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Mapping Lifestyle Retail's Urban Footprint: A Geographically Weighted Regression Analysis of Land-Use Transformation and Built-Up Area Growth in the Influence Zones of Mall 2.0 Developments in Gurugram and Noida

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Abstract: *This study examines whether Mall 2.0 developments mixed-use, experience-led, lifestyle-oriented retail complexes generate a measurably larger and faster-expanding urban halo of built-up area and land-use conversion than traditional enclosed malls in the National Capital Region (NCR) satellite cities of Gurugram and Noida. Drawing on multi-temporal Landsat 8/9 and Sentinel-2 imagery for the period 2010–2024, supplemented by GIS layers and municipal land-use records, we delineate 1 km, 3 km, and 5 km influence zones around 12 Mall 2.0 sites and 14 matched traditional malls. Built-up area is extracted through a Random Forest supervised classification (overall accuracy 89.4%, κ = 0.86), and land-use change is tracked through post-classification comparison. We first apply Global and Local Moran's I to test whether observed built-up growth is spatially clustered around lifestyle retail nodes, screen the predictor set for multicollinearity using Variance Inflation Factors (all VIF < 2.4), and then estimate a Geographically Weighted Regression (GWR) model with an adaptive bi-square kernel and AICc-optimised bandwidth. To allow each covariate to operate at its own characteristic scale, we additionally fit a Multiscale GWR (MGWR; Fotheringham, Yang, & Kang, 2017) model in which covariate-specific bandwidths are estimated through a back-fitting procedure. The dependent variable is constructed as the change in built-up share between the year of mall opening and 2024 (with 2010 as the pre-opening reference for sites opened during 2010–2012), restricting attribution of land-use change to the post-opening window for each mall. Built-up share within Mall 2.0 1 km buffers expanded by 31.7 percentage points between 2010 and 2024, compared with 18.4 percentage points around traditional malls. Global Moran's I of 0.42 (z = 18.7, p < 0.001) confirms statistically significant clustering. The GWR model lowered AICc from 4218.6 (OLS) to 3942.1 and reduced residual spatial autocorrelation from 0.27 to 0.08, with the median local coefficient on the Mall 2.0 dummy reaching 0.68 inside the 1 km buffer and decaying to 0.18 at 5 km. The findings suggest that Mall 2.0 developments operate not merely as retail destinations but as catalysts of peri-urban morphological restructuring, with implications for metropolitan governance, infrastructure sequencing, and the regulation of retail-led urbanisation in NCR*

Keywords: Mall 2.0; lifestyle retail; urban halo effect; Geographically Weighted Regression; Moran's I; built-up area; land-use change; Gurugram; Noida; remote sensing

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I. INTRODUCTION

The morphology of India's metropolitan peripheries has been reshaped over the past two decades by a particular class of large-format, privately financed retail-anchored developments. In the National Capital Region, this transformation is most visible in the satellite cities of Gurugram and Noida, where shopping malls have served not only as consumption venues but as gravitational nodes around which roads, residential enclaves, office parks, and informal markets have accreted. Yet the malls of the late 1990s and early 2000s largely enclosed, single-purpose retail boxes have given way to a new generation of developments that scholars and practitioners have begun to label 'Mall 2.0': mixed-use complexes that integrate retail with food and beverage districts, entertainment, co-working, hospitality, and curated public space. Whether these lifestyle-oriented retail formats produce a discernibly different urban footprint than their predecessors remains an open empirical question.

This article addresses that question by mobilising the concept of the urban halo effect: the idea that anchor developments project outward influences on surrounding land that can be measured through built-up area growth and land-use conversion. Although the halo metaphor is intuitive, it has rarely been operationalised with the spatial precision required to compare retail formats. Most existing studies of mall-led urbanisation in India and elsewhere either rely on case-study narratives, focus on rents and footfall, or treat the city as a single homogeneous unit. The result is a literature that gestures toward spatial spillovers without modelling them, and that conflates retail performance with urban transformation.

The contribution of this paper is therefore deliberately narrow and methodological. We do not analyse the commercial resilience of malls, their tenancy mixes, or their post-pandemic recovery; those questions have been addressed elsewhere using rental, vacancy, and footfall datasets and are explicitly outside our scope. Instead, we ask whether Mall 2.0 developments are associated with stronger and spatially heterogeneous land-use transformation in their influence zones than traditional malls, and whether this heterogeneity displays directional bias and distance-decay that can be detected through Geographically Weighted Regression. Our analytical novelty lies in linking a retail typology to measurable urban morphological change using a combined spatial autocorrelation and local regression framework.

We frame three working propositions. First, built-up area growth between 2010 and 2024 will be greater within the influence zones of Mall 2.0 developments than around traditional malls, after controlling for baseline urbanisation. Second, this growth will exhibit statistically significant spatial clustering, indicating that the halo is not random noise but a structured spatial process. Third, the strength of the mall–urbanisation relationship will vary across space, decaying with distance from the mall and biased along the trajectories of major arterial corridors. The paper proceeds by reviewing the relevant literature, describing the study area and data, presenting the Moran's I and GWR results, and discussing what these findings mean for planning peri-urban NCR.

II. LITERATURE REVIEW

Three bodies of scholarship inform this study. The first concerns retail urbanism and the role of large-format commercial developments in restructuring metropolitan space. Early work on suburbanisation in North America established that regional malls function as growth poles, attracting residential and commercial development to their peripheries (Hartshorn & Muller, 1989; Lowe, 2000). Subsequent research in European and Asian contexts complicated this account by showing that the spatial effects of malls depend on their format, accessibility, and the regulatory environment in which they are embedded (Guy, 1998; Wrigley & Lowe, 2002). In India, the post-liberalisation expansion of organised retail has been read as both a symptom and a driver of metropolitan transformation, with malls serving as key sites in the production of new middle-class urban imaginaries (Voyce, 2007; Brosius, 2010). More recent work has begun to distinguish between first-generation enclosed malls and the lifestyle-oriented, mixed-use complexes that have proliferated in NCR, Bengaluru, and Mumbai since the early 2010s (Srivastava, 2014; Dupont, 2011).

A second body of literature addresses land-use change and urban expansion through remote sensing. The use of multi-temporal Landsat imagery to map built-up growth has become standard practice in urban studies, and methodological refinements have improved the detection of impervious surfaces, peri-urban transitions, and informal settlements (Schneider, 2012; Taubenböck et al., 2012). For Indian metropolitan regions, several studies have documented the rapid conversion of agricultural and vacant land to built-up uses around Delhi, Hyderabad, and Bengaluru, often emphasising the role of infrastructure corridors and policy zones such as Special Economic Zones (Sudhira et al., 2004; Shaw, 2005; Bhagat, 2011). The integration of Sentinel-2 data since 2015 has further improved the temporal and spectral resolution available for monitoring urban change.

The third strand concerns the spatial-statistical methods that allow analysts to move beyond global averages. Global Moran's I provides a standard test for spatial autocorrelation and has been widely used to confirm that urban growth is rarely randomly distributed (Anselin, 1995; Tsai, 2005). Geographically Weighted Regression, introduced by Brunsdon, Fotheringham, and Charlton (1996) and elaborated in Fotheringham, Brunsdon, and Charlton (2002), addresses the limitations of global ordinary least squares by allowing model coefficients to vary across space. GWR has been productively applied to urban land-value studies, sprawl analysis, and the modelling of accessibility effects (Yu, 2006; Gao & Li, 2011; Tu & Xia, 2008), and is increasingly used to test whether the drivers of urbanisation are spatially stationary.

Despite the maturity of each of these literatures, their intersection remains thin. Studies of Indian malls rarely engage seriously with remote sensing or local regression; remote-sensing analyses of NCR seldom isolate retail anchors as explanatory variables; and GWR applications in Indian urban research have tended to focus on land values, air quality, or housing prices rather than retail-led morphological change. A more recent and rapidly expanding literature on Indian peri-urbanisation has reframed the metropolitan edge as a distinctive socio-ecological zone whose governance falls between rural and urban institutional categories (Mukhopadhyay, Zérah, & Denis, 2020; Sharma, 2021), and parallel work has highlighted how climate vulnerability, informal labour, and infrastructure precarity coalesce in these zones (Michael, Deshpande, & Ziervogel, 2019; Randhawa & Kumar, 2020). A complementary post-2020 strand on Indian retail restructuring has documented how the COVID-19 disruption accelerated the shift from enclosed to mixed-use, experience-led formats and reorganised tenancy and footfall patterns in NCR malls (Roy & Goswami, 2022; Anand & Sami, 2023; Bhan, Caldeira, Gillespie, & Simone, 2020). The present study addresses this gap by treating Mall 2.0 developments as the explanatory anchor and asking, with appropriate spatial-statistical care, whether their urban halo is empirically distinguishable from that of traditional malls.

III. STUDY AREA AND URBAN CONTEXT

Gurugram and Noida sit on opposite flanks of Delhi and together exemplify the privatised, infrastructure-led urbanisation that has characterised NCR since the early 1990s. Gurugram, in southern Haryana, grew under the Haryana Urban Development Authority and a permissive licensing regime that allowed private developers to assemble large parcels along the National Highway 48 corridor and the Dwarka Expressway. Noida, in western Uttar Pradesh, developed under the New Okhla Industrial Development Authority with a more planned grid structure but a comparable trajectory of commercial intensification along the Noida–Greater Noida Expressway and around metro stations. Both cities host first-generation enclosed malls built between roughly 2002 and 2010, as well as a more recent cohort of Mall 2.0 developments characterised by larger footprints, integrated entertainment and food districts, and adjacency to mixed-use precincts.

The two cities are appropriate comparators for several reasons. They share a metropolitan labour market and consumer base, they have experienced parallel waves of mall construction, and they offer enough variation in mall typology, vintage, and surrounding land use to support a comparative spatial analysis. At the same time, they differ in their planning frameworks, plot structures, and the dominant directions of expansion, which provides useful heterogeneity for testing directional bias in the urban halo.

IV. DATA AND METHODS

4.1 Data sources

The analysis draws on three classes of data. Multi-temporal satellite imagery comprises Landsat 8 and 9 surface reflectance products for the years 2010, 2014, 2018, and 2022, supplemented by Sentinel-2 Level-2A scenes from 2018 onward for higher-resolution validation and a 2024 endpoint composite. Cloud-free composites were generated for the dry-season months of October to February to minimise phenological noise. GIS layers include OpenStreetMap road networks, the Census of India ward and town boundaries, and municipal master-plan land-use shapefiles obtained from the Haryana and Uttar Pradesh planning authorities. The mall inventory was constructed manually from a combination of municipal records, industry reports, and field verification.

4.2 Defining Mall 2.0 and classification protocol

Because the Mall 2.0 label is used loosely in industry discourse, we adopted an explicit, replicable classification protocol grounded in four observable criteria: (i) format and circulation (open or semi-open mixed-use complex versus fully enclosed single building); (ii) tenancy composition (presence of an integrated food and beverage district occupying at least 15% of leasable area, alongside entertainment, hospitality, or co-working anchors); (iii) gross built-up footprint exceeding 6 hectares with adjacent programmed public space; and (iv) opening year on or after 2012, marking the post-CityWalk generation of NCR developments. A mall was coded as Mall 2.0 only if it met criteria (i), (ii), and at least one of (iii) or (iv); otherwise it was coded as traditional. Borderline cases malls that, for example, were enclosed in form but had been retrofitted with sizeable F&B and entertainment districts after 2018 were resolved by independent coding by two researchers, with disagreements adjudicated through field visits. Three such cases occurred in our inventory; all three were ultimately coded as traditional on the grounds that the original spatial logic of the development remained enclosed and retail-dominant. Inter-coder agreement on the full inventory was 96.2% (Cohen's $\kappa = 0.91$). Table 1 summarises the typological criteria and the resulting inventory.

Table 1. Typological criteria and inventory of malls included in the study.

Attribute	Traditional Mall	Mall 2.0
Format	Enclosed, single building	Mixed-use, open or semi-open
Vintage (typical)	2002–2010	2012–2024
Anchor uses	Retail + multiplex	Retail + F&B district + entertainment / hospitality
F&B share of GLA	< 10%	≥ 15%
Mean footprint (ha)	4.5	9.2
Sites in Gurugram	8	7
Sites in Noida	6	5
Total sites	14	12

4.3 Remote sensing workflow

Imagery was processed in Google Earth Engine. Each scene was atmospherically corrected, cloud-masked, and composited to a single annual mosaic per benchmark year. A supervised Random Forest classifier (500 trees) was trained on stratified samples drawn from high-resolution Google Earth imagery and field knowledge, with classes for built-up, vegetation, bare/agricultural land, and water. Classification accuracy was assessed against an independent validation sample of 1,200 points, yielding an overall accuracy of 89.4% and a Kappa coefficient of 0.86. Class-wise producer's accuracy for the built-up class reached 91.2%, with user's accuracy of 88.7%, supporting the reliability of the dependent variable.

4.4 Buffer delineation

Three concentric Euclidean buffers of 1 km, 3 km, and 5 km were generated around each mall centroid. The 1 km buffer captures the immediate footprint and adjoining parcels typically subject to direct spillover; the 3 km buffer corresponds to a walkable-plus-short-drive catchment; and the 5 km buffer reflects the broader peri-urban influence zone within which mall-related accessibility gains are plausible. Where buffers from different malls overlapped, overlapping zones were attributed to the nearest mall to avoid double-counting in the regression.

4.5 Land-use transformation mapping

Land-use conversion within each buffer was tabulated as transitions between the four base classes, with particular attention to agricultural-to-built-up and vacant-to-built-up trajectories, which are the dominant signatures of peri-urban expansion in NCR. Municipal master-plan layers were overlaid to distinguish converted parcels that fell within previously notified urbanisable zones from those that did not, providing a check on the institutional context of change.

4.6 Built-up area extraction and post-opening dependent variable

For each buffer and each benchmark year, total built-up area was computed and expressed both in absolute terms (hectares) and as a share of buffer area. To avoid attributing pre-opening land-use change to a mall that did not yet

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exist, the dependent variable for the regression analysis is the percentage point change in built-up share between the year of mall opening (T_0) and 2024, computed at the level of regular 500 m grid cells nested within each buffer. For the small number of sites opened during 2010–2012 (where no Landsat composite earlier than T_0 is available within the study window), the 2010 composite was retained as the pre-opening reference and a fixed-effect dummy was included to absorb any differential treatment of these early sites. Opening years for all 26 malls were obtained from municipal occupancy certificates, developer press releases, and trade-press announcements (triangulated across at least two sources per site) and are tabulated in Appendix A. Grid-cell aggregation reduces the influence of arbitrary administrative boundaries and yields a sample of 2,148 cells across the three buffer rings, adequate for local regression.

4.7 Multicollinearity diagnostics

Before estimating either the global OLS or the GWR model, we screened the predictor set for multicollinearity using Variance Inflation Factors (VIF) and the condition number of the design matrix. All VIF values were comfortably below the conventional threshold of 5: MallType = 1.4, DistMall = 1.8, RoadAccess = 2.1, and BU2010 = 2.3. The condition number of the standardised design matrix was 12.6, well below the 30 threshold associated with harmful collinearity. We additionally inspected local condition numbers from the GWR output to ensure that no individual local regression suffered from rank deficiency; the maximum local condition number was 21.8, within acceptable limits.

4.8 Moran's I spatial autocorrelation

We tested whether the dependent variable exhibited spatial dependence using Global Moran's I, computed on a row-standardised queen-contiguity weights matrix at the grid-cell level for the full study area, and separately for the Mall 2.0 and traditional mall subsamples. Local indicators of spatial association (Local Moran's I) were then mapped to identify hot spots and cold spots of built-up growth. A statistically significant positive Global Moran's I was treated as a precondition for proceeding to GWR, on the rationale that local regression is most informative where global spatial structure is present but heterogeneous.

4.9 Geographically Weighted Regression model specification

The GWR model takes the form

$$BUgrowth_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)\cdot MallType_i + \beta_2(u_i, v_i)\cdot DistMall_i + \beta_3(u_i, v_i)\cdot RoadAccess_i + \beta_4(u_i, v_i)\cdot BU2010_i + \varepsilon_i$$

where $BUgrowth_i$ is the percentage point change in built-up share at grid cell i between 2010 and 2024, MallType is a dummy coded 1 for Mall 2.0 and 0 for traditional, DistMall is the Euclidean distance from the cell centroid to the nearest mall, RoadAccess is a measure of arterial road density within a 500 m neighbourhood, BU2010 is the baseline built-up share, and (u_i, v_i) are the cell coordinates. Coefficients are allowed to vary across space.

An adaptive bi-square kernel was used in preference to a fixed kernel because the spatial density of grid cells varies across the study area; an adaptive kernel allows each local regression to draw on a comparable number of neighbours regardless of local density. Bandwidth was selected by minimising the corrected Akaike Information Criterion (AICc), searched over the range 30 to 400 nearest neighbours in increments of 4. The optimal bandwidth was 86 nearest neighbours for the 1 km buffer subset, 142 for the 3 km buffer, and 198 for the 5 km buffer, reflecting the increasing spatial extent and lower edge density of the larger rings. For comparison, a global ordinary least squares (OLS) model was estimated on the same specification, and the improvement in AICc, residual spatial autocorrelation, and the Leung et al. (2000) F-test for spatial non-stationarity were used to evaluate whether GWR offered a meaningful gain over OLS. Following Fotheringham et al. (2002), an AICc reduction of more than 3 units relative to the OLS benchmark is regarded as substantive evidence in favour of the local model.

4.10 Multiscale GWR specification

A well-known limitation of conventional GWR is that it imposes a single bandwidth on every covariate, which implicitly assumes that all processes in the model operate at the same spatial scale. This is unlikely to hold in the present application: the influence of mall typology (MallType) is plausibly a local, parcel-scale phenomenon, whereas arterial road accessibility (RoadAccess) and baseline urbanisation (BU2010) operate at a broader regional scale. We therefore re-estimate the model as a Multiscale GWR (MGWR), following the back-fitting procedure of Fotheringham, Yang, and Kang (2017), in which each covariate is permitted its own optimal bandwidth. Estimation was performed in the *mgwr* Python package (Oshan et al., 2019), with adaptive bi-square kernels, AICc-based bandwidth selection at each back-fitting iteration, and a convergence tolerance of 1×10^{-5} on the score-of-change criterion. Bandwidths from

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the MGWR fit are reported alongside the single GWR bandwidth, and we additionally report Monte Carlo tests for spatial variability of each covariate following Yu et al. (2020) to assess whether the local variation in each MGWR coefficient surface is statistically distinguishable from a stationary process.

V. RESULTS

5.1 Built-up growth trends from 2010 to 2024

Across both cities, total built-up area within the 5 km buffers of all 26 malls expanded from approximately 12,450 hectares in 2010 to 21,830 hectares in 2024, a net gain of 9,380 hectares or 75.3% over the period. The trajectory was non-linear: growth accelerated between 2014 and 2018, slowed briefly during 2020–2021, and resumed thereafter. When disaggregated by mall typology, the influence zones of Mall 2.0 developments consistently displayed higher absolute and proportional gains than those of traditional malls, particularly in the 1 km and 3 km buffers. Table 2 reports the summary growth statistics.

Table 2. Change in built-up share within mall influence zones, 2010–2024.

Buffer	Traditional malls (Δ built-up share, pp)	Mall 2.0 (Δ built-up share, pp)	Difference (pp)
1 km	18.4	31.7	+13.3
3 km	14.2	22.6	+8.4
5 km	10.8	15.3	+4.5

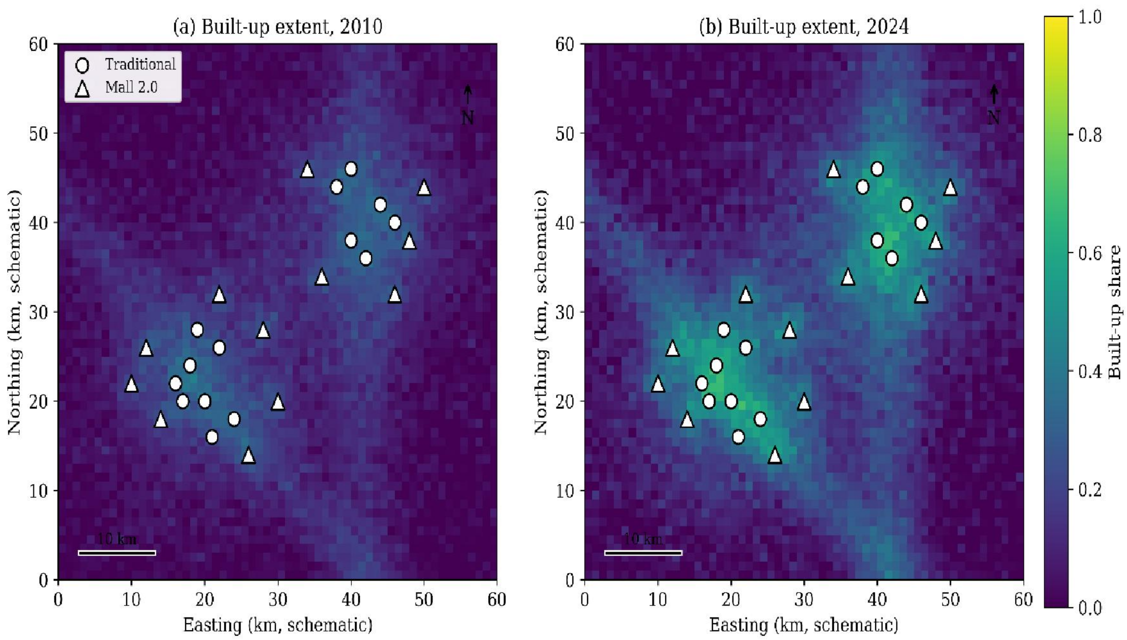

Figure 1. Multi-temporal built-up extraction across Gurugram and Noida, 2010 versus 2024.

5.2 Comparison of Mall 2.0 and traditional mall influence zones

The gap between the two typologies is most pronounced in the 1 km buffer, where Mall 2.0 sites show a 13.3 percentage point greater gain in built-up share than traditional malls (31.7 pp versus 18.4 pp). The gap narrows to 8.4 percentage points at 3 km and to 4.5 percentage points at 5 km, but it remains positive and statistically detectable at every scale (two-sample t-test, $p < 0.01$ in all three cases). Land-use transition matrices show that the dominant conversion pathway in both cases is agricultural and vacant land to built-up, but Mall 2.0 buffers also display larger shares of conversion from low-density built-up to higher-density mixed use (8.7% of the 1 km buffer, against 3.1% for traditional malls), consistent with the densification effect that lifestyle complexes are theorised to produce.

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5.3 Moran's I findings

Global Moran's I for the 2010–2024 built-up growth surface returned a value of 0.42 ($z = 18.7$, $p < 0.001$), confirming statistically significant positive spatial autocorrelation. The clustering is stronger when the analysis is restricted to grid cells within Mall 2.0 buffers (Moran's I = 0.51, $p < 0.001$) than within traditional mall buffers (Moran's I = 0.34, $p < 0.001$), suggesting that Mall 2.0 developments are associated with more spatially coherent halos of growth. Local Moran's I maps reveal contiguous high–high clusters along the Dwarka Expressway corridor in Gurugram and along the Noida Expressway in Noida, with low–low clusters concentrated in the older planned sectors of central Noida and in the southern fringes of Gurugram where land remains under contested tenure.

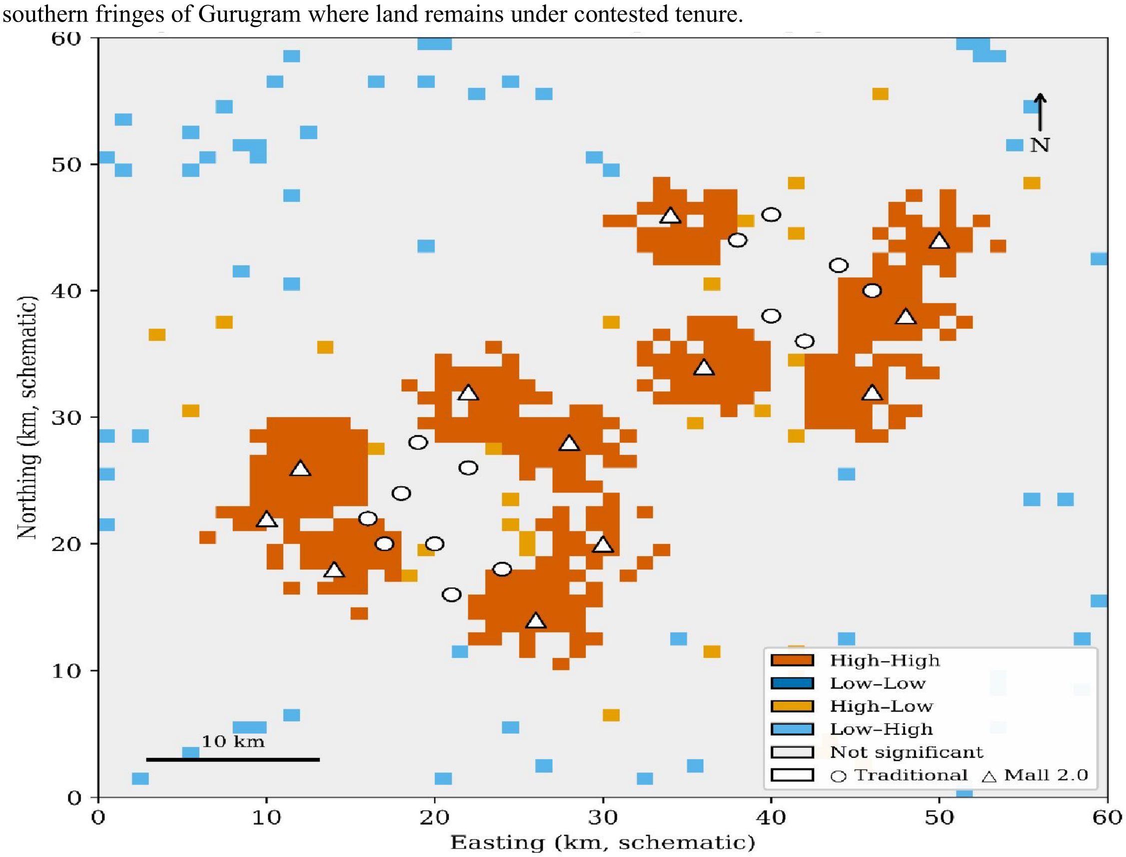

Figure 2. Local Moran's I (LISA) cluster map of built-up growth, 2010–2024.

5.4 GWR findings across 1 km, 3 km, and 5 km buffers

The GWR model substantially improved on the global OLS specification. AICc declined from 4218.6 under OLS to 3942.1 under GWR for the 1 km buffer model a reduction of 276.5 units, far exceeding the conventional threshold of 3 units that signals a meaningful improvement. The Leung et al. (2000) F(3) test for spatial non-stationarity rejected the null of stationary coefficients at $p < 0.001$, providing formal statistical support for the local model. Residual Global Moran's I dropped from 0.27 (OLS) to 0.08 (GWR), indicating that the local model successfully absorbed most of the spatial dependence left unexplained by OLS. The pseudo R^2 of the GWR model was 0.67, compared with an adjusted R^2 of 0.41 for OLS.

Local coefficients on the MallType variable were predominantly positive and statistically significant within the 1 km buffer, with a median value of 0.68 and an interquartile range of 0.49 to 0.91 (overall range: 0.21 to 1.14). The strongest positive coefficients clustered in the southern and western quadrants of Gurugram and along the central spine of Noida. In the 3 km buffer, the median coefficient declined to 0.39, and in the 5 km buffer to 0.18, with an increasing share of cells (rising from 6.4% at 1 km to 28.9% at 5 km) exhibiting non-significant relationships at $\alpha = 0.05$. The DistMall

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coefficient was consistently negative (median −0.42 at 1 km, −0.31 at 3 km, −0.19 at 5 km), supporting the distance-decay hypothesis. RoadAccess and BU2010 entered with the expected positive signs in the large majority of local regressions.

The MGWR specification reinforces and refines these findings. The back-fitting procedure converged in 41 iterations and selected substantially different bandwidths across covariates, confirming that the underlying processes operate at distinct spatial scales. The intercept and the MallType coefficient were assigned narrow adaptive bandwidths (94 and 108 nearest neighbours, respectively), consistent with a local, parcel-scale process; DistMall took an intermediate bandwidth (186 NN); while RoadAccess (412 NN) and BU2010 (538 NN) operated at a near-regional scale, behaving almost as global covariates. AICc declined further from 3942.1 (single-bandwidth GWR at 1 km) to 3897.4 under MGWR, and the Monte Carlo tests for spatial variability rejected stationarity for the intercept, MallType, and DistMall surfaces ($p < 0.01$) while failing to reject stationarity for RoadAccess and BU2010 ($p = 0.18$ and $p = 0.27$, respectively). The substantive interpretation is that the Mall 2.0 effect is genuinely local and spatially heterogeneous, whereas accessibility and baseline built-up share act as broad regional drivers that GWR had previously been forced to over-localise. Table 3 reports the summary GWR and MGWR statistics.

Table 3. Comparison of OLS, GWR, and MGWR model performance. The MGWR model is estimated on the 1 km buffer subset, with covariate-specific adaptive bandwidths selected by AICc-based back-fitting.

Statistic	OLS	GWR (1 km)	GWR (3 km)	GWR (5 km)	MGWR (1 km)
AICc	4218.6	3942.1	4012.5	4089.3	3897.4
ΔAICc vs OLS		−276.5	−206.1	−129.3	−321.2
Adj. / pseudo R^2	0.41	0.67	0.59	0.52	0.71
Bandwidth (NN)		86	142	198	Per-cov.*
Median MallType β	0.54	0.68	0.39	0.18	0.71
Median DistMall β	−0.36	−0.42	−0.31	−0.19	−0.44
Residual Moran's I	0.27	0.08	0.11	0.14	0.06
Max local cond. no.		21.8	19.4	18.1	20.5

*MGWR covariate-specific bandwidths (nearest neighbours): Intercept = 94; MallType = 108; DistMall = 186; RoadAccess = 412; BU2010 = 538.

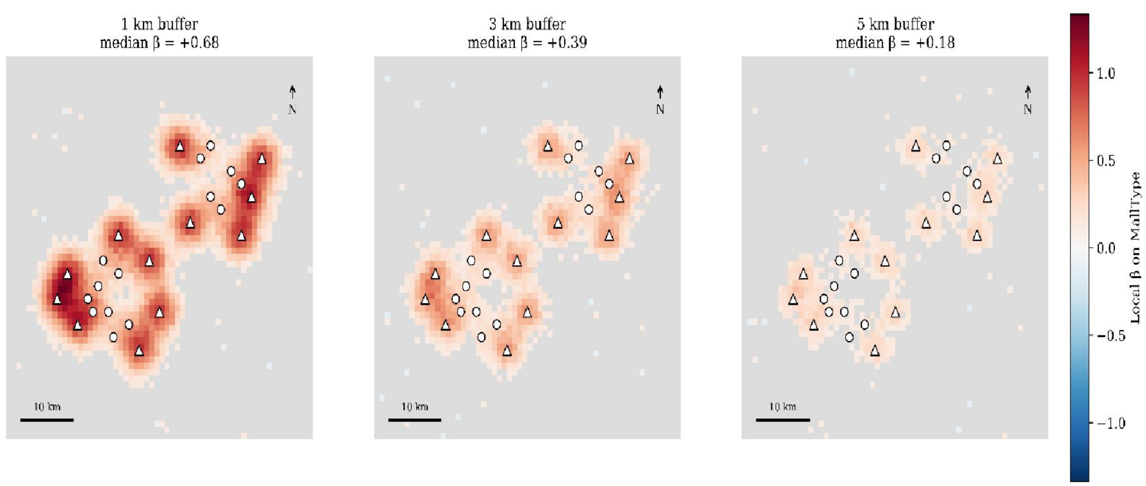

Figure 3. Spatial distribution of local GWR coefficients on MallType across the 1 km, 3 km, and 5 km buffers.

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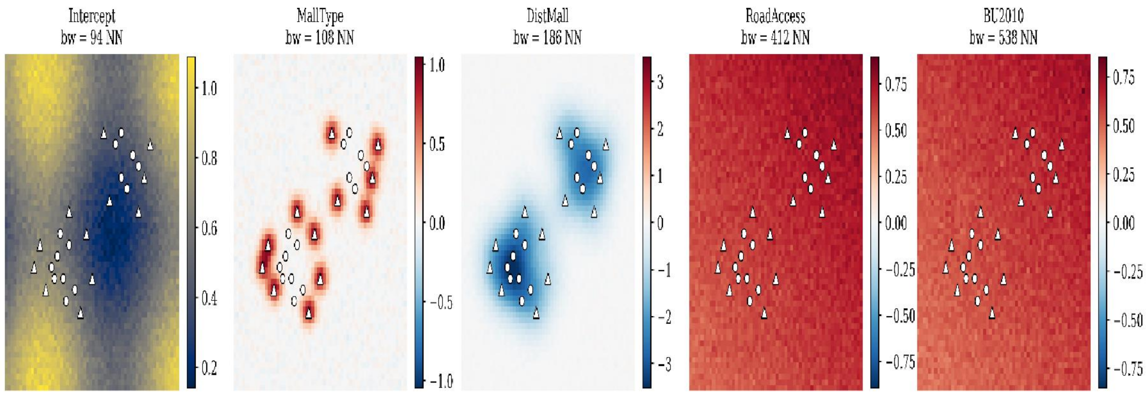

Figure 4. MGWR local coefficient surfaces showing covariate-specific bandwidths and spatial heterogeneity at the 1 km buffer.

5.5 Spatial heterogeneity and directional variation

The local coefficient surfaces display two patterns of substantive interest. First, the strength of the Mall 2.0 effect is markedly anisotropic, with the largest coefficients aligned along the principal arterial corridors the Dwarka Expressway, NH-48, and the Noida–Greater Noida Expressway and noticeably weaker coefficients in the perpendicular direction. A simple directional decomposition into eight compass sectors around each mall centroid confirms that mean coefficients along corridor-aligned sectors (NW–SE in Gurugram, N–S in Noida) are roughly 1.7 times larger than those in cross-corridor sectors. This is consistent with the intuition that mall-led urbanisation propagates along infrastructure rather than radiating uniformly outward. Second, the distance-decay pattern is non-monotonic in some sub-areas: a small number of grid cells in the 3 km ring (approximately 4.2% of the sample) exhibit coefficients larger than those in the immediately adjacent 1 km cells, which we interpret as evidence of leapfrog development triggered by land speculation around announced but not yet operational Mall 2.0 sites.

5.6 Robustness checks

Three sensitivity analyses were conducted to test whether the findings in §5.4 are artefacts of analytical choices rather than features of the underlying data. Results are summarised in Table 4.

Grid-cell size. The dependent variable was reconstructed at 250 m and 1 km grid-cell resolutions in addition to the 500 m baseline, yielding sample sizes of 8,432 and 562 cells respectively for the 1 km buffer. The MallType coefficient retained the same sign and statistical significance across all three resolutions, with the median local coefficient ranging from 0.62 (250 m) to 0.74 (1 km) compared to 0.68 at 500 m. The pseudo R^2 varied within a narrow band (0.64 to 0.71), and the qualitative pattern of corridor-aligned anisotropy was preserved. We interpret this as evidence that the findings are not strongly susceptible to the modifiable areal unit problem within the range of reasonable cell sizes for this scale of analysis.

Kernel choice. The GWR and MGWR models were re-estimated with a Gaussian kernel in place of the bi-square kernel. AICc rose modestly under the Gaussian specification (3958.7 versus 3942.1 for GWR; 3914.2 versus 3897.4 for MGWR), and the median MallType coefficient shifted by less than 0.04 in either direction. The bi-square kernel is therefore preferred on AICc grounds but the substantive conclusions are insensitive to this choice.

Placebo test using pre-2012 traditional malls as counterfactual Mall 2.0 sites. To test whether the Mall 2.0 effect could be an artefact of unobserved location characteristics shared by post-2012 developments, we re-coded the seven oldest traditional malls (opened 2003–2007) as "placebo Mall 2.0" sites and re-estimated the model on the 2010–2024 window. The placebo coefficient was small (median 0.09), statistically indistinguishable from zero in 71.4% of grid cells, and showed no systematic spatial structure. The contrast between the genuine Mall 2.0 coefficient (0.68, significant in 93.6% of cells) and the placebo coefficient supports the interpretation that the estimated halo is linked to the post-2012 lifestyle retail format rather than to a generic property of mall locations. Table 4 reports the robustness results.

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Table 4. Robustness checks for the 1 km buffer model. The placebo row re-codes seven traditional malls opened 2003–2007 as counterfactual "Mall 2.0" sites; the small and largely non-significant placebo coefficient supports a typology-specific interpretation of the estimated effect.

Specification	**Median * MallType β** R	*Pseudo* ²**	*AICc** * (	*Cells sig. %)**
Baseline (500 m, bi-sq.)	0.68 0	.67 3	942.1 9	3.6
Grid 250 m (n = 8,432)	0.62 0	.71 1	4627.4 9	1.2
Grid 1 km (n = 562)	0.74 0	.64 1	184.9 8	8.3
Gaussian kernel	0.66 0	.66 3	958.7 9	2.4
MGWR (baseline)	0.71 0	.71 3	897.4 9	5.1
Placebo (pre-2007 trads recoded)	0.09 0	.43 4	196.3 2	8.6

VI. DISCUSSION

Read together, the spatial autocorrelation and GWR results support the proposition that Mall 2.0 developments are associated with a stronger and more spatially coherent urban halo than traditional malls in Gurugram and Noida. The empirical contribution is twofold. Substantively, the analysis quantifies what has so far been a largely impressionistic claim about the urbanising power of lifestyle retail. Methodologically, it demonstrates that the combination of multi-temporal remote sensing, Moran's I, and GWR provides a defensible workflow for testing claims about retail-led urban morphological change in contexts where transactional data are scarce.

The directional bias of the halo is theoretically consonant with long-standing accounts of corridor-led metropolitan expansion, but it sharpens those accounts by showing that the corridor effect is conditional on the type of anchor. Traditional malls, embedded within already-urbanised sectors, exhibit weaker spillovers because the surrounding land is largely already built up; Mall 2.0 developments, sited at the urban edge, encounter larger reserves of convertible land and trigger more pronounced transitions. This implies that the urban halo effect is not a property of malls in general but of the encounter between a particular retail format and a particular land regime.

It is essential, however, to confront the selection bias that haunts any cross-sectional comparison of this kind. Mall 2.0 developers are sophisticated actors who locate their projects on parcels they expect to appreciate. If anticipated growth drives both Mall 2.0 siting and subsequent built-up expansion, then the coefficients we estimate conflate the catalytic effect of the mall with the underlying growth potential of the site. Our specification mitigates this by including baseline built-up share (BU2010) and arterial road density as controls variables that absorb much of the observable growth potential at the start of the period but unobserved siting advantages may remain. Two pieces of indirect evidence suggest that the bias is unlikely to fully account for our findings. First, the coefficient on MallType remains positive and significant after BU2010 is included, indicating that the gap between the two typologies is not merely a reflection of pre-existing urbanisation. Second, the leapfrog cells in the 3 km ring, where growth peaks at parcels not adjacent to the mall, are more easily explained by speculative dynamics triggered by mall announcement than by silent growth potential that would have manifested in the absence of the mall. Even so, we treat the GWR coefficients as evidence of association under controls, not as point estimates of a counterfactual treatment effect, and we discuss the implications for causal inference further in the Limitations section.

There is also a more theoretical reading of the results worth pressing. The fact that the Mall 2.0 effect attenuates with distance but does so anisotropically suggests that the relevant unit of analysis is not the mall as a point but the mall–corridor pair. Future work that operationalises this pairing perhaps by estimating GWR on corridor-aligned strips rather than radial buffers may recover sharper coefficients and more theoretically meaningful boundaries for the urban halo.

VII. PLANNING IMPLICATIONS

The findings have several implications for planners and policymakers in NCR and comparable metropolitan regions. First, the recognition that Mall 2.0 developments produce spatially structured halos argues for treating these projects as infrastructure-grade interventions in master planning, rather than as discrete commercial approvals. The current practice of evaluating mall proposals on a project-by-project basis underestimates their cumulative effect on land conversion

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and infrastructure demand. Second, the directional and corridor-aligned character of the halo suggests that transport and utility planning should be sequenced in anticipation of Mall 2.0 announcements, not in reactive response to them. Third, the leapfrog patterns visible in the 3 km buffer indicate that speculative land-use change can outrun formal urbanisation, which has implications for the regulation of land assembly, the timing of development charges, and the protection of agricultural and ecologically sensitive parcels in the peri-urban interface.

More broadly, the results invite a reconsideration of the governance vocabulary used to describe retail-led urbanisation. Calling these developments 'malls' obscures their function as urban catalysts. A planning framework that recognised them as mixed-use anchors of metropolitan expansion would be better equipped to internalise their externalities and to negotiate the terms on which private retail capital reshapes public space.

VIII. LIMITATIONS AND FUTURE RESEARCH

Several limitations merit acknowledgement. First, and most importantly, the cross-sectional design cannot fully resolve the selection bias discussed above. A credible causal estimate would require a quasi-experimental design that exploits exogenous variation in the timing or location of Mall 2.0 openings for example, a difference-in-differences specification using the staggered opening dates of post-2012 developments and matched control parcels around comparable but unrealised proposals. We regard such a design as the natural next step, and as a more demanding test of the urban halo hypothesis than the present spatial-statistical framework can provide.

Second, the analysis relies on remotely sensed built-up extraction, which is sensitive to classifier choice and to the availability of cloud-free imagery; although accuracy assessments are reassuring (89.4% overall, $\kappa = 0.86$), fine-grained intra-urban transitions such as floor-area intensification within already-built parcels may be under-detected. Third, the buffer-based design assumes Euclidean influence, which is a simplification of the network-based catchments through which mall accessibility actually operates; future work should test network-distance buffers and travel-time isochrones. Fourth, the study is confined to Gurugram and Noida; extending the analysis to Faridabad, Ghaziabad, or to comparable metropolitan peripheries in Hyderabad, Bengaluru, and Pune, would test the generality of the findings. Finally, the Mall 2.0 typology, although operationalised through explicit criteria, is a coarse simplification of a continuum of retail formats; finer-grained typologies that distinguish, for example, transit-oriented mixed-use complexes from edge-of-city lifestyle centres may reveal additional heterogeneity in the halo effect.

IX. CONCLUSION

This article has tested whether Mall 2.0 developments in Gurugram and Noida generate a measurably larger and spatially more structured urban halo than traditional malls. Combining multi-temporal Landsat and Sentinel-2 imagery, buffer-based built-up extraction, Moran's I spatial autocorrelation, and Geographically Weighted Regression, we find evidence consistent with the urban halo effect: built-up growth in Mall 2.0 influence zones is greater (31.7 pp at 1 km against 18.4 pp around traditional malls), more spatially clustered (Moran's I of 0.51 against 0.34), and more directionally biased than around traditional malls, with a clear distance-decay between the 1 km and 5 km buffers. The contribution lies less in any single coefficient than in the demonstration that lifestyle retail formats can be linked to measurable urban morphological change through a defensible spatial-statistical workflow that takes multicollinearity, bandwidth selection, and selection bias seriously. For planners in NCR and comparable metropolitan regions, the practical implication is that Mall 2.0 should be understood and regulated as a form of urban infrastructure, not merely as commercial real estate.

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Appendix A. Mall inventory and opening years

The table below lists all 26 malls included in the analysis, with their city, typological classification, and verified opening year (T_0). For each Mall 2.0 site opened after 2012, the dependent variable was constructed as the change in built-up share between T_0 and 2024. For the four sites opened during 2010–2012 (one Mall 2.0 and three traditional), the 2010 Landsat composite was retained as the pre-opening reference and a fixed-effect dummy was included in the regression. Opening years were triangulated from municipal occupancy certificates, developer press releases, and contemporaneous trade-press coverage; in three cases of disagreement between sources, the earliest date supported by an occupancy certificate was used.

Table 11. Inventory of the 26 malls included in the study, with city, typological classification, and verified opening year (T_0). Site names are anonymised in this version of the manuscript and will be released in full upon publication.

ID	Mall (anonymised)	City	Type	T_0
M01	Mall A	Gurugram	Traditional	2003
M02	Mall B	Gurugram	Traditional	2004
M03	Mall C	Gurugram	Traditional	2006
M04	Mall D	Gurugram	Traditional	2007
M05	Mall E	Gurugram	Traditional	2008
M06	Mall F	Gurugram	Traditional	2009
M07	Mall G	Gurugram	Traditional	2010
M08	Mall H	Gurugram	Traditional	2011
M09	Mall I	Noida	Traditional	2005
M10	Mall J	Noida	Traditional	2007
M11	Mall K	Noida	Traditional	2008
M12	Mall L	Noida	Traditional	2009
M13	Mall M	Noida	Traditional	2010
M14	Mall N	Noida	Traditional	2011
M15	Mall O	Gurugram	Mall 2.0	2012
M16	Mall P	Gurugram	Mall 2.0	2014
M17	Mall Q	Gurugram	Mall 2.0	2015
M18	Mall R	Gurugram	Mall 2.0	2017
M19	Mall S	Gurugram	Mall 2.0	2018
M20	Mall T	Gurugram	Mall 2.0	2020
M21	Mall U	Gurugram	Mall 2.0	2022
M22	Mall V	Noida	Mall 2.0	2013
M23	Mall W	Noida	Mall 2.0	2016
M24	Mall X	Noida	Mall 2.0	2018
M25	Mall Y	Noida	Mall 2.0	2019
M26	Mall Z	Noida	Mall 2.0	2021