certification)	×	×	√	×	×	×
28	Rainforest Alliance Certified	×	×	√	√	√	√
29	Fair Trade Certification	×	×	√	×	√	×
30	GAP (Good Agricultural Practices)	√	×	√	√	×	√
31	JAS (Japan Agricultural Standards)	×	×	√	√	√	√
32	EFSA (European Food Safety Authority)	×	×	√	×	×	×
33	SFA (Singapore Food Agency)	×	×	√	×	×	×

Note: see four principles of IFOAM in detail at https://www.ifoam.bio/why-organic/shaping-agriculture/four-principles-organic.

Supplementary Table 16 The authoritative certifications for sustainable electronic products

No	Label/Certification	Energy Efficiency	Durability/ Reliability	Recyclable Material	Reduced Hazardous	Environmental Protection	Safety
1	TISI (Thai Industrial Standards Institute)	√	×	×	×	√	√
2	SIRIM (SIRIM QAS)	√	×	×	×	×	√
3	SGS MIL Standard Certified	√	×	×	×	×	√
4	RoHS (Restriction of Hazardous Substances Directive)	×	√	×	√	×	×
5	WEEE (Waste Electrical and Electronic Equipment Directive)	×	×	√	×	√	×
6	National Energy Efficiency Label (Thailand & Malaysia)	√	×	×	×	×	×
7	EPEAT (Electronic Product Environmental Assessment Tool)	√	×	×	×	√	×
8	UKCA Mark (UK Conformity Assessed Mark)	×	×	×	√	√	√
9	CE Mark (Conformité Européenne Mark)	×	×	×	√	√	√
10	E-mark (European E-mark compliance with UNECE)	×	×	×	×	√	√
11	MSDS (Material Safety Data Sheet)	×	×	×	√	√	×
12	ISO 14001 (Environmental Management System)	×	×	×	√	√	×
13	NSF/ANSI Standards	×	×	×	√	×	√

14	Energy Star (ENERGY STAR Energy Efficiency Certification)	√	×	×	×	√	×
15	ISO/TS 16949 (replaced by IATF 16949 in 2016)	×	√	×	×	×	×
16	WQA (Water Quality Association Certification)	×	×	×	×	√	√
17	ISO 9001 (Quality Management System)	×	√	×	×	×	×

Note: although safety is widely recognized as the priority in uses of electronic and electrical devices, we exclude certifications that only involve safe requirements to emphasize our focus on sustainability attributes of products. For example, IEC 60950-1 Standard is an international standard solely for safety assurance that should be excluded.

Supplementary Note 14: Significance of Applying BPN and LPM Methods

Overall, by defining and performing both BPN and LPM methods in the modeling process, we capture a multidimensional view of the urban intention-behavior gaps:

(1) BPN (Measurement of magnitude gap). It measures the total volume of "lost" green action and the values of this measurement indicate,

   a. Zero: Indicates perfect realization efficiency, i.e., for every unit of intention expressed by the citizens, there is a corresponding unit of action.
   b. Positive Values: Quantify unrealized green potential, where high-intensity aspirations are not translated into action, suggesting structural barriers.
   c. Negative Values: Indicate under-expressed intentions. In a city context, this often highlights accidental green behaviors, which are driven by economic necessity, cultural norms, or default municipal infrastructure rather than conscious environmental motivation.

(2) LPM (Measurement of threshold gap): It measures the proportion of the population failing to translate a commitment mindset into a commitment habit.

   a. Zero: Indicates a threshold alignment, i.e., the mean probability of intention equals the mean probability of behavior. It means the region has reached a steady state where the number of people who have been psychologically won over (passed x_0) is exactly balanced by the number of people who have successfully crossed the behavioral habit threshold.
   b. Positive Values**:** Indicate a threshold failure, where a citizen has crossed the psychological threshold for sustainable commitment but has not yet crossed the corresponding behavioral threshold.
   c. Negative Values: Identify habitual outliers, i.e., individuals whose behavioral frequency has surpassed the threshold despite maintaining low subjective intention.

This dual-framework approach ensures that our region-level diagnostics are robust against the limitations of single-metric scales. LPM captures the threshold transition, while BPN quantifies the unrealized magnitude. Specifically, LPM identifies cities on the verge of adoption by focusing on whether psychological tipping points have triggered behavioral habits, the BPN distinguishes between cities that have a broad but shallow engagement and those that have a high-capacity deficit.

Supplementary Note 15: Models to Measure Geospatial Characteristics

In this section, we quantify the geospatial characteristics for regions within our sample.

Urban Built-up area Boundaries

The built-up area boundaries were extracted from the Global Urban and Rural Settlement (GURS) dataset (Z. Liu et al., 2024) using a custom Python workflow. First, we applied a binary closing operation (with a 500m radius) to the raster to fill internal gaps and smooth settlement patches. The final raster masks were converted into vector polygons using the 'rasterio.features.shapes' module. To ensure topological consistency and reduce data redundancy, the resulting boundaries were cleaned and simplified with a 100-meter tolerance via the 'shapely.simplify' function.

Green Exposure Index (GEI)

The Green Exposure Index (GEI) quantifies the population-weighted level of vegetation exposure within an urban area. Rather than measuring proximity to discrete green spaces, the index is derived from continuous vegetation intensity as represented by the Normalized Difference Vegetation Index (NDVI). Specifically, the urban area is represented as a set of raster pixels, each associated with an NDVI value and a corresponding population count. The GEI is calculated as the population-weighted average NDVI, given by:

$$GEI = \frac{\sum_i NDVI_i \cdot Pop_i}{\sum_i Pop_i} \tag{3}$$

where $NDVI_i$ is the NDVI value of pixel i, and Pop_i represents the population of pixel i.
GEI reflects a form of passive and habitual exposure to green environments, rather than intentional visits. Prior research in environmental psychology suggests that repeated exposure to natural environments can enhance environmental identity, pro-environmental norms, and moral obligations (J. Wang et al., 2024).

Blue exposure index (BEI)

The Blue Exposure Index (BEI) is conceptually analogous to GEI but focuses on urban water bodies, including rivers, lakes, canals, and other blue spaces within the built-up area. The index is calculated as:

$$BEI = \frac{\sum_{i \in W_{buffer}} Pop_i}{\sum_i Pop_i} \tag{4}$$

where W_{buffer} denotes the buffer extent of urban water bodies. In this study, a buffer distance of 500m is adopted. Blue spaces are often associated with psychological restoration, emotional well-being, and perceived quality of life (Maes et al., 2021). Emerging evidence suggests that regular exposure to water environments may also strengthen place attachment and environmental concern. We therefore posit that higher blue exposure may contribute to greater consistency between stated green consumption intentions and actual purchasing behavior.

Cropland ratio (CLR)

The farmland exposure ratio was calculated to quantify the abundance of farmland surrounding each city's built-up area. Land use/cover data were obtained from the European Space Agency (ESA) WorldCover v200 dataset at 10-m resolution.
For each city, the built-up area was computed from the dissolved geometry. A 5-km buffer zone was generated around the built-up boundary, and the cropland area within this buffer was extracted by masking the ESA WorldCover raster and counting cropland pixels. The cropland ratio is the ratio of farmland area within the 5-km buffer to the city's built-up area.
Pérez-Ramírez et al. (2021) demonstrated that participatory collective farming acts as a leverage point for fostering human-nature connectedness. Accordingly, the proportion of cropland was calculated as a proxy for passive exposure to peri-urban farmland, which may strengthen urban residents' psychological connection to nature and subsequent green

consumption intention.

Coastal accessibility index (CA)

For coastal cities, we further construct a Coastal Accessibility indicator to capture residents' spatial proximity to the coastline. This indicator reflects the ease with which urban populations can access coastal environments, typically measured using distance-based or buffer-based approaches and weighted by population distribution. A simplified population-weighted accessibility measure can be expressed as:

$$CA = \frac{\sum_i \min(distance)}{N} \tag{5}$$

where $\min(distance)$ is the minimum distance from living building polygon i to the coastline. Coastal environments often heighten public awareness of marine pollution, ecosystem vulnerability, and climate-related risks such as sea-level rise. We hypothesize that higher coastal accessibility may strengthen residents' environmental risk perception, thereby reducing the say–do gap in sustainable consumption.

Per capita park space (PPS) and park space proportion (PSP)

On the city scale, we compute two commonly used indicators of green space supply.

(1) Per capita green space:

$$PPS = \frac{A_G}{Pop_B} \tag{6}$$

(2) Green space proportion:

$$PSP = \frac{A_G}{A_B} \tag{7}$$

where A_G is the total area of green spaces within the built-up area, A_B is the built-up area, and Pop_B is the total population within the built-up area. These indicators reflect the aggregate provision of green spaces, but do not account for their spatial distribution or actual accessibility. In the context of this study, they serve as baseline controls to distinguish overall green space supply from experiential exposure and use. The urban green space environment also influences residents' environmental awareness (Ngo & Lung, 2023).

Landscape structure indices: Patch Density (PD), Largest Patch Index (LPI), and Patch Dispersion Index (PDI)

Beyond total area, the spatial configuration of park spaces may substantially influence how residents perceive and interact with urban nature. We therefore adopt several landscape ecological metrics:

(1) Patch Density (PD):

$$PD = \frac{N_P}{A_B} \tag{8}$$

where N_P is the number of park space patches.

(2) Largest Patch Index (LPI):

$$LPI = \frac{\max(A_{P_i})}{A_B} \times 100 \tag{9}$$

where A_{G_i} is the area of green patch i.

We use spatial evenness to represent the degree of spatial dispersion of park spaces.

$$d_i = \min dist((x_i, y_i), (x_j, y_i))$$
$$PDI = \frac{\sigma(d_i)}{\mu(d_i)} \tag{10}$$

High patch density typically indicates fragmented park spaces, whereas a high LPI suggests the presence of a dominant green core. Fragmentation may reduce usability and perceptual salience of park spaces, potentially weakening their influence on environmental attitudes and behavior. Conversely, more aggregated park spaces may facilitate repeated use and stronger environmental engagement.

Park space accessibility index (PA)

Green Space Accessibility captures the ease with which residents can reach park spaces within a reasonable travel distance, often operationalized using buffer-based or network-based methods. A population-weighted accessibility measure can be expressed as:

$$PA = \frac{\sum_{i \in B} Pop_i \cdot I(d_i < d_o)}{\sum_{i \in B} Pop_i} \quad (11)$$

where d_i is the distance from population cell iii to the nearest park space, and d_o is a predefined accessibility threshold.

Accessibility represents a critical link between spatial provision and actual use. Studies have shown that more accessible park spaces are more readily integrated into residents' daily routines, potentially reinforcing pro-environmental attitudes via increased frequency of nature contact (Y. Liu et al., 2022).

Gross Domestic Product

Gridded total Gross Domestic Product (GDP) data at 30 arc-second resolution for the year 2020 were obtained from the existing study (Kummu et al., 2025). For each city, total GDP and per capita GDP were calculated by masking the gridded GDP raster with built-up area boundary. The total GDP within the built-up area was summed directly from the masked grid cells, while per capita GDP was computed by dividing the total GDP by the corresponding built-up population.

Summary of geospatial data sources

Supplementary Table 17 summarizes the geospatial datasets used in this study, including their sources, acquisition time, spatial resolution, data format, and the geospatial indicators derived from each dataset. Multiple open-access geospatial datasets were integrated to characterize the spatial structure and environmental conditions of cities.

Park locations, residential polygons, and water bodies were obtained from OpenStreetMap, which provides detailed and frequently updated volunteered geographic information. The detailed tag information can be found in the code openly available. Coastline data were sourced from Natural Earth. Population distribution data were derived from WorldPop for the year 2020 at a spatial resolution of $100m$. Vegetation conditions were represented by the Normalized Difference Vegetation Index (NDVI) derived from Landsat 8 imagery processed within Google Earth Engine. Land-use information was obtained from the European Space Agency WorldCover product with a spatial resolution of $10m$. To ensure spatial consistency in the analysis, all raster datasets were resampled and standardized to a spatial resolution of $30m$.

These datasets were used to derive a set of geospatial indicators describing park accessibility, green environment, built environment, and Desakota characteristics.

Supplementary Table 17 Geospatial data sources

Object	Data source	Time	Spatial resolution	Format	Geospatial Characteristic
Park polygons	Open Street Map (OSM) (tags: park, garden, et al.) Python package OSMnx (default endpoint: https://overpass-api.de/api)	\	\	Vector	PPS, PSP, PD, LPI, PDI, PA
Residential polygons	OSM (tags: house, apartment, residential, et al.)	\	\	Vector	CA, PA
Water polygons	OSM (tags: water, lake river, et al.)	\	\	Vector	BEI
Coastline	Natural Earth. Coastline (1:10m Physical Vectors). Retrieved from https://www.naturalearthdata.com/downloads/10m-physical-vectors/10m-coastline/	\	10m	Vector	CA
Population	Gridded population data for the year 2020 at 100 m resolution (~3 arc-seconds) were obtained from WorldPop. https://hub.worldpop.org/geodata/listing?id=69	2020	100m	Raster	GEI, BEI, PPS
Gross Domestic Product	Gridded total GDP at 30 arc-second resolution for the year 2020 (Kummu et al., 2025). The dataset is available at Zenodo: https://doi.org/10.5281/zenodo.10976733	2020	1km	Raster	GDP per capita
Urban Built-up Areas	Global Urban and Rural Settlement (GURS) (Z. Liu et al., 2024). The dataset is available at Zenodo: https://zenodo.org/records/11160893	2020	30m	Raster	Urban Built-up Boundaries, DI
Vegetation	Normalized Difference Vegetation Index (NDVI) derived from Landsat 8SLI (Google Earthengine)	2020	30m	Raster	GEI
Land Use	European Space Agency (ESA) WorldCover V200 https://esa-worldcover.org/en/data-access	2021	10m	Raster	DI, CLR

Supplementary Note 16: Statistical Models

Mathematical Formulation of the Mediation Analysis

To quantify the mediating role of NC between spatial configurations and consumer behavior outcomes, we estimated a standard mediation model using a system of ordinary least squares (OLS) regressions (Baron & Kenny, 1986). This allowed us to isolate the paths $(a, b, c, and\ c')$.

All variables were standardized prior to model fitting. Let Y represent the outcome variable, X the spatial predictor (Green Exposure or Desakota), M the mediator (NC), and γ the vector of coefficients for the sociodemographic controls.

(1) Total Effect (Path c)

The outcome was first regressed on the spatial predictor and covariates to establish the total effect, independent of the mediator:

$$Y = cX + \gamma\ Controls + \epsilon \tag{12}$$

(2) Predictor-to-Mediator Effect (Path $\boldsymbol{a}$)

The mediator was regressed on the spatial predictor and covariates:

$$M = aX + \gamma\ Controls + \epsilon \tag{13}$$

(3) Direct Effect (Path $\boldsymbol{c'}$) and Mediator-to-Outcome Effect (Path $\boldsymbol{b}$)

The outcome was regressed simultaneously on both the spatial predictor and the mediator, alongside covariates. The coefficient $\boldsymbol{c'}$ represents the direct effect of the spatial index independent of NC:

$$Y = c'X + bM + \gamma\ Controls + \epsilon \tag{14}$$

(4) Estimation of the Indirect Effect ($\boldsymbol{a} \times \boldsymbol{b}$)

The indirect effect, which quantifies the portion of the spatial index's impact that flows specifically through NC, is the product of the coefficients from Path a and Path b.

Because the sampling distribution of the indirect effect ($a \times b$) is the product of two normally distributed variables, it is inherently asymmetric and skewed. Consequently, standard error approximations that assume normality (such as the Sobel test) are prone to inaccuracies and low power (MacKinnon et al., 2004). To robustly test the significance of the indirect effect, we utilized a percentile bootstrapping approach as recommended by Preacher and Hayes (2004, 2008). We generated 1,000 bootstrap resamples of the dataset (sampling with replacement) and recalculated the $a \times b$ product for each iteration. We used this empirical distribution to construct 95% confidence intervals and calculate two-sided p-values, providing a highly rigorous test of the mediated pathway. For the Total (c) and Direct (c') effects, standard OLS standard errors were used to calculate 95% confidence intervals $\beta \pm 1.96$ ×standard error.

Model Optimization and the Functional Dynamics of Spatial Morphologies

To accurately capture the structural drivers of observed market behavior and account for complex urban dynamics, we employed a tripartite modelling strategy comparing linear, left-censored, and non-linear specifications. All predictors and outcome variables were z-standardized prior to estimation to allow for direct comparability of effect sizes.

(1) Linear Baseline (OLS): We first estimated standard OLS regression models to establish a baseline linear relationship between the spatial indices and observed market behavior. The model is specified as:

$$Y_i = \beta_0 + \beta_1 X_i + \sum_{j=1}^{n} \gamma_j Z_{ij} + \epsilon_i \tag{15}$$

Where Y_i is the z-standardized observed market behavior for city i, X_i is the specific spatial index (*Desakota* or Green Exposure), Z_{ij} represents the vector of controlled socio-demographic covariates, and ϵ_i is the normally distributed error term.

(2) Left-Censored Regression (Tobit): Initial visual inspection of the data revealed a distinct horizontal clustering at the lower bound of observed behavior. Standard OLS yields biased and inconsistent parameter estimates when the dependent variable is censored. To correct for this "floor effect" (a base-level minimum of market participation), we specified a Tobit model based on a latent variable Y_i^*:

$$Y_i^* = \beta_0 + \beta_1 X_i + \sum_{j=1}^{n} \gamma_j Z_{ij} + \epsilon_i \tag{16}$$

The observed market behavior Y_i is left-censored at the empirical minimum threshold c (defined strictly as the minimum empirical z-score of the outcome variable in each domain, $c \approx -1.2$):

$$Y_i = \begin{cases} Y_i^*, & Y_i^* > c \\ c, & Y_i^* \leq c \end{cases} \tag{17}$$

This specification allows us to recover the latent structural effect (β_1) obscured by the zero-bound of market participation.

(3) Generalized Additive Models (GAM): To detect non-monotonic threshold effects without imposing a rigid polynomial structure *a priori*, we fitted GAMs using thin-plate regression splines. The GAM framework allows the relationship between spatial exposure and sustainable behaviour to flexibly follow the data. The model is specified as:

$$Y_i = \beta_0 + s(X_i) + \sum_{j=1}^{n} \gamma_j Z_{ij} + \epsilon_i \tag{18}$$

Where $s(X_i)$ represents the non-parametric thin-plate regression spline function applied to the spatial index. The optimal degree of smoothing was determined via generalised cross-validation. The effective degrees of freedom (edf) are reported in **Supplementary Table 5**, where an $edf > 1$ indicates significant non-linearity.

Supplementary Note 17: Distributional Diagnosis and Transformation Strategy

To ensure the robustness of our statistical analyses and mitigate the disproportionate influence of extreme outliers, we systematically evaluated the distributional properties of all continuous variables prior to modeling. The sample skewness for each variable was computed to formally assess departures from normality. We established a rigorous *priori* threshold, defining variables with an absolute skewness exceeding 1.5 as highly skewed and requiring transformation.

For these highly skewed variables, we applied a dynamically shifted natural logarithmic transformation. Standard logarithmic transformations are undefined for zero values, which frequently occur in our spatial and environmental metrics. To resolve this without introducing arbitrary constants (e.g., adding 1), we computed a variable-specific shift parameter, denoted as c. For any given variable X, the parameter c was defined as half of its minimum strictly positive value:

$$c = \frac{\min_{X \in (0,+\infty)}(X)}{2} \tag{19}$$

The transformed variable X' was subsequently calculated as:

$$X' = \ln(X + c) \tag{20}$$

The execution of this transformation was governed by a strict mathematical feasibility constraint. The transformation was only applied if the condition $\min(X) + c > 0$ was satisfied, ensuring all shifted values remained strictly positive prior to logarithmic scaling.

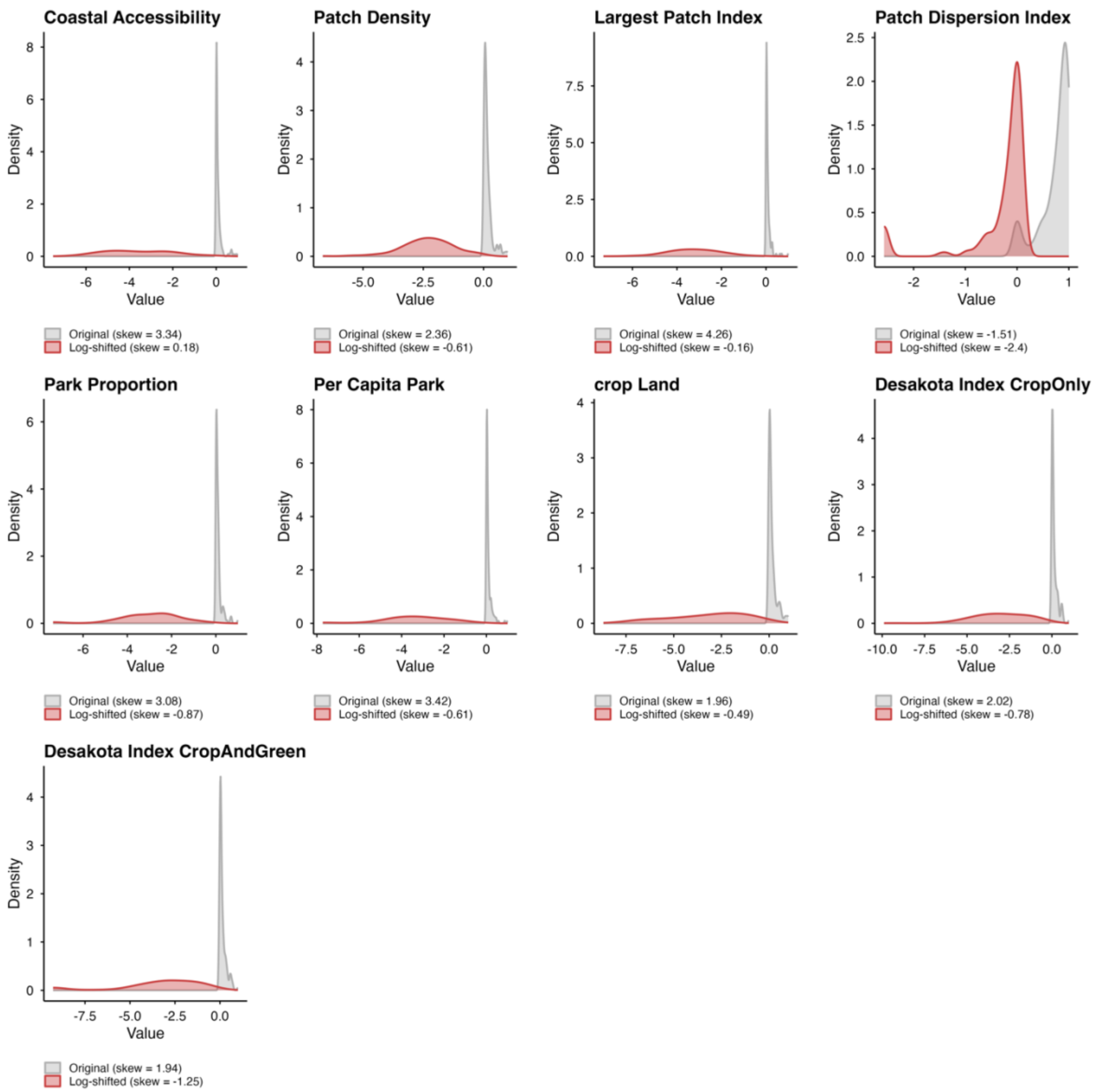
Supplementary Table 18 Skewness diagnosis and transformation decisions for spatial and behavioral variables

Variable	N	Skewness (Raw)	Skewness (Transformed)	Feasible	Transformed
Coastal Accessibility	149	3.343	0.184	Yes	Yes
Park Accessibility within 300m	148	1.069	-1.895	Yes	No
Park Accessibility within 500m	148	0.530	-1.819	Yes	No
Blue Exposure Index	146	0.408	-2.077	Yes	No
Patch Density	142	2.361	-0.613	Yes	Yes
Largest Patch Index	142	4.258	-0.160	Yes	Yes
Patch Dispersion Index	142	-1.511	-2.395	Yes	Yes
Green Exposure Index	147	0.047	-2.550	Yes	No
Park Proportion	147	3.079	-0.872	Yes	Yes
Per Capita Park	147	3.424	-0.607	Yes	Yes
crop Land	148	1.960	-0.490	Yes	Yes
Desakota Index CropOnly	134	2.016	-0.775	Yes	Yes
Desakota Index CropAndGreen	148	1.937	-1.252	Yes	Yes
RG Grocery BPN	125	-0.321	—	No	No
RB Grocery BPN	125	0.799	—	No	No
RG Grocery LPM	125	-0.253	—	No	No
RB Grocery LPM	125	0.725	-0.360	Yes	No
RG Electronic BPN	125	-0.517	—	No	No
RB Electronic BPN	125	1.306	-1.133	Yes	No
RG Electronic LPM	125	-0.485	—	No	No
RB Electronic LPM	125	1.351	0.511	Yes	No

Note: The table details the sample size (N), raw skewness, and transformed skewness for all evaluated variables. A variable was flagged as requiring transformation if the absolute value of its raw skewness exceeded the predefined threshold of 1.5. For these highly skewed variables (highlighted in amber), a shifted natural log transformation was applied to normalize the distribution. This method shifts all values by adding half of the smallest positive non-zero value observed in that variable's distribution prior to applying the logarithm. The 'Feasible' column indicates whether this transformation could be mathematically computed; dashes (—) denote instances where transformed skewness was not calculated.

The comprehensive diagnostic results for all evaluated variables are presented in **Supplementary Table 18**. Our predefined decision rule strictly dictated that a variable was transformed if and only if two conditions were simultaneously met: (1) its absolute sample skewness was greater than 1.5, and (2) the shifted-log transformation was mathematically feasible. For instance, variables such as *Coastal Accessibility* (Raw Skewness = 3.343) and *Largest Patch Index* (Raw Skewness = 4.258) strictly met both criteria and were subsequently transformed. Conversely, variables that failed the feasibility check (e.g., *RG Grocery BPN*) or exhibited skewness below the 1.5 threshold (e.g., *Park Accessibility within 300m*) were retained on their original scale.

The visual efficacy of this shifting strategy is demonstrated in **Supplementary Fig. 10**. The density plots contrast the raw distributions (grey shaded areas), which are typically characterized by severe right-skewness and zero-inflation, against the log-shifted distributions (red shaded areas). For the eight positively skewed variables, the raw distributions are characterized by a sharp concentration near zero and extended right tails; the data-driven shift parameter successfully disperses these extreme concentrations, yielding substantially more symmetric profiles. The one exception is Patch Dispersion Index, whose original distribution is left-skewed (skewness = −1.51); here, the shifted-log transformation marginally increases absolute skewness (to −2.40), a trade-off we retain for pipeline consistency given that the raw value only narrowly exceeds the 1.5 threshold.



Supplementary Fig. 10. Density distributions of original versus log-shifted spatial variables. The figure illustrates the effect of a shifted natural logarithm transformation applied to seven spatial variables identified as highly skewed (|skewness| > 1.5). In each panel, the grey shaded area denotes the probability density of the raw, untransformed data, which generally exhibit severe positive skewness (characterized by a sharp peak near zero and a long right tail). The red shaded area displays the probability density of the same variable following the `shifted-log` transformation. This normalization method shifts all values by adding half of the smallest positive non-zero value observed in the respective distribution prior to applying the logarithm. Skewness values before and after transformation are provided in the legend beneath each plot.

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