Innovative Data Solutions for Inclusive Cities: The IDEAtlas User Portal

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Abstract

Addressing the challenge of mapping deprived urban areas (DUAs) globally requires both technical innovation and user engagement. The IDEAtlas project developed a novel approach to monitor DUAs by combining advanced Earth Observation (EO) technologies with a user-centered design. Central to this is our IDEAtlas User Portal, a data platform that provides scalable, accessible, and participatory mapping solutions in support of Sustainable Development Goal (SDG) 11.1.1. The portal provides outputs from a custom Multi-Branch Convolutional Neural Network (MB-CNN) model trained on freely available Sentinel-1 and Sentinel-2 data, enriched with ancillary open datasets such as building footprints. Presently, the portal offers binary settlement maps, with future plans to include deprivation severity indices, and multi-temporal urban growth maps for the period 2019 to 2023. A unique feature of the IDEAtlas platform is its two-tier access model: an open section offering 100 by 100 m gridded outputs for public use, and a protected section for sensitive, city-level data. In the protected section, users can validate outputs. The user validation is an essential element of our Living Labs and is done in the form of continuous stakeholder collaboration. Through Living Labs and iterative user feedback across eight global cities, the portal has demonstrated how involving local governments, NGOs, and community organizations can enhance data quality, relevance, foster ownership, and empower decision-making. Early user engagements, such as the update of Argentina's RENABAP informal settlement registry, highlight the portal's operational value. By coupling technological scalability with participatory validation. Thus, the IDEAtlas User Portal represents a significant step toward inclusive, evidence-based urban planning and policymaking.

1. Introduction

Low- and Middle-Income Countries (LMICs) are experiencing rapid urbanization, much of which is concentrated in deprived urban areas (DUAs) (Abascal et al., 2022), often referred to as slums and informal settlements (Figure 1). These areas typically lack access to services, infrastructure, and durable housing, and are more frequently exposed to hazards as compared to the planned urban spaces (United Nations, 2022). SDG Target 11.1 emphasizes the need for adequate, safe, and affordable housing, along with basic services and slum upgrading (United Nations, 2022). Although Indicator 11.1.1 is classified as Tier 1 (UN-Habitat, 2018), with established methodologies and data produced by over 50% of relevant countries, the data often remain outdated, inconsistent, and unavailable at the city scale, as they are primarily derived from national household sample surveys.

Numerous studies have utilized Earth Observation (EO) models to map informal settlements, employing approaches ranging from classical machine learning to advanced deep-learning techniques (Ajami et al., 2019; Badmos et al., 2018; Engstrom et al., 2019; Najmi et al., 2022; Owusu et al., 2024; Prabhu et al., 2021; Williams et al., 2020; Wurm and Taubenböck, 2018). However, these models are frequently tailored to specific cities and tested only in central locations of cities or similar urban contexts (Boanada-Fuchs et al., 2024). Most models treat outputs as final results without integrating local context, often excluding user engagement (Kuffer et al., 2021). Consequently, reference data curated by researchers through on-screen digitizing lack local knowledge and fail to capture the diverse characteristics of settlements across metropolitan regions (e.g., outskirts of cities) and different types of cities (e.g., different continents) (Samper et al., 2024).

Figure 1. Densely built-up deprived urban area, Medellin, Colombia.

The reason for these challenges is that large-scale demonstrations commonly face a lack of reference data. Furthermore, such large-scale demonstrations need large computational resources and tailored deep-learning models to deal with the heterogeneity of cities and reference data (Stark et al., 2024). The IDEAtlas project aims to address these critical challenges with global EO-based DUA mapping approaches. These approaches include mapping at a metropolitan scale that consists of the outskirts of areas where a large part of the settlements are often located. High dynamics have been observed in recent studies in the outskirts towards peri-urban areas (Kolowa et al., 2024; Samper et al., 2024). However, mapping efforts in these areas are hindered by the lack and inconsistency of local reference data, and the limited adaptability of models to diverse urban morphologies.

Through pilot implementations in eight globally distributed cities (Nairobi, Medellin, Mumbai, Salvador, Buenos Aires, Jakarta, Mexico City, and Lagos), IDEAtlas aims to develop EO-based models that are able to be trained on limited and locally validated reference data that show consistency across different socio-economic and spatial contexts (Figure 2). Through iterative improvements by local stakeholder feedback and participatory validation, that have been implemented in the IDEAtlas Living Labs, we aim to enhance both the reference data quality and model outputs. Overall, our approach is emphasizing the necessity of a user- and data-centric approach.

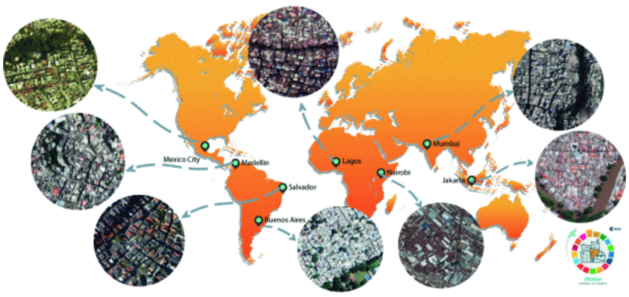

Figure 2. Global sample of case study cities.

2. Methodology

IDEAtlas, an ESA-funded project, addresses the transferability and scalability limitations of present EO mapping approaches of DUAs by developing advanced methodologies for mapping deprived urban areas globally while prioritizing user engagement (Tareke et al., 2024). To improve the mapping of DUAs, IDEAtlas developed hybrid modelling approaches that integrate free-cost Earth Observation (EO) data with open ancillary urban datasets, including building footprints, road networks, and green space indicators.

By combining these complementary data sources, we aim to move beyond the limitations of morphology-based mapping and capture the complex, multi-dimensional realities of urban deprivation across cities. A core component of our methodology is the establishment of an integrated, user-centered approach (Figure 3). One central element in this user-centered approach is our portal where local actors, e.g., local and national government agencies, NGOs, and community organizations, can access model outputs, validate results, and contribute feedback. Continuous engagements with local stakeholders are central to ensuring that the mapping outputs are contextually relevant, trusted, and usable for operational decision-making.

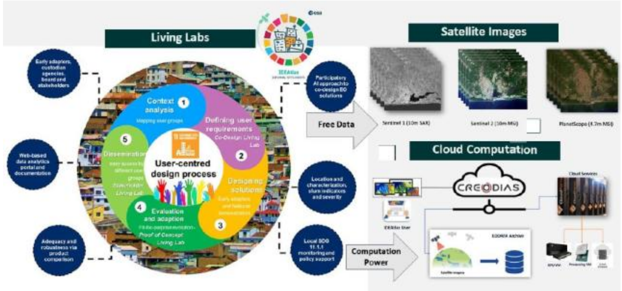

Figure 3. IDEAtlas User and Data-Centric Workflow.

While we will primarily use free-cost high-resolution EO data (e.g., Sentinel-2), not commercial very-high-resolution data, to ensure scalability and accessibility. We developed lightweight deep learning models that are tailored to optimize performance even with moderate data resolution. Combined with iterative refinement through community-enhanced reference datasets, our goal is to achieve mapping accuracies in the range of 70–80%, (Figure 4), sufficient to support regular SDG 11.1.1 reporting and to deliver practical, actionable insights for local and national stakeholders (Kuffer et al., 2021). The accuracy threshold was defined together with your diverse city users (Figure 5) to support their work.

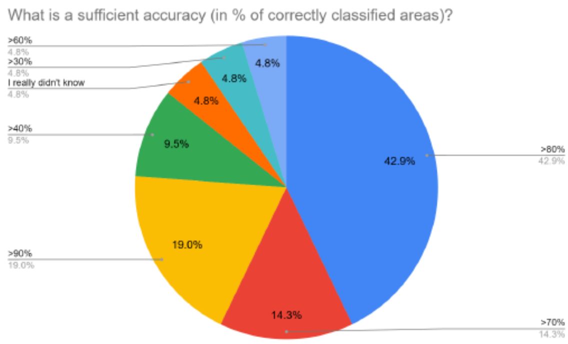

Figure 4. Required mapping accuracies by the IDEAtlas users, extracted from a user need survey (N=21).

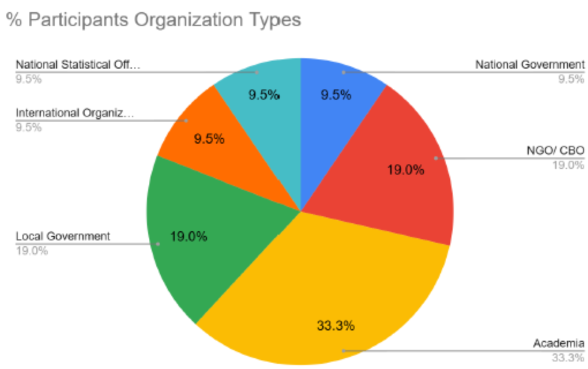

Figure 5. IDEAtlas user need survey, user organization types (N=21).

Thus, the IDEAtlas project developed a Multi-Branch Convolutional Neural Network (MB-CNN) (Figure 6) building on the U-Net architecture (Ronneberger et al., 2015) that combines within one network the following aspects:

- Learns spatial-contextual features from free-cost EO images;
- Integrates multiple EO data types (SAR and Optical) with geospatial features;
- Extracts consistent informal settlement extents (binary maps) and a slum severity index (a continuous scale from 0 to 1, where extents can be defined by thresholding);
- Produces multi-temporal maps of settlement extents for 2019–2023;
- City-level metrics are derived by combining settlement maps with population density data, offering valuable insights for urban planning.

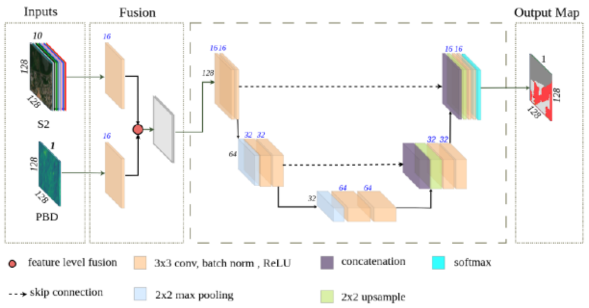

Figure 6. IDEAtlas Multi-Branch Convolutional Neural Network (MB-CNN).

To ensure effective collaboration with local stakeholders, IDEAtlas has developed a user-centric portal (https://portal.ideatlas.eu). This portal (Figure 7) enables visualization of model outputs and facilitates feedback on both reference data and model results. Co-designed with user input, the portal has an open section for gridded model outputs and a protected section for engaging with city users while protecting sensitive data. The protection of data is essential, particularly in areas prone to high eviction pressures. Feedback and data collected through this portal are integral to iteratively refining the models, which leverage free-access Copernicus satellite data (Sentinel-1 and 2).

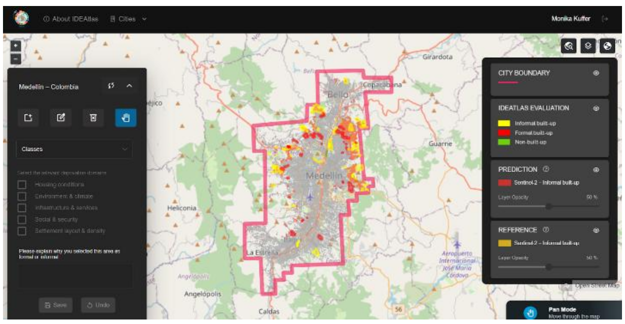

Figure 6. IDEAItals user and data-centred approach to map deprived urban areas. User Portal to Co-create models.

The IDEAtlas project also introduced IDEABench, the first open-access benchmark dataset dedicated to Deprived Urban Area (DUA) mapping, containing thousands of patches labelled across three classes (deprived, non-deprived, and non-built-up areas) using multi-source EO inputs. This dataset supports the research community in developing and testing new AI methods for urban deprivation mapping.

3. Results

Overall, IDEAtlas successfully demonstrates that a scalable, user-validated, and ethically sound Earth Observation solution is feasible, even across highly diverse urban environments. Our results are providing operational data and a web-based portal to support SDG 11.1.1 monitoring and inclusive urban policy development.

A central element of the project is its user-centred design, incorporating continuous interaction with local partners through Living Labs (co-anchors, early adopters, and other stakeholders). These collaborations helped to identify information needs, enhance reference data, and improve the produced maps. This iterative process has significantly improved model accuracy (Table 1) in several steps (version of reference data). Typically, the first version of reference data, we acquired from cities, had omissions and inconsistencies or represented data in formats that were aggregated to administrative units.

Table 1. MB-CNN performance comparison across eight cities using initial reference data (V1) and refined reference data (V2).

Model	City	Reference V1			Reference V2			
		P	R	F1	P	R	F1	F1 (WA)
MB-CNN	Nairobi	0.79	0.85	0.79	0.76	0.86	0.81	0.84
	Medellín	0.72	0.78	0.75	0.84	0.76	0.80	0.92
	Mumbai	0.70	0.70	0.70	0.83	0.79	0.82	0.88
	Salvador	0.61	0.61	0.61	0.63	0.69	0.66	0.84
	Buenos Aires	0.50	0.68	0.57	0.58	0.58	0.58	0.88
	Lagos	0.37	0.70	0.48	0.37	0.70	0.48	0.92
	Jakarta	0.28	0.44	0.34	0.30	0.33	0.31	0.83
	Mexico City	0.15	0.36	0.21	0.26	0.35	0.30	0.84

Through an iterative co-creation process, involving in-person and virtual workshops, stakeholders were directly engaged in reviewing preliminary outputs, annotating additional areas, and validating model predictions. The use of the IDEAtlas portal allowed us to iteratively improve the reference data that ultimately enabled reliable detection of DUAs across diverse global cities (Figure 7). Overall, after the first iteration, the improved reference data showed a consistent improvement in the model outputs of the pilot cities. As a result, model accuracy improved substantially across multiple cities: in Mumbai, Medellín, Salvador, and Mexico City, iterative reference data refinement led to F1-score increases. Although the improvements were modest in some cities like Jakarta and Lagos, these findings affirm the importance of continued local engagement in building trustworthy spatial models.

Thus, the validation results across eight diverse cities, i.e., Accra, Nairobi, Mexico City, Medellin, Mumbai, Salvador, Buenos Aires, and Jakarta, demonstrated robust model performance, with weighted average F1 scores ranging from 0.65 to 0.82 (Table 1). In cities like Nairobi and Medellin, the integration of Sentinel-2 imagery with building density information substantially boosted mapping accuracy, achieving F1 scores up to 0.79. However, in cities like Jakarta and Lagos, complex urban morphologies and inconsistencies in reference data posed challenges, underlining the necessity for continuous stakeholder engagement and refinement processes.

The IDEAtlas portal proved to be not just a research tool but a decision-support system. An outstanding example is Buenos Aires (Figure 7), where the portal outputs revealed newly forming informal settlements that were missing in the official data of the National Registry of Informal Settlements (RENABAP). Building upon these findings, RENABAP's field teams conducted ground surveys to verify and update their database. This dual-purpose use of IDEAtlas outputs, both refining the reference data for the project and simultaneously empowering local actors with actionable insights, highlights the transformative potential of open, participatory Earth Observation platforms.

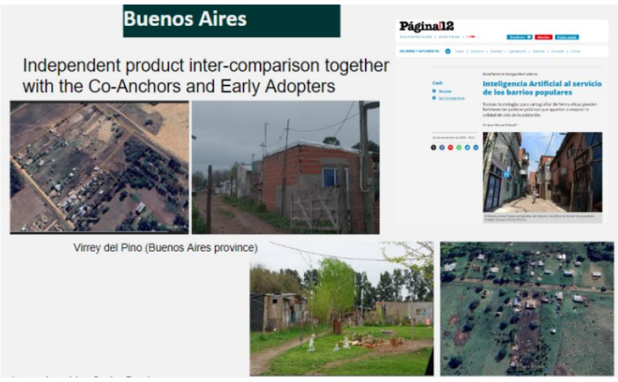

Figure 8. Early adaption of the IDEAtlas mapping outputs to guide the national slum registry in Argentina.

Thus, the living Labs conducted across the pilot cities confirmed the critical value of integrating local knowledge. Workshops with policymakers, urban planners, NGOs, and community groups not only validated model outputs but also guided improvements in reference data quality and user-centered model features. Stakeholder surveys revealed that 50% of participants are already using IDEAtlas outputs in practice, highlighting strong early adoption.

In sum, the integration of community-sourced feedback, and operational geospatial tools has contributed to the scalability, relevance, and societal impact of IDEAtlas products. Our results are supporting both scientific innovation and local capacity building in urban monitoring.

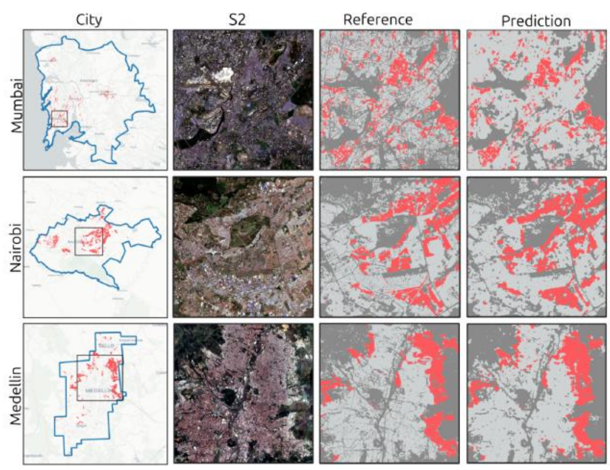

Figure 8. Examples of mapping outputs at the metropolitan scale and accuracy results.

4. Discussion

The IDEAtlas project demonstrates the critical importance of combining technical innovation with participatory approaches to address the complex challenge of mapping deprived urban areas (DUAs) globally (Kuffer et al., 2023). While machine learning models (Prabhu, 2024; Wang et al., 2019), such as the custom MB-CNN architecture developed in this project, have made significant strides in automating and scaling urban deprivation mapping, the results underline that purely algorithmic solutions are insufficient when tackling socio-spatial phenomena characterized by heterogeneity, informality, and invisibility (Tareke et al., 2024).

Another critical lesson is the dual role of the IDEAtlas portal, not only supporting scientific validation but also functioning as an operational tool for local decision-making. Thus, the portal has proven valuable for local decision-making and local data collection. For instance, in Buenos Aires, it identified newly forming informal settlements previously omitted from the National Registry of Informal Settlements (RENABAP). Building on this work, RENABAP's field teams are presently exploring the scale of the mapping approach to a country scale. At the country scale, the utility of an Earth Observation mapping approach is obvious, as it guides field surveys to update their database and improve their understanding of these areas. This example illustrates the dual benefits of validation and enhancing IDEAtlas reference datasets while empowering local partners with updated, actionable data. Generally, the strong uptake of IDEAtlas products by early adopters across all pilot cities (with over 50% actively using the outputs) shows the demand for scalable, accessible urban monitoring solutions tailored to the needs of policy actors.

The need for frequently updated maps, such as annual updates, relates to the high dynamics of cities and, in particular, DUAs (Liu et al., 2019). Common dynamics are the expansion in the outskirts of cities, densification in central areas, and the sudden disappearance of settlements, e.g., caused by evictions (Figure 9) (Adebayo, 2020; Githira, 2016).

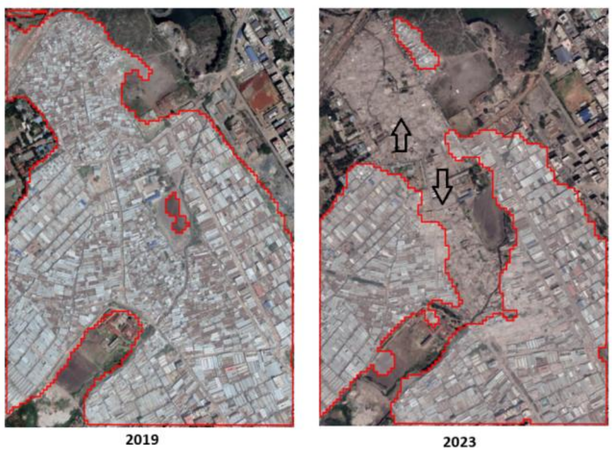

Figure 9. Example of temporal dynamics (evicted slum area) in Nairobi, Kenya.

One of the most significant insights from the IDEAtlas demonstrations is that user engagement is not ancillary but foundational. Across eight diverse cities, Living Labs involved diverse local users, ranging from local and national governments, NGOs, community members, academia, and the private sector.

The users provided crucial contextual insights that substantially improved model outputs. User feedback helped correct incomplete or outdated reference datasets, revealed omitted settlements (e.g., smaller and newer settlements), and allowed for the refinement of model predictions through iterative validation. Our findings call for a broader shift in GeoAI toward user- and data-centric AI models that emphasize inclusivity, adaptability, and local relevance.

Despite the considerable progress, challenges remain. Differences in local definitions of informality, the variability of settlement morphologies, and the limitations of high-resolution EO data (e.g., Sentinel-2), as compared to very-high-resolution data, continue to constrain model accuracy in complex urban contexts. This problem has appeared, particularly in cities like Jakarta and Lagos. Our results also highlighted that data aggregation at administrative levels (e.g., census tracts) can obscure intra-urban variability, being a major bottleneck for training deep-learning networks. Such aggregated data, which are common in many cities, stress the need for granular, flexible mapping frameworks. Future improvements could consider the inclusion of additional Earth Observation data (e.g., high-resolution night light images (Abascal et al., 2023; Linares Arroyo et al., 2024)) and socioeconomic ancillary data where feasible while balancing costs and privacy concerns.

Finally, the IDEAtlas results show that urban resilience cannot be disentangled from issues of social equity and data justice (Kuffer et al., 2025; Patel et al., 2012). Identifying deprived areas and relating results to other forms of spatial and environmental justice reveal not just technical patterns but systemic inequalities that require attention and the combination of maps of DUAs with other issues of spatial inequalities (Figure 10) Future work will continue to embed community engagement at the core of mapping efforts and invest in long-term capacity building for local users to ensure sustained impact.

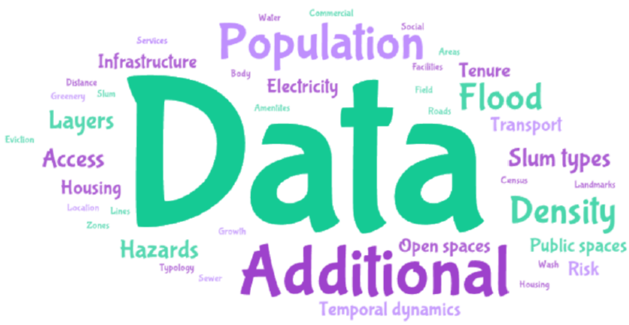

Figure 10. Integration of IDEATLAS data with additional datasets, and results of our user survey.

5. Conclusion

The data- and user-centric IDEAtlas approach emphasises the importance of investing resources in local reference data. Most studies invest the majority of resources in the development of models, and very limited resources are used in reference data. Within IDEAtlas, we swapped this to a massive investment in reference data that accurately reflects the complexity and diversity of deprived urban areas and responds to user data needs. High-quality, context-specific reference datasets are essential not only for improving model performance but also for ensuring that outputs are meaningful and actionable for local users. The experience from multiple pilot cities demonstrates that without continuous local input and validation, even technically advanced models risk misrepresenting the often very complex patterns and dynamics on the ground.

Equally critical is to ensure that model outputs are accessible, interpretable, and useful for local stakeholders. The IDEAtlas portal developed a user-friendly platform (with more than 95% user satisfaction) that facilitates direct engagement, allowing users not just to consume data but to actively contribute data, providing feedback and validation tools. Our participatory approach contributed substantially to the technical innovation and societal impact via co-developing trusted data that have a good potential for user uptake. Successful urban monitoring must treat communities not only as mapping subjects but as co-creators of knowledge. Investments in open platforms, capacity development, and iterative validation processes are essential to achieving trusted, scalable, and sustainable solutions for urban deprivation mapping and monitoring in rapidly urbanizing regions.

In conclusion, the IDEAtlas project showcases a promising pathway toward scalable, participatory, and ethically EO-based urban monitoring approaches, offering critical insights for achieving SDG 11.1.1 and beyond.

Acknowledgements

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