

Global Increases in Built-Up Volume Indicate More Divergent and Less Dispersed Urban Expansion Patterns

Corresponding Author: Professor Yingcheng Li

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

This study makes a timely and valuable contribution to the global urban expansion literature by foregrounding the three-dimensional (3D) aspects of urban growth, an area that remains underexplored compared to its two-dimensional (2D) counterpart. By introducing and operationalizing two novel indices—Centrality Index (CI) and Intensity Index (II)—the authors provide a compelling empirical framework to categorize and analyze patterns of 3D urban expansion in over 1,800 cities worldwide. The analytical rigor and the scale of the dataset are impressive, and the interpretation of results is generally well-aligned with existing knowledge on urban morphology and sustainability.

The paper introduces a promising analytical framework to capture the centrality and intensity of 3D urban expansion, but the framing in the introduction leaves the reader uncertain about the core motivation driving the study. Specifically, it is unclear whether the impetus for this work stems primarily from (a) recent technological advances and data availability—particularly improvements in remote sensing and building height data—or from (b) a theoretical and empirical recognition that global urban expansion is transitioning from a predominantly 2D (horizontal) phenomenon to a more 3D (vertical) one. This distinction is not trivial.

These are both compelling and legitimate starting points, but they represent different research orientations. The former is methodological and data-driven, implying that the research is filling a technical gap in our ability to measure and compare urban form in 3D. The latter is conceptual and theory-driven, suggesting that urban development processes themselves have changed in ways that require new analytical lenses.

The two motivations are not mutually exclusive, and indeed, the study could be strengthened by embracing them in parallel. However, the authors need to articulate this dual framing more explicitly. At present, the introduction blends these motivations in a way that feels implicit and unresolved. A more deliberate framing would not only sharpen the study's narrative but also better guide the reader in understanding its broader significance—whether as a methodological advance, a conceptual reframing, or both.

Another area of concern lies in the potential collinearity or redundancy between the 3D and 2D Centrality Index (CI) measures. While the paper highlights a strong correlation between the two, it raises the question of whether the 3D CI truly offers independent and added information about vertical expansion, or whether it primarily reflects spatial trends already captured in the 2D CI. Without stronger statistical tests (e.g., variance inflation factor analysis, partial correlation, or residual-based comparisons), it remains unclear to what extent vertical growth patterns are being uniquely captured. This is especially important since the study's key conclusions rest on differences between the 2D and 3D indices. The authors could further clarify this relationship by quantifying the net contribution of verticality after controlling for horizontal patterns, or by examining cases where the two indices diverge substantially and explaining why. While this limitation does not preclude publication, it warrants more explicit discussion or analytical validation.

The reported high correlation between 2D-CI and 3D-CI ($r = 0.916$) also raises concerns about the added value of the 3D Centrality Index. In many cases, especially where height gradients mirror horizontal expansion, 3D-CI may not provide substantially new insights. Moreover, in cities with centralized high-rise clusters and sprawling low-rise suburbs, 3D-CI may overemphasize central volumetric outliers, potentially misrepresenting vertical structure as horizontal concentration. The paper would benefit from further analysis to isolate the unique contribution of height to centrality and assess whether 3D-CI

captures distinct spatial variance beyond 2D-CI.

The CI and II thresholds used to define expansion types (e.g., HC-HI, LC-LI) rely on mean-based cutoffs, which may oversimplify underlying distributions or obscure regional nuances. A sensitivity analysis using percentile-based thresholds or cluster-based classification might improve robustness. Nonetheless, the methodological choices are overall reasonable and align with the standards of large-scale spatial analysis in this field.

Another key conceptual issue lies in the potential structural coupling between the 3D Centrality Index (3D-CI) and the Intensity Index (II). Although the two are presented as capturing distinct aspects of urban expansion—spatial concentration versus vertical intensity—they are both directly derived from the same variable: built-up volume. Specifically, 3D-CI is computed as a distance-weighted average of volume, while II represents the city-wide average building height (volume divided by footprint). This shared dependency on volume raises concerns about whether these indicators are truly orthogonal dimensions of urban structure.

In practice, their relationship may be heavily influenced by urban morphology. For instance, if tall buildings are concentrated near city centers, both 3D-CI and II will be high; conversely, if high-rise developments emerge in peripheral areas, 3D-CI may decline while II remains high. Such patterns imply that the spatial and vertical metrics are interdependent, and any classification based on their combination (e.g., HC-HI, LC-HI) may be influenced more by structural biases than independent mechanisms.

Reviewer #2

(Remarks to the Author)

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Reviewer #3

(Remarks to the Author)

Review of "Global Increases in Built-Up Volume Indicate More Divergent and Less Dispersed Urban Expansion Patterns"

Overall Evaluation
This manuscript addresses a timely and important topic in urban studies and sustainable development. It provides a novel 3D perspective on urban expansion by examining not only the increase in built-up volume but also its spatial distribution within cities, an aspect often neglected in global studies. The authors introduce new metrics – a 3D Centrality Index (CI) and Intensity Index (II) – to characterize how vertically and how centrally cities are growing. Using an extensive dataset of 1,944 cities worldwide (covering ~2 billion people), the study uncovers key global patterns: for example, urban expansion in 3D tends to be less dispersed (more centralized) than in 2D, and the Global South shows greater vertical expansion but often with low centrality (e.g. many African cities exhibit tall growth that is not concentrated in city centers). These findings are highly relevant to sustainable urban development, as 3D urban form influences energy use and carbon emissions. Overall, the manuscript is significant and original. It advances the field by bridging the gap between two-dimensional sprawl metrics and three-dimensional urban form, offering insights with clear implications for urban planning and climate policy. The work is generally well executed and, in my assessment, suitable for publication in Nature Communications after addressing some revisions detailed below.

Major Strengths

Importance and Novelty: The study tackles a critical question of how cities grow upward vs outward, which has direct implications for land use efficiency and sustainability. Prior global analyses of urban growth have largely focused on horizontal expansion; by incorporating the vertical dimension and spatial centrality, this work fills an important knowledge gap. The concept of analyzing 3D urban expansion patterns (HC-HI, LC-HI, etc.) is innovative and yields new insights that traditional 2D analyses would miss. This level of novelty and global scope is commendable and of high interest to the urban sustainability research community.

Data Breadth and Global Coverage: The analysis is built on an impressively broad dataset (Global Human Settlement Layer and other remote sensing sources) covering nearly two thousand cities worldwide. Such global coverage enhances the robustness and general relevance of the findings. The inclusion of diverse cities (across continents, development levels, etc.) allows the authors to draw meaningful comparisons between, for example, patterns in North America vs. Africa. This comprehensive scope strengthens the paper's contribution to global urban studies.

Methodological Innovation: The authors develop and apply two new indices – a 3D Centrality Index and a 3D Intensity Index – to quantify urban expansion patterns. The Centrality Index measures how concentrated new development is around urban centers, while the Intensity Index captures the average height (vertical intensity) of new constructions. Integrating these two dimensions is a clever approach to classify cities into four expansion typologies. The methodology (e.g. identifying multiple urban centers via LISA, ensuring indices are size-neutral) is sound and rigorously described. Establishing these metrics is a valuable contribution that other researchers can build upon.

Analysis of Drivers and Implications: Beyond describing patterns, the paper uses a machine learning model (LightGBM with SHAP analysis) to explore socioeconomic and environmental correlates of the 3D expansion patterns. This adds explanatory depth – for instance, highlighting that baseline urban form (e.g. existing centrality, building height) and city size are strong predictors of a city's expansion pattern. The discussion insightfully connects the findings to broader implications,

such as the trade-off between vertical growth improving land-use efficiency but potentially increasing commuting-related carbon emissions in certain patterns. Linking empirical results to sustainability challenges and policy considerations enhances the impact of the work.

Major Issues and Suggestions for Improvement

While the manuscript is strong, there are several issues that should be addressed to improve its clarity and robustness:

Exclusion of Urban Renewal: A key limitation is that the study captures only outward expansion and does not account for urban “renewal” or densification within existing built-up areas. The authors do acknowledge this limitation, noting that their method cannot detect volume increases without footprint change. They argue that vertical redevelopment (common in developed cities) would, if included, likely increase the measured centrality and intensity in Global North cities, widening the contrast with the Global South. This is an important point, and the manuscript should ensure it is communicated very clearly and up-front. I recommend the authors emphasize in the abstract and conclusions that their results pertain to outward expansion only (new urban areas from 2000–2018), and do not capture vertical growth via redevelopment. Additionally, if possible, provide some quantitative sense of how big this effect might be. For example, could the authors cite studies or data on urban renewal impacts, or at least qualitatively discuss where this limitation is most consequential? Strengthening the discussion of this limitation will make the conclusions more rigorous and prevent over-interpretation of the findings.

Threshold Definition for CI and II (Classification Robustness): The four expansion pattern categories (HC-HI, LC-HI, HC-LI, LC-LI) are defined by whether a city’s CI and II are above or below the “average” (mean) values. This binary thresholding is convenient but somewhat arbitrary, and it raises questions about robustness. The authors should clarify how the threshold was determined (it appears to be the global mean of each index; if so, was this done separately for CI and II?). It would strengthen the paper to demonstrate that the patterns identified are not an artifact of the particular threshold choice. For example, did the authors test using median instead of mean, or examine sensitivity if the threshold shifts slightly? Since the resulting category sizes are somewhat imbalanced (e.g., only ~17% of cities are HC-HI, whereas ~30% are LC-LI), one wonders if the “average” values lie in a skewed part of the distribution. A brief analysis or rationale about threshold selection and stability would be valuable. Alternatively, the authors could consider a clustering approach or provide quantitative justification (e.g., bimodality in the index distributions) for the dichotomous split. Ensuring the classification is robust will increase confidence in all subsequent pattern-based analyses.

Support for Regional Differences (Fig. 3 and Table 1): The manuscript claims significant regional and country-level differences in 3D expansion patterns, citing Figure 3 (city examples) and Table 1 (counts of cities in each category for selected countries). While the data presented do indicate contrasts – for instance, 92.7% of US cities are in the low-intensity categories (HC-LI or LC-LI) whereas a much larger share of Chinese cities are high-intensity (HC-HI or LC-HI) – the presentation could be improved to more convincingly support these comparisons. Table 1 is useful, but it only lists a handful of countries without explanation of why those were chosen. Are they simply illustrative examples, or the top emitters, or largest urban populations? The authors should clarify the selection and perhaps include additional key regions or a summary (e.g. an aggregate for “North America vs Europe vs Asia vs Africa”) to better highlight regional trends. Similarly, while Figure 3 (visualizations of representative cities) is a nice qualitative illustration of each pattern, it does not on its own demonstrate regional prevalence differences. The global map in Fig. 2c already shows geographic distribution by city; perhaps the authors could more directly highlight regional patterns there or in the text. In summary, I encourage the authors to strengthen the analysis of regional differences – for example, by reporting the percentage of cities in each pattern for each continent or income group – to bolster the claims of divergent regional dynamics. As a minor point, ensure that all statements about regional trends are backed by data (statistical or descriptive) in figures/tables or the Supplementary Information, so readers can verify them easily.

Model Accuracy and Interpretation: The use of a multi-class LightGBM model to identify correlates of expansion patterns is an excellent approach. The model’s accuracy is reported as 65.1%, significantly above a 25% random guess baseline (for four classes). This indeed suggests the features chosen have predictive power, but I urge caution in how this result is interpreted. At 65% accuracy, the model is only moderately successful, meaning it still misclassifies roughly one in three cities. The authors describe this as a “strong predictive capacity”, which might be an overstatement. I recommend the authors temper this language and provide a bit more detail on model evaluation. For instance, was the 65.1% accuracy obtained via cross-validation or on a held-out test set? Providing this detail will assure readers the result is not overfit. It would also help to report class-specific performance (confusion matrix, precision/recall for each pattern) because a high overall accuracy could still mean certain categories (perhaps the smaller HC-HI class) are predicted poorly. If one class dominates the accuracy, that would affect how we interpret the SHAP importance of features. Including these additional metrics, perhaps in a supplement, would improve confidence that the model’s insights (e.g. the top predictors like MBH, BUC, etc.) are reliable. Finally, the authors should clarify that the model reveals associations, not causation – it identifies correlates of where different patterns occur, but this should not be over-interpreted as a causal mechanism without further evidence.

Generalization of Concepts and Policy Implications: The manuscript draws broad conclusions using its new terminology and makes some policy-relevant statements. Generally, this is fine, but the authors should be careful about over-generalization. For example, the title refers to “more divergent and less dispersed” patterns, which is somewhat abstract phrasing. It might help to more explicitly define what “divergent” means in this context (divergent across regions? diverging from historical norms?). In the Discussion, the authors mention that as urbanization shifts to Africa and South Asia (with predominantly LC-HI and LC-LI patterns), these patterns may increase land-use efficiency but also heighten commuting carbon emissions. While this insight is important, it should be communicated with nuance – real outcomes will depend on local transportation infrastructure, planning policies, etc. I suggest the authors moderate the policy implications to acknowledge context: e.g., vertical expansion in peripheral areas could lead to more driving emissions if transit options remain poor. In general, ensure that newly introduced concepts (like the four-pattern typology names or “path dependency” of expansion) are clearly explained and that any recommendations are proportionate to the evidence. This will prevent readers or policymakers from misapplying the findings beyond their scope.

Clarity of Presentation (Figures and Language)

The manuscript is well written in a clear and scholarly style. The logic flows well from introducing the problem to presenting results and discussion. I noted no major grammatical errors. Technical terms and acronyms (CI, II, HC-HI, etc.) are mostly

defined and used consistently. One suggestion is to provide an acronym glossary or ensure all acronyms (especially in figures) are explained upon first use, given the large number of variables and indices introduced (MBH, BPOPU, IBV, etc.). The overall organization (with a combined analysis of 2D vs 3D, then pattern identification, then drivers) is effective. The figures are generally of high quality and informative:

Figure 1 and Figure 2 nicely illustrate the core quantitative findings. In Fig. 2a, plotting the four categories in CI–II space is helpful; the use of 0.5th–99.5th percentile limits to handle outliers is reasonable. Just ensure the axes are clearly labeled with units or index definitions (e.g., CI and II are dimensionless indices – perhaps indicate “Centrality Index (unitless)” or similar). The conceptual diagrams in Fig. 2b and the map in Fig. 2c add clarity. One minor thought: if any cities were excluded (124 cities where centers didn’t overlap, per methods), perhaps note on the map or figure caption that the map shows 1,820 cities (if I recall correctly) to avoid confusion.

Figure 3 provides compelling visual examples of each expansion pattern using representative cities. The visuals (with grids normalized by area, etc.) are useful for readers to intuitively grasp what HC-HI vs LC-LI patterns look like on the ground. The figure is clear. To enhance it, consider labeling each city and its pattern in the subpanels, and maybe include the city name in the caption (currently it says “including examples like Shanghai and Berlin...” but perhaps explicitly label them in the panels). This will help readers who may not recognize the skylines or layouts.

Figure 4 and associated Supplementary Figures: The SHAP value plots are appropriate for explaining the model results. Ensure the color scheme and labels are accessible (color-blind friendly) and that each feature’s acronym is expanded in the figure or caption for clarity (e.g., TR = Terrain Relief, etc.). The ranking of feature importance (Fig. 4a) is good; perhaps also report the overall model R^2 or pseudo- R^2 if available, to give a sense of variance explained. The supplement figures (S6–S11, S13, S15, S17, S19, etc., as referenced) seem to contain additional supportive analysis; it’s good that these are provided for thoroughness.

In terms of language, my only suggestions are minor: avoid subjective terms like “strong predictive capacity” as noted, and consider simplifying a few long sentences for readability. Otherwise, the tone and clarity meet the standards of Nature Communications. The abstract effectively summarizes the findings, and the introduction contextualizes the work with recent literature. I also appreciate that the authors cite very recent studies (through 2024) which shows the manuscript is up-to-date.

Recommendation
In conclusion, I am positive about this manuscript and its contributions. The study is ambitious in scope and offers valuable insights into urban expansion patterns that are highly relevant for sustainable urban development scholarship and practice. The evidence presented generally supports the conclusions, and the work is within the scope of Nature Communications in terms of broad interest and scientific rigour. However, before acceptance, the authors should address the above issues to strengthen the paper. Most of the concerns (urban renewal limitation, threshold robustness, clarity of figures, etc.) can be resolved with additional explanation, minor analyses, or revisions to the text and do not require new data collection. I believe these revisions will considerably improve the clarity and impact of the work. **Recommendation: Accept with minor revisions.** Once the authors have incorporated the suggested clarifications and improvements, I am confident that the paper will be suitable for publication in Nature Communications.

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

Thank you for your thorough and thoughtful revisions. I have carefully reviewed the revised manuscript as well as your point-by-point responses to my previous comments. Overall, I am pleased to see that the authors have addressed all major concerns raised in the first round.

The rewritten Introduction now clearly articulates both the conceptual motivations and the methodological innovations behind incorporating 3D urban expansion. This significantly improves the framing and readability of the study.

The newly added comparative analysis and Supplementary Note 1 effectively demonstrate the distinct yet related dimensions of 2D and 3D centrality. This addresses my previous concern about potential conceptual overlap.

The extended analysis and Supplementary Note 2 convincingly show how these two indices capture different facets of urban form and together shape 3D expansion trajectories. This clarification strengthens the theoretical contribution.

The robustness checks (including alternative classification approaches and LightGBM performance verification) presented in Supplementary Note 3 adequately respond to my earlier request. The results appear consistent and reinforce the reliability of your findings.

Overall, the manuscript has been substantially improved and now presents a clear, rigorous, and compelling contribution to the literature on 3D urban expansion and urban morphology.

Reviewer #2

(Remarks to the Author)

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career

Researchers who co-review manuscripts.

Open Access This Peer Review File is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

In cases where reviewers are anonymous, credit should be given to 'Anonymous Referee' and the source.

The images or other third party material in this Peer Review File are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

To view a copy of this license, visit <https://creativecommons.org/licenses/by/4.0/>

Response Letter NCOMMS-24-83684

Response to Reviewer #1

We greatly appreciate your positive and constructive comments and suggestions. We are very pleased that you recognize our study's timely and valuable contribution to urban expansion literature, especially by foregrounding the crucial 3D aspects of urban growth. We appreciate your commendation of our novel Centrality and Intensity Indices, the impressive analytical rigor, and the extensive dataset, noting how our interpretations align with existing urban morphology and sustainability knowledge.

We have carefully revised the paper based on these comments and would like to highlight the major changes in the structure of the paper in the following aspects:

- We rewrote the Introduction section to clearly articulate the dual motivation of this work: the conceptual objective of capturing the three-dimensional nature of urban expansion, and the methodological advance enabled by recent improvements in remote sensing and building height data.
- Second, we added a comparative analysis of 2D and 3D centrality indices, confirming that they are correlated but reflecting distinct dimensions of urban spatial structure. To provide a detailed explanation of this issue, we have added **Supplementary Note 1**.
- Third, we further examined the relationship between 3D centrality and intensity, showing that these two indices capture different aspects of city form and jointly explain the diversity of 3D expansion trajectories. To provide a detailed explanation of this issue, we have added **Supplementary Note 2**.
- Fourth, we performed robustness checks of city classification, demonstrating that both the typological patterns and the predictive performance of LightGBM models remain consistent under alternative classification approaches. To provide a detailed explanation of this issue, we have added **Supplementary Note 3**.

Below, we provide point-by-point responses to your comments.

Comment 1:

The paper introduces a promising analytical framework to capture the centrality and intensity of 3D urban expansion, but the framing in the introduction leaves the reader uncertain about the core motivation driving the study. Specifically, it is unclear whether the impetus for this work stems primarily from (a) recent technological advances and data availability—particularly improvements in remote sensing and building height data—or from (b) a theoretical and empirical recognition that global urban expansion is transitioning from a predominantly 2D (horizontal) phenomenon to a more 3D (vertical) one. This distinction is not trivial.

These are both compelling and legitimate starting points, but they represent different research orientations. The former is methodological and data-driven, implying that the research is filling a technical gap in our ability to measure and compare urban form in 3D. The latter is conceptual and theory-driven, suggesting that urban development processes themselves have changed in ways that require new analytical lenses.

The two motivations are not mutually exclusive, and indeed, the study could be strengthened by embracing them in parallel. However, the authors need to articulate this dual framing more explicitly. At present, the introduction blends these motivations in a way that feels implicit and unresolved. A more deliberate framing would not only sharpen the study's narrative but also better guide the reader in understanding its broader significance—whether as a methodological advance, a conceptual reframing, or both.

Response:

We appreciate your comment regarding the core motivation of our study and agree that articulating a clearer dual framing will significantly strengthen the narrative. You correctly identified that our impetus stems from both (a) recent technological advances and data availability and (b) a theoretical and empirical recognition of the increasingly important 3D (vertical) dimension of urban expansion.

We have revised the introduction to address this point by more explicitly articulating this dual framing.

- We have strengthened the conceptual and theory-driven motivation by clearly stating that the “evolving nature of urban development”, from predominantly 2D sprawl to increasingly 3D densification, necessitates new analytical lenses and frameworks to capture this compounded, three-dimensional reality:

This evolving nature of urban development—where 3D expansion is becoming an increasingly significant phenomenon alongside traditional 2D sprawl—creates a pressing need for analytical frameworks that can capture this compounded, three-dimensional reality. (page 2).

- We have introduced a concluding sentence that explicitly states our study is “motivated by a dual imperative”, clearly listing both the data availability and the critical need to understand changing urban development patterns:

Against this background, this study is motivated by a dual imperative: (1) the unprecedented availability of high-resolution 3D urban data, which now makes possible a comprehensive global analysis that was previously out of reach; and (2) an urgent need to better understand the complex and evolving patterns of global urban expansion, which are increasingly defined by vertical growth and densification. Together, these imperatives point to critical knowledge gaps in our current understanding of 3D urban expansion, particularly in terms of its spatial distribution and broader implications. (page 2)

Comment 2:

Another area of concern lies in the potential collinearity or redundancy between the 3D and 2D Centrality Index (CI) measures. While the paper highlights a strong correlation between the two, it raises the question of whether the 3D CI truly offers independent and added information about vertical expansion, or whether it primarily reflects spatial trends already captured in the 2D CI. Without stronger statistical tests (e.g., variance inflation factor analysis, partial correlation, or residual-based comparisons), it remains unclear to what extent vertical growth patterns are being uniquely captured. This is especially important since the study's key conclusions rest on differences between the 2D and 3D indices. The authors could further clarify this relationship by quantifying the net contribution of verticality after controlling for horizontal patterns, or by examining cases where the two indices diverge substantially and explaining why. While this limitation does not preclude publication, it warrants more explicit discussion or analytical validation.

The reported high correlation between 2D-CI and 3D-CI ($r = 0.916$) also raises concerns about the added value of the 3D Centrality Index. In many cases, especially where height gradients mirror horizontal expansion, 3D-CI may not provide substantially new insights. Moreover, in cities with centralized high-rise clusters and sprawling low-rise suburbs, 3D-CI may overemphasize central volumetric outliers, potentially misrepresenting vertical structure as horizontal concentration. The paper would benefit from further analysis to isolate the unique contribution of height to centrality and assess whether 3D-CI captures distinct spatial variance beyond 2D-CI.

Response:

Thank you and we agree that it is important to verify whether 3D-based CI offers independent information on vertical expansion beyond what is already captured by 2D-based CI. To address this concern, we performed two diagnostic analyses: (1) a condition index test based on the eigenvalues of the correlation matrix, and (2) a residual-based analysis.

The Pearson correlation coefficient between 3D-based CI and 2D-based CI is 0.916 ($p < 0.001$), confirming a strong linear relationship. However, the condition index equals 22.85, which is below the common multicollinearity threshold (30), indicating that the two indices are correlated but not redundant.

In the residual analysis, we regressed 3D-based CI on 2D-based CI and examined the unexplained component. The residual variance (1.6) relative to the total variance of 3D-based CI (9.8) suggests that about 16% of 3D-CI's variance cannot be explained by 2D-CI. This independent portion reflects meaningful divergence from purely horizontal patterns, particularly in cities where high-rise clusters emerge unevenly within the built-up area. Details of the condition index and residual analyses have been provided in **Supplementary Note 1**.

As visually illustrated in Fig. 1a, although the 2D-based CI and 3D-based CI generally

follow a similar trend, there are substantial variations between them. Each horizontal slice of the scatter plot corresponds to multiple cities sharing the same 2D-based CI value but exhibiting a wide range of 3D-based CI values. For instance, when the 2D-based CI is 50, the corresponding 3D-based CI values range from approximately 49 to 55 across cities.

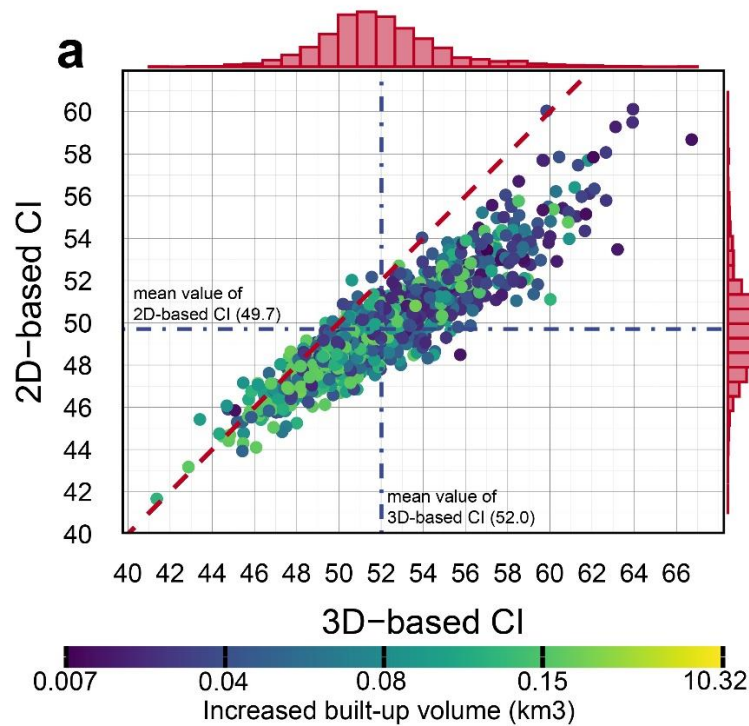


Fig. 1a Statistical distribution of 2D- and 3D-based CI scores.

This divergence can be conceptually understood by considering two hypothetical urban expansion scenarios. In both scenarios, cities exhibit identical horizontal expansion patterns and the same total amount of vertical growth—meaning they share identical 2D-based CI and II values. However, in the first scenario, high-rise buildings are concentrated near the city center, whereas in the second, they are dispersed toward the urban periphery. This directly addresses the reviewer’s insightful point: in a city with a “*centralized high-rise cluster and sprawling low-rise suburbs*,” the 3D-based CI would indeed be high, correctly identifying the intense volumetric concentration in the center. Conversely, in the second scenario, a similarly high 2D-based CI would be paired with a lower 3D-based CI, accurately reflecting the dispersal of vertical mass. Thus, rather than misrepresenting structure, the 3D-based CI is precisely capturing the difference between these two distinct urban forms that the 2D-based CI alone would conflate. These distinct spatial configurations of vertical development would lead to differentiated outcomes in terms of population distribution, commuting patterns, economic agglomeration, and microclimate effects. Critically, the 3D-based CI is able to capture this difference, while the 2D-based CI cannot (even when combined with the II indicator).

These findings demonstrate that although the 3D-based CI and 2D-based CI are closely related—which is expected, as building volume derives from both footprint and height—the 3D-based CI retains statistically significant independent information. It captures the volumetric dimension of spatial concentration, which modifies or amplifies horizontal centrality in a meaningful way.

Accordingly, we have revised the Result section in our main text to clarify this point, presented below for your easy reference:

In addition to the overall correlation between 2D and 3D measurements, further diagnostic tests (see Supplementary Note 1) indicate the vertical concentration represents a distinct though related dimension of urban spatial structure. (page 3)

Comment 3:

The CI and II thresholds used to define expansion types (e.g., HC-HI, LC-LI) rely on mean-based cutoffs, which may oversimplify underlying distributions or obscure regional nuances. A sensitivity analysis using percentile-based thresholds or cluster-based classification might improve robustness. Nonetheless, the methodological choices are overall reasonable and align with the standards of large-scale spatial analysis in this field.

Response:

In response, we performed comprehensive sensitivity tests, comparing the baseline mean-based classification with (a) a median-based scheme and (b) a hierarchical clustering solution; full details and results are reported in **Supplementary Note 3**. Below we summarize three lines of evidence that support the robustness of our results.

First, we quantified concordance between the mean-based and alternative schemes using Cohen’s Kappa. The median-based scheme shows high agreement with the mean-based classification ($\kappa = 0.83$), while the clustering-based scheme yields a moderate agreement ($\kappa = 0.54$). These statistics indicate that the median threshold produces near-identical assignments, and that the clustering approach—while more data-driven and somewhat more polarized—does not produce wholly different typologies.

Second, the continental and regional distributions of the four patterns remain effectively unchanged across classification methods. The principal spatial hierarchies reported in Results (Section 2- Four patterns of 3D urban expansion)—for example, the relative prevalence of HC–HI in Asia & Oceania and Europe, HC–LI dominance in North America, and the concentration of LC–HI and LC–LI in rapidly expanding regions—are preserved under both median and clustering schemes (see Supplementary Table S6). This demonstrates that our substantive geographic conclusions are not an artifact of the mean-based cutoffs.

Third, to assess whether downstream inferences are sensitive to the choice of classification, we re-trained the LightGBM classifier using the median- and clustering-derived labels and conducted SHAP-based interpretation for each model. We evaluated

the full set of predictors rather than any single indicator. The results are highly consistent: (1) the overall ranking pattern of variable importance is preserved across models (the same set of top predictors appears repeatedly, although exact rank order varies slightly), and (2) the direction and qualitative shape of the relationships between individual predictors and each expansion pattern remain stable.

To make these robustness checks transparent to readers, we have added two brief pointers in the Results section and the Materials and Methods section, respectively:

*Findings from this categorization remain consistent when alternative classification methods, including median-based and clustering-based schemes, are used (see **Supplementary Note 3**). (pages 5-6)*

*We evaluate the robustness of the mean-based classification of 3D urban expansion patterns using two alternative methods: a median-based approach and a hierarchical clustering approach (see **Supplementary Note 3** for details). Cohen's Kappa statistic indicated excellent agreement between the mean- and median-based schemes, and moderate agreement with the clustering-based method. While the clustering approach reclassify a small number of cities located near category boundaries, the overall regional distribution of patterns remain highly consistent across all three methods. Robustness is further supported by training LightGBM models on the alternative classifications, which produce stable results in both the relative importance and directional effects of key predictors. These consistent outcomes reinforce the reliability of our main findings on the drivers of different 3D expansion patterns. (page 18)*

Full tables, Kappa statistics, regional breakdowns, variable-importance comparisons, and illustrative SHAP plots for each alternative model are provided in **Supplementary Note 3**. Together, these analyses demonstrate that the typology and all subsequent results are robust to alternative thresholding strategies, and that the mean-based scheme provides a consistent and interpretable basis for large-scale cross-city comparison.

Comment 4:

Another key conceptual issue lies in the potential structural coupling between the 3D Centrality Index (3D-CI) and the Intensity Index (II). Although the two are presented as capturing distinct aspects of urban expansion—spatial concentration versus vertical intensity—they are both directly derived from the same variable: built-up volume. Specifically, 3D-CI is computed as a distance-weighted average of volume, while II represents the city-wide average building height (volume divided by footprint). This shared dependency on volume raises concerns about whether these indicators are truly orthogonal dimensions of urban structure.

In practice, their relationship may be heavily influenced by urban morphology. For instance, if tall buildings are concentrated near city centers, both 3D-CI and II will be high; conversely, if high-rise developments emerge in peripheral areas, 3D-CI may

decline while II remains high. Such patterns imply that the spatial and vertical metrics are interdependent, and any classification based on their combination (e.g., HC-HI, LC-HI) may be influenced more by structural biases than independent mechanisms.

Response:

We agree that, in principle, both metrics are derived from the same underlying variable—built-up volume—and thus their independence warrants empirical validation. In response, we have conducted additional statistical analyses to examine their relationship, and the results are included in the revised manuscript and detailed in **Supplementary Note 2**.

Although both indices originate from volumetric information, their empirical association is weak. The Pearson correlation coefficient between 3D-based CI and II is -0.203 ($p < 0.001$), indicating that cities with highly centralized 3D structures do not necessarily exhibit high average vertical intensity. This result remains consistent even after controlling for confounding factors such as population size and GDP per capita (partial correlation $r = -0.195$, $p < 0.001$), confirming that the limited correlation is not simply driven by scale effects. Furthermore, a residual-based regression analysis shows that 96% of the total variance in 3D-based CI cannot be explained by 3D-based II. These results collectively indicate that the two indices are not structurally redundant but instead describe complementary dimensions of urban volumetric form—3D-based CI captures the spatial concentration of built-up volume, while II reflects its average vertical intensity across the urban fabric (see more in **Supplementary Note 2**).

We have accordingly added the following statement in the main text:

*In spite of being calculated based on the same built-up volume dataset, the weak correlation between CI and II measurements indicate that the two indicators capture distinct aspects of vertical urban structure (see **Supplementary Note 2**). (page 5)*

We also acknowledge the reviewer's point that both indices may be influenced by underlying urban morphology—for instance, whether tall buildings cluster in central or peripheral areas. However, we argue that this morphological influence is not a methodological flaw but a substantive feature of our typology. The spatial arrangement of vertical elements is precisely what differentiates distinct growth configurations. In this sense, the combined use of CI and II allows us to distinguish meaningful volumetric patterns, such as HC-HI versus LC-HI forms, which reflect fundamentally different modes of urban development. Recognizing where and how vertical intensity manifests across urban space is crucial for understanding sustainability and planning implications, and this dual-metric framework provides a conceptually and empirically justified way to capture that complexity.

Response to Reviewer #2

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Response:

We appreciate that you are participating in Nature Communications' initiative to support Early Career Researchers in peer review, and we value the insightful comments you have provided.

Response to Reviewer #3

We sincerely appreciate your comprehensive and encouraging review. In response, we have made a series of substantial revisions to strengthen the analytical rigor and conceptual clarity of the paper.

- We incorporated an explicit discussion and assessment of the potential influence of urban renewal, clarifying how renewal activities may affect the interpretation of our findings. To provide a detailed explanation of this issue, we have added **Supplementary Note 5**.
- We performed a comprehensive robustness test of the city classification, confirming that the identified typologies and related main conclusion remain consistent under alternative clustering and thresholding methods. To provide a detailed explanation, we have added **Supplementary Note 3**.
- We presented regional variations across expansion modes more clearly.
- We conducted a more comprehensive evaluation of the LightGBM model. To provide a detailed explanation, we have added **Supplementary Note 4**.
- We expanded the discussion on the generalization of concepts and policy implications, situating our findings within broader urban development and planning frameworks.
- We refined the language and visual presentation throughout the manuscript to enhance clarity and readability.

Below, we provide our point-by-point responses to your comments.

Comment 1:

Exclusion of Urban Renewal: A key limitation is that the study captures only outward expansion and does not account for urban “renewal” or densification within existing built-up areas. The authors do acknowledge this limitation, noting that their method cannot detect volume increases without footprint change. They argue that vertical redevelopment (common in developed cities) would, if included, likely increase the measured centrality and intensity in Global North cities, widening the contrast with the Global South. This is an important point, and the manuscript should ensure it is communicated very clearly and up-front. I recommend the authors emphasize in the abstract and conclusions that their results pertain to outward expansion only (new urban areas from 2000–2018), and do not capture vertical growth via redevelopment. Additionally, if possible, provide some quantitative sense of how big this effect might be. For example, could the authors cite studies or data on urban renewal impacts, or at least qualitatively discuss where this limitation is most consequential? Strengthening the discussion of this limitation will make the conclusions more rigorous and prevent over-interpretation of the findings.

Response:

Thank you for highlighting this limitation. To address this concern, we have performed a targeted assessment, reported in **Supplementary Note 5**, and revised the manuscript accordingly.

We first clarified the conceptual scope of “urban renewal” in this study, defining it as redevelopment or reconstruction that increases built-up volume without expanding the building footprint. This definition distinguishes it from routine renovation and from infill development on previously vacant urban plots, the latter of which is captured by our method. Because comprehensive, regionally comparable data are limited, we assembled and synthesized available quantitative evidence for the study period, focusing on the best-documented cases (United States and China) and on cross-regional indicators that allow informed inference for other regions. Key findings are:

United States: The U.S. Environmental Protection Agency (EPA) data for 209 metropolitan areas (2000–2009) indicate that ~21% of new housing was built as infill within previously developed areas¹. Because infill includes both redevelopment and new construction on vacant urban parcels, the share attributable to pure redevelopment (i.e., renewal without footprint change) is plausibly lower—likely < 20% for that decade.

China: Official reconstruction statistics for 2023 report the initiation of approximately 1.59 million rebuilt housing units². When scaled by average unit area, this corresponds to roughly 15% of the recent new residential floor area^{3,4}. However, as large-scale renewal programs in China intensified after 2009⁵, the share during 2000–2018 was plausibly somewhat lower.

Cross-regional inference: Multi-temporal remote-sensing analyses that map upward-dominant versus outward-dominant growth indicate that upward-dominant patterns are more prevalent in advanced economies (notably Europe and East Asia) and less prevalent in Latin America, India and Africa⁶. While upward dominance is not identical to renewal, it correlates with a greater prevalence of redevelopment-oriented vertical growth.

Synthesis: Taken together, available evidence indicates that genuine redevelopment—defined as renewal that increases built volume without expanding the urban footprint—typically accounts for several tens of percent of new construction in developed and East Asian contexts, but remains far less prevalent across much of the Global South during the study period. On a conservative global average for 2000–2018, redevelopment likely represents no more than ~15% of total new urban construction, with higher shares in Europe and East Asia, and substantially lower contributions in Latin America, South Asia, and Africa.

Because renewal tends to occur in central urban areas^{7,8}, including such processes would increase measured 3D centrality in places where renewal is concentrated—primarily in the Global North and parts of East Asia. Therefore, incorporating renewal

would strengthen the main geographic contrast reported in the manuscript (i.e., Global North cities would show even higher 3D-based centrality relative to Global South cities), rather than undermine it.

To make these points clear to readers, we have clarified this limitation upfront in both the Abstract and Discussion. In the revised Abstract, we now explicitly state:

The North-South centrality gap would further widen if vertical redevelopment within existing built-up footprints is considered.

In the revised Discussion section, we now explicitly state (**pages 12-13**):

This study focuses on outward urban expansion and does not account for urban renewal, i.e. the redevelopment of existing built-up footprints. Unlike simple building renovation, urban renewal typically involves replacing low-rise or aging structures with high-rise developments concentrated in urban centers, thus contributing substantially to vertical growth^{40,41}. Although this process is beyond the detection scope of our method (which identifies only built-up footprint expansion), its potential impact warrants consideration. Available evidence suggests that the proportion of urban renewal relative to total urban growth remains modest globally—generally below 15% during the study period—with somewhat higher shares in Europe and East Asia and lower shares in regions such as Latin America, India, and Africa (see Supplementary Note 5). Given that urban renewal is most common in city centers, the inclusion of urban renewal would likely amplify the centrality of 3D growth, particularly in Global North and East Asian cities. Consequently, incorporating urban renewal would strengthen rather than challenge the observed North–South centrality gap in 3D urban expansion. Future research should investigate how urban renewal interacts with existing patterns of 3D expansion and examine its environmental sustainability implications, particularly in the context of ongoing urbanization in the Global South.

References:

1. Ramsey, K. Residential Construction Trends in America’s Metropolitan Regions: 2012 Edition. (U.S. Environmental Protection Agency, 2012).
2. Statistical Communiqué of the People’s Republic of China on the 2023 National Economic and Social Development. (National Bureau of Statistics of China, Beijing, 2023).
3. China Population Census Yearbook 2020. (National Bureau of Statistics of China, Beijing, 2020).
4. National Real Estate Development and Sales in 2022. (National Bureau of Statistics of China, Beijing, 2022).
5. He, S. & Wu, F. China’s emerging neoliberal urbanism: Perspectives from urban redevelopment. *Antipode* **41**, 282-304 (2009).
6. Froliking, S., Mahtta, R., Milliman, T., Esch, T. & Seto, K. C. Global urban structural growth shows a profound shift from spreading out to building up. *Nat.*

Cities **1**, 555-566 (2024).

7. der Krabben, E. v. & Needham, B. Land readjustment for value capturing: a new planning tool for urban redevelopment. *Town Plan. Rev.* **79**, 651-672 (2008).
8. Broitman, D. & Koomen, E. The attraction of urban cores: Densification in Dutch city centres. *Urban Stud.* **57**, 1920-1939 (2020).

Comment 2:

Threshold Definition for CI and II (Classification Robustness): The four expansion pattern categories (HC-HI, LC-HI, HC-LI, LC-LI) are defined by whether a city's CI and II are above or below the "average" (mean) values. This binary thresholding is convenient but somewhat arbitrary, and it raises questions about robustness. The authors should clarify how the threshold was determined (it appears to be the global mean of each index; if so, was this done separately for CI and II?). It would strengthen the paper to demonstrate that the patterns identified are not an artifact of the particular threshold choice. For example, did the authors test using median instead of mean, or examine sensitivity if the threshold shifts slightly? Since the resulting category sizes are somewhat imbalanced (e.g., only ~17% of cities are HC-HI, whereas ~30% are LC-LI), one wonders if the "average" values lie in a skewed part of the distribution. A brief analysis or rationale about threshold selection and stability would be valuable. Alternatively, the authors could consider a clustering approach or provide quantitative justification (e.g., bimodality in the index distributions) for the dichotomous split. Ensuring the classification is robust will increase confidence in all subsequent pattern-based analyses.

Response:

As this important issue was also raised by the first reviewer, our response here is largely consistent with our reply to Reviewer #1's Comment 3.

We agree that clarifying the thresholding rationale and assessing its robustness are essential for ensuring the validity of the four-pattern typology. In our main analysis, the thresholds for the Centrality Index (CI) and Intensity Index (II) were independently determined using their respective global mean values across all cities (mean CI and mean II). This approach offers a balanced and intuitive distinction between cities exhibiting above- and below-average levels of 3D centrality and intensity. Nevertheless, as the reviewer rightly notes, mean-based thresholds may be influenced by distributional skewness, and therefore we further tested the robustness of our classification using alternative thresholding methods.

To address this concern, we conducted comprehensive sensitivity analyses comparing the baseline mean-based classification with two alternative schemes: (a) a median-based thresholding and (b) a hierarchical clustering-based classification. The results are reported in **Supplementary Note 3**, and the main outcomes are summarized below.

First, we assessed the classification agreement between the mean-based and alternative schemes using Cohen's Kappa statistic. The median-based scheme shows high

agreement with the mean-based classification ($\kappa = 0.83$) and, as expected, produces a slightly more balanced partition of cities above and below each threshold. The clustering-based scheme yields a moderate but acceptable agreement ($\kappa = 0.54$), reflecting its tendency to produce more polarized groupings driven by the intrinsic data structure. These results confirm that while clustering highlights stronger contrasts, it does not produce fundamentally different typologies.

Second, the spatial consistency of the results is strong. The continental and regional distributions of the four expansion patterns remain highly similar under all three schemes. The spatial hierarchies highlighted in Results section (Four patterns of 3D urban expansion)—for example, the dominance of HC–HI in Asia & Oceania and Europe, HC–LI in North America, and LC–HI/LC–LI in rapidly expanding regions—are all preserved (see **Supplementary Table S5**). Hence, the observed global differentiation of 3D expansion modes is not an artifact of the specific threshold choice.

Third, we tested model consistency by re-estimating the LightGBM classifier under each classification scheme and performing SHAP-based interpretation for all models. The findings are highly consistent across methods:

- The relative ranking of predictor importance remains stable, with the same key variables repeatedly emerging as top contributors; and
- The direction and qualitative form of each variable’s relationship with the four expansion types are nearly identical.

These results confirm that neither the explanatory hierarchy nor the mechanism interpretation is dependent on how the thresholds are defined.

To make these robustness checks transparent to readers, we have added two brief pointers in the Results section and the Materials and Methods section, respectively:

*Findings from this categorization remain consistent when alternative classification methods, including median-based and clustering-based schemes, are used (see **Supplementary Note 3**). (pages 5-6)*

We evaluate the robustness of the mean-based classification of 3D urban expansion patterns using two alternative methods: a median-based approach and a hierarchical clustering approach (see Supplementary Note 3 for details). Cohen’s Kappa statistic indicated excellent agreement between the mean- and median-based schemes, and moderate agreement with the clustering-based method. While the clustering approach reclassify a small number of cities located near category boundaries, the overall regional distribution of patterns remain highly consistent across all three methods. Robustness is further supported by training LightGBM models on the alternative classifications, which produce stable results in both the relative importance and directional effects of key predictors. These consistent outcomes reinforce the reliability of our main findings on the drivers of different 3D expansion patterns. (page 18)

Full Kappa statistics, spatial breakdowns, variable-importance comparisons, and SHAP visualizations for all alternative models are provided in [Supplementary Note 3](#). Together, these analyses demonstrate that the typology and all subsequent results are robust to alternative thresholding strategies, and that the mean-based scheme provides a consistent and interpretable basis for large-scale cross-city comparison.

Comment 3:

Support for Regional Differences (Fig. 3 and Table 1): The manuscript claims significant regional and country-level differences in 3D expansion patterns, citing Figure 3 (city examples) and Table 1 (counts of cities in each category for selected countries). While the data presented do indicate contrasts – for instance, 92.7% of US cities are in the low-intensity categories (HC-LI or LC-LI) whereas a much larger share of Chinese cities are high-intensity (HC-HI or LC-HI) – the presentation could be improved to more convincingly support these comparisons. Table 1 is useful, but it only lists a handful of countries without explanation of why those were chosen. Are they simply illustrative examples, or the top emitters, or largest urban populations? The authors should clarify the selection and perhaps include additional key regions or a summary (e.g. an aggregate for “North America vs Europe vs Asia vs Africa”) to better highlight regional trends. Similarly, while Figure 3 (visualizations of representative cities) is a nice qualitative illustration of each pattern, it does not on its own demonstrate regional prevalence differences. The global map in Fig. 2c already shows geographic distribution by city; perhaps the authors could more directly highlight regional patterns there or in the text. In summary, I encourage the authors to strengthen the analysis of regional differences – for example, by reporting the percentage of cities in each pattern for each continent or income group – to bolster the claims of divergent regional dynamics. As a minor point, ensure that all statements about regional trends are backed by data (statistical or descriptive) in figures/tables or the Supplementary Information, so readers can verify them easily.

Response:

We have made the following changes to address this comment concerning the presentation of regional differences in 3D urban expansion patterns.

First, we have updated Table 3 to include aggregated statistics for each continent/major region (Africa, Latin America and the Caribbean, Asia and Oceania, North America, Europe). This provides a clearer overview of continental-level trends. We have also clarified that the specific countries listed within each region in Table 3 were chosen based on having the largest number of sample cities in our dataset for that respective region, thus serving as robust and representative illustrative examples. This is noted in the table caption ([page 8](#)).

Second, to further strengthen the analysis and avoid redundancy, we have added a concise summary sentence at the end of the second paragraph of the Discussion section that synthesizes the key regional divergences observed. This directly follows the

detailed country-level examples:

Overall, high-intensity 3D expansion is notably prevalent in East Asia, while low-intensity patterns characterize North America, and a mix of low-centrality patterns is dominant in Africa, Latin America and South Asia, with Europe showing a more diverse distribution. (page 8)

Comment 4:

Model Accuracy and Interpretation: The use of a multi-class LightGBM model to identify correlates of expansion patterns is an excellent approach. The model's accuracy is reported as 65.1%, significantly above a 25% random guess baseline (for four classes). This indeed suggests the features chosen have predictive power, but I urge caution in how this result is interpreted. At 65% accuracy, the model is only moderately successful, meaning it still misclassifies roughly one in three cities. The authors describe this as a "strong predictive capacity", which might be an overstatement. I recommend the authors temper this language and provide a bit more detail on model evaluation. For instance, was the 65.1% accuracy obtained via cross-validation or on a held-out test set? Providing this detail will assure readers the result is not overfit. It would also help to report class-specific performance (confusion matrix, precision/recall for each pattern) because a high overall accuracy could still mean certain categories (perhaps the smaller HC-HI class) are predicted poorly. If one class dominates the accuracy, that would affect how we interpret the SHAP importance of features. Including these additional metrics, perhaps in a supplement, would improve confidence that the model's insights (e.g. the top predictors like MBH, BUC, etc.) are reliable. Finally, the authors should clarify that the model reveals associations, not causation – it identifies correlates of where different patterns occur, but this should not be over-interpreted as a causal mechanism without further evidence.

Response:

To address these concerns, we have substantially expanded the model evaluation and clarified the interpretation of its predictive capacity and scope.

First, we now provide a detailed evaluation of the multi-class LightGBM model, including a transparent explanation of its training, validation, and testing procedures in **Supplementary Note 4**. We explain that the model was trained using 10-fold cross-validation for hyperparameter tuning, and the reported overall accuracy of 65.1% was obtained on a *held-out test set* that was entirely unseen during training. This approach offers an unbiased estimate of model generalization and strengthens the credibility of the reported results.

Second, we now include additional performance metrics in Table S7, including *Precision*, *Recall*, and *F1-score* for each of the four expansion categories as well as the macro-averaged and weighted-averaged metrics. The results show that while class-specific performance varies (with HC-HI being relatively less well predicted due to smaller sample size and feature overlap), the model maintains balanced performance

overall, with a *weighted-average F1-score of 0.646* and a *macro-averaged F1-score of 0.611*. These metrics confirm that the model's predictive ability is not dominated by any single class and that its insights regarding feature importance are consistent across categories.

Third, we fully acknowledge the reviewer's caution regarding the interpretation of our results. In the revised manuscript and Supplementary Information, we have clarified that the model identifies *associative patterns* rather than *causal mechanisms*. Accordingly, the SHAP-based feature importance results are interpreted as indicators of the strength and direction of correlations, not as evidence of causality. The revised text in the manuscript now reads (pages 8-9):

The model attains an overall accuracy of 65.1% on a held-out test set, notably higher than the random prediction baseline of 25% (given the four categories). Performance varies across classes, with LC-LI showing the highest recall and HC-HI exhibiting relatively lower precision and F1-score, while the weighted average F1-score (0.646) indicates a generally consistent predictive capability across classes. We therefore characterize the model as demonstrating moderate yet robust predictive performance, effectively capturing the key associations between urban expansion patterns and their underlying drivers (see Supplementary Note 4 for detailed evaluation metrics). It is important to note, however, that these results reveal correlational rather than causal relationships, and thus should be interpreted as indicative associations rather than direct causal mechanisms.

Comment 5:

Generalization of Concepts and Policy Implications: The manuscript draws broad conclusions using its new terminology and makes some policy-relevant statements. Generally, this is fine, but the authors should be careful about over-generalization. For example, the title refers to “more divergent and less dispersed” patterns, which is somewhat abstract phrasing. It might help to more explicitly define what “divergent” means in this context (divergent across regions? diverging from historical norms?). In the Discussion, the authors mention that as urbanization shifts to Africa and South Asia (with predominantly LC-HI and LC-LI patterns), these patterns may increase land-use efficiency but also heighten commuting carbon emissions. While this insight is important, it should be communicated with nuance – real outcomes will depend on local transportation infrastructure, planning policies, etc. I suggest the authors moderate the policy implications to acknowledge context: e.g., vertical expansion in peripheral areas could lead to more driving emissions if transit options remain poor. In general, ensure that newly introduced concepts (like the four-pattern typology names or “path dependency” of expansion) are clearly explained and that any recommendations are proportionate to the evidence. This will prevent readers or policymakers from misapplying the findings beyond their scope.

Response:

We have substantially revised the manuscript to improve clarity, precision, and interpretive nuance in response to this comment.

First, we acknowledge the reviewer's suggestion to clarify the term "divergent" in the title. In the revised manuscript, we explicitly explain "divergent" in the Discussion section to reflect two dimensions of meaning:

- **Multi-dimensional perspective:** Our study diverges from conventional 2D assessments by incorporating both the vertical and concentration dimensions of urban expansion. This provides a more comprehensive and differentiated understanding of growth patterns beyond the traditional sprawl–compact dichotomy. This clarification has been added in the second paragraph of the Discussion (**page 11**):

The four 3D urban expansion patterns identified based on the Centrality Index (CI) and Intensity Index (II) offer deeper insights into 3D urban forms and their implications for environmental sustainability, representing a divergence from simpler 2D classifications by considering both the vertical and agglomeration dimensions of urban growth.

- **Increased inter-city disparities:** Our analysis demonstrates that disparities in centrality among cities are greater when viewed in 3D than in 2D, revealing a more pronounced North–South contrast. Cities in the Global South (particularly in Africa and Latin America, excluding most Chinese cities) show smaller differences between their 3D- and 2D-based CI scores than those in the Global North, while their II values indicate taller newly built structures. Together, these results underscore that the North–South divergence is a defining feature of 3D urban expansion. This clarification appears in the first paragraph of the Discussion (**page 11**):

Moreover, the 3D perspective reveals a more divergent contrast between the Global South and the Global North. On the one hand, cities in the Global South—particularly in Africa and Latin America, with the exception of most Chinese cities—generally display smaller differences between 3D- and 2D-based CI scores than those observed in the Global North. This also suggests that the North-South contrast is more pronounced for 3D urban expansion, compared to what 2D analyses reveal (Fig. S3 and S4). On the other hand, our analysis of the Intensity Index (II) for 3D urban expansion reveals that cities in the Global South generally feature taller newly constructed buildings than their counterparts in the Global North. This aligns with previous findings suggesting that urbanization in the Global South consumes less per capita land^{29,34} and that vertical expansion plays a dominant role in the global urbanization process¹⁰.

Second, as suggested, we have clarified the meanings of newly introduced concepts such as the four-pattern typology and path dependency:

- Parenthetical explanations for each of the four 3D expansion patterns are now added upon their first mention in the second paragraph of the Discussion, and again in the final paragraph for consistency (**page 12**). Although these were defined earlier in the Results section, this repetition ensures clarity for readers who may begin directly with the Discussion.
- A concise explanation of path dependency has also been added in the third paragraph of the Discussion (**page 12**):

Specifically, cities with higher centrality at a base period tend to exhibit higher centrality in their subsequent spatial growth phases.

Third, we revised the policy implications to better reflect contextual variability, as recommended. The revised final paragraph of the Discussion (**page 13**) now explicitly acknowledges that the sustainability outcomes of different 3D expansion patterns depend on local infrastructure, planning, and socioeconomic contexts. The updated text reads as follows:

Future expansion will likely be driven by cities in Africa and South Asia, which are primarily characterized by LC-HI (Low Centrality and High Intensity) and LC-LI (Low Centrality and Low Intensity) patterns of 3D urban expansion. While these patterns may improve land-use efficiency to some extent, they are also likely to present challenges in reducing commuting-related carbon emissions. It is important to acknowledge that the real outcomes of these patterns will be highly dependent on local contexts, including the quality of transportation infrastructure, the effectiveness of land-use planning policies, and socioeconomic factors. For example, vertical expansion in peripheral areas could lead to significantly higher driving emissions if public transit options remain poor or if car-centric development is incentivized. Conversely, with strategic investments in multimodal transit and integrated land-use planning, these patterns could be managed to support more sustainable urban development. Therefore, policymakers should consider these findings with nuance, developing context-specific strategies that address both land-use efficiency and emissions reduction tailored to their unique urban development trajectories and infrastructure capabilities.

Comment 6:

Clarity of Presentation (Figures and Language): The manuscript is well written in a clear and scholarly style. The logic flows well from introducing the problem to presenting results and discussion. I noted no major grammatical errors. Technical terms and acronyms (CI, II, HC-HI, etc.) are mostly defined and used consistently. One suggestion is to provide an acronym glossary or ensure all acronyms (especially in figures) are explained upon first use, given the large number of variables and indices introduced (MBH, BPOPU, IBV, etc.). The overall organization (with a combined analysis of 2D vs 3D, then pattern identification, then drivers) is effective. The figures are generally of high quality and informative.

Response:

We have implemented the reviewer's suggestion to ensure that all acronyms are defined upon first use, particularly given the number of variables and indices used in the study. Besides, in the revised manuscript, each variable abbreviation is now clearly defined within the caption of Figure 4, allowing readers to understand the terminology directly where the variables are introduced.

Comment 7:

Figure 1 and Figure 2 nicely illustrate the core quantitative findings. In Fig. 2a, plotting the four categories in CI–II space is helpful; the use of 0.5th–99.5th percentile limits to handle outliers is reasonable. Just ensure the axes are clearly labeled with units or index definitions (e.g., CI and II are dimensionless indices – perhaps indicate “Centrality Index (unitless)” or similar). The conceptual diagrams in Fig. 2b and the map in Fig. 2c add clarity. One minor thought: if any cities were excluded (124 cities where centers didn't overlap, per methods), perhaps note on the map or figure caption that the map shows 1,820 cities (if I recall correctly) to avoid confusion.

Response:

We appreciate the reviewer's suggestions regarding axis labeling and clarification of the number of cities displayed. We have implemented these revisions in the updated manuscript as follows:

- The captions of Figures 1 and 2 have been revised to explicitly state that the Centrality Index (CI) and Intensity Index (II) are dimensionless indicators.
- We have added notes to the captions of Figure 1b and Figure 2c indicating that the maps and diagrams represent results “across 1,820 sample cities.” This clarification ensures transparency regarding the scope of the analysis and eliminates potential confusion.

Comment 8:

Figure 3 provides compelling visual examples of each expansion pattern using representative cities. The visuals (with grids normalized by area, etc.) are useful for readers to intuitively grasp what HC-HI vs LC-LI patterns look like on the ground. The figure is clear. To enhance it, consider labeling each city and its pattern in the subpanels, and maybe include the city name in the caption (currently it says “including examples like Shanghai and Berlin...” but perhaps explicitly label them in the panels). This will help readers who may not recognize the skylines or layouts.

Response:

Thank you for your positive assessment of Figure 3 and for recognizing its effectiveness in illustrating urban expansion patterns. In response to your comments, we have revised Figure 3 as follows:

- Cities and their corresponding countries are now clearly indicated in the upper-left

corner of each subfigure.

- Cities in the same row belong to the same continent/region, providing additional geographical context.
- Cities in the same column correspond to the same expansion pattern, facilitating direct comparison of how the pattern manifests across different cities.
- The figure caption has been updated accordingly to explain these visual arrangements.

Comment 9:

Figure 4 and associated Supplementary Figures: The SHAP value plots are appropriate for explaining the model results. Ensure the color scheme and labels are accessible (color-blind friendly) and that each feature's acronym is expanded in the figure or caption for clarity (e.g., TR = Terrain Relief, etc.). The ranking of feature importance (Fig. 4a) is good; perhaps also report the overall model R^2 or pseudo- R^2 if available, to give a sense of variance explained. The supplement figures (S6–S11, S13, S15, S17, S19, etc., as referenced) seem to contain additional supportive analysis; it's good that these are provided for thoroughness.

Response:

Thank you for your valuable feedback on Figure 4 and the associated Supplementary Figures. In response:

- We have ensured that all variable abbreviations are defined within the caption of Figure 4, and we have adjusted the color schemes to be accessible and color-blind friendly.
- We have included standard performance metrics—accuracy, precision, and F1-score—in the Figure 4 caption, which more appropriately reflect the model's predictive performance.

Comment 10:

In terms of language, my only suggestions are minor: avoid subjective terms like “strong predictive capacity” as noted, and consider simplifying a few long sentences for readability. Otherwise, the tone and clarity meet the standards of Nature Communications. The abstract effectively summarizes the findings, and the introduction contextualizes the work with recent literature. I also appreciate that the authors cite very recent studies (through 2024) which shows the manuscript is up-to-date.

Response:

We have carefully reviewed the manuscript and implemented your minor suggestions. Several long sentences have been divided for improved readability. In addition, subjective expressions such as “strong predictive capacity” have been replaced with

more precise and objective wording to ensure a consistently academic tone throughout the manuscript.

Comment 11:

Recommendation: In conclusion, I am positive about this manuscript and its contributions. The study is ambitious in scope and offers valuable insights into urban expansion patterns that are highly relevant for sustainable urban development scholarship and practice. The evidence presented generally supports the conclusions, and the work is within the scope of Nature Communications in terms of broad interest and scientific rigour. However, before acceptance, the authors should address the above issues to strengthen the paper. Most of the concerns (urban renewal limitation, threshold robustness, clarity of figures, etc.) can be resolved with additional explanation, minor analyses, or revisions to the text and do not require new data collection. I believe these revisions will considerably improve the clarity and impact of the work.

Recommendation: Accept with minor revisions. Once the authors have incorporated the suggested clarifications and improvements, I am confident that the paper will be suitable for publication in Nature Communications.

Response:

Thank you very much for your comprehensive review and constructive feedback. We would like to assure you that we have carefully considered and addressed all the issues raised, including those related to the limitations of urban renewal detection, the robustness of threshold selection, and the clarity of figures, among others.

Response Letter NCOMMS-24-83684A

Response to Reviewer #1

Comment:

Thank you for your thorough and thoughtful revisions. I have carefully reviewed the revised manuscript as well as your point-by-point responses to my previous comments. Overall, I am pleased to see that the authors have addressed all major concerns raised in the first round.

The rewritten Introduction now clearly articulates both the conceptual motivations and the methodological innovations behind incorporating 3D urban expansion. This significantly improves the framing and readability of the study.

The newly added comparative analysis and Supplementary Note 1 effectively demonstrate the distinct yet related dimensions of 2D and 3D centrality. This addresses my previous concern about potential conceptual overlap.

The extended analysis and Supplementary Note 2 convincingly show how these two indices capture different facets of urban form and together shape 3D expansion trajectories. This clarification strengthens the theoretical contribution.

The robustness checks (including alternative classification approaches and LightGBM performance verification) presented in Supplementary Note 3 adequately respond to my earlier request. The results appear consistent and reinforce the reliability of your findings.

Overall, the manuscript has been substantially improved and now presents a clear, rigorous, and compelling contribution to the literature on 3D urban expansion and urban morphology.

Response:

We appreciate your positive feedback and are glad to hear that the revised manuscript is now considered clear, rigorous, and compelling. Thank you for your valuable contribution to this study.

Response to Reviewer #2

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review

manuscripts.

Response:

We appreciate that you are participating in Nature Communications' initiative to support Early Career Researchers in peer review, and we value the insightful comments you have provided.