PEAK Urban

Towards a More Sustainable Urban Growth Through a Data-Driven Framework for Modelling, Planning, and Control.

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This brief highlights the value of using a data-driven urban-growth framework to predict the impact of certain administrative and political decisions in the long-term expansion or densification of a city. When the framework is used as part of the urban planning cycle (see Figure 1), it provides an avenue to make decisions that contribute to sustainable growth. For other urban stakeholders, like utility companies, the framework can provide valuable insights to plan for future demand of services and infrastructure.

Urbanisation is a complex socio-economic process that shapes the built environment by converting formerly rural areas into urban settlements.

Urban growth takes place due to continued urbanisation, migration, and densification or expansion, within the existing urban fabric of a city. As a result, the environment, demographics and social structures of urban and rural places are transformed, leading to the emergence of different settlements, occupations, lifestyles, cultures and behaviours (Montgomery et al., 2004).

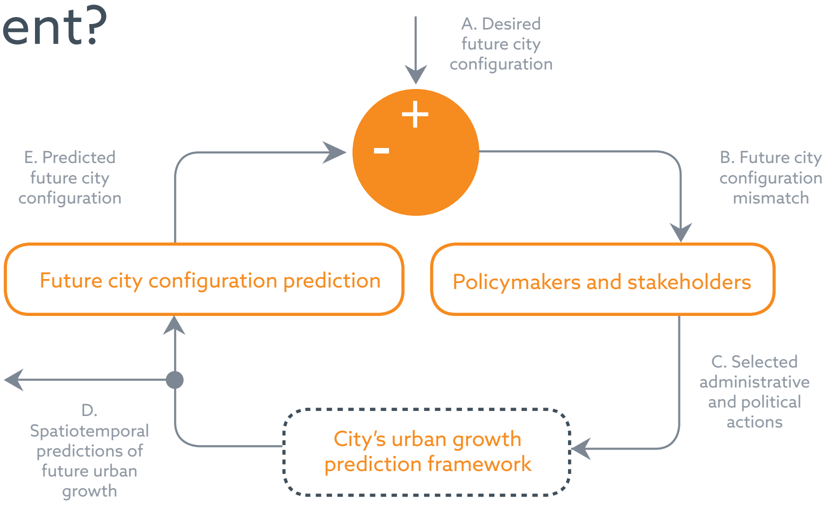
The management of urban growth can contribute to — or deter from — sustainable development. As a result, the study of the types of urban footprint growth in cities of low- and middle-income countries is essential. These countries often lack the necessary tools to anticipate the impact of political or administrative decisions on the spatial distribution of cities. The adjustment of a master plan can drastically change the shape, size and densification patterns of these cities, for better or for worse. Without the right tools, such adjustments can trigger unanticipated changes in land prices, promote informal settlements in city peripheries, accelerate deforestation, increase spatial mismatch and segregation or worsen urban sprawl — all of which are changes that pose serious threats for urban sustainability.

Policymakers in low and middle-income countries face economic and technical constraints. Consequently, urban planning in many cities occurs without a prior and complete urban prospective analysis. In some cases, policymakers rely on coarse land-use forecast models. These models are often based on rules (Clarke 1997) to understand how the city will look in the decades ahead. However, models based on pre-defined and fixed rules can only provide a very rough approximation of the urban growth forecast. These models cannot incorporate interactions not explicitly encoded into the original ruleset.

Effective urban planning requires an understanding of how a city will change in the future.

Urban planning that takes into account future city growth can contribute to sustainable, thriving urban living. Existing methods to forecast city growth, expansion and densification are not sufficiently effective in providing adequate information for policy decisions conducive to future sustainable development. **A data-driven prediction framework that uses machine learning (Gómez et al. 2019) provides a more nuanced and precise understanding of future growth, and can deliver key information to policymakers in order to achieve desired results.**

How can policy makers and planners put in place policies that will result in future sustainable development?



Using a data-driven framework based on machine learning that captures historical trends.

Cities in low and middle-income countries, particularly those that are growing rapidly in Asia and Africa and those that have strong constraints in terms of available land to grow, as in the case of various Latin American cities, require an understanding of how current policies can affect future development. A clear understanding of the implications of policies on future urban growth, expansion and development is critical.

To address this gap, Gómez et al. 2019 created a data-driven prediction framework, which uses machine learning and can be applied worldwide to help policymakers guide a city's spatial growth. This framework can reveal the spatiotemporal evolution of cities in the upcoming decades under different policy scenarios. Policymakers and planners can compare the outcomes of policy choices to make informed decisions (see Figure 1)

The iterative selection of potential action-based scenarios enables practitioners to develop stronger and more reliable policies to achieve desired city goals.

Figure 1: The block diagram shows the proposed "planning and control" simulation cycle for urban policymaking. It assumes that planning departments and policymakers aim to achieve certain desired future urban configurations based on present-day actions.

A. Desired future city configurations can include, among others, a given population density; a desired ratio of green spaces to development; a safe distance margin between settlements and high-hazard areas; and a maximum walking distance from residential areas to public transport.

B. During the first iteration of the simulation, there are no predictions; therefore, the future city configuration mismatch corresponds to the desired future city configurations.

C. Urban planners and policymakers propose administrative and political actions to achieve the desired configurations. These actions may include changes to master plans, protected areas, future housing projects, or the provision of public infrastructure.

D. With a given set of selected actions, planning departments and policymakers can use a customised urban growth framework for their city to estimate yearly spatiotemporal predictions of future urban growth. These predictions show future estimates of the distribution of population, urban land, and city appearance as seen from an aerial viewpoint.

E. Planning departments can extract the future urban configurations of their cities based on the urban growth predictions. If predicted configurations differ from those desired, planning departments and policymakers can compute and analyse their differences, modify administrative and policy actions, and perform the simulation again. Once the desired configuration is achieved or the mismatch cannot be reduced any further through reasonable policies, the simulation exercise concludes.

The framework can be adapted to any city because the key variables required can be extracted from data sources that are available worldwide free of charge. Among these variables are the population distribution, the urban built-up area, and the urban appearance. It uses a data-driven approach based on machine learning to capture those relationships directly from historical records and avoids any pre-defined relationships among input variables. It should be noted that the success of the framework in predicting urban growth depends on the length of the available historical records and the "smoothness" of the region growth itself. The framework can incorporate planned interventions, but we do not expect it to predict the impact of rare or "black swan" events, such as those derived from wars or pandemics, unless it has been exposed to several said events during the training phase.

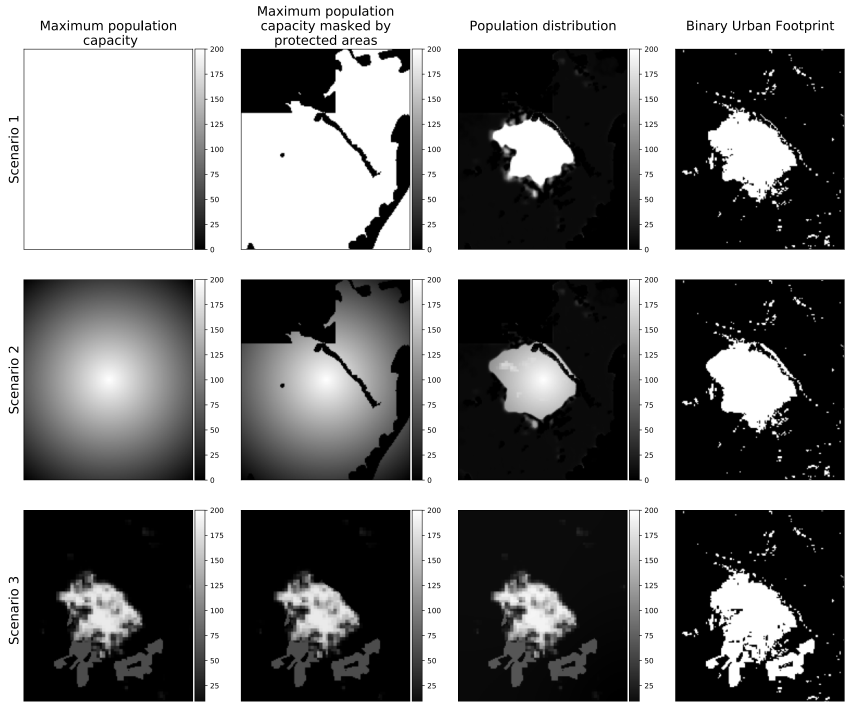


Figure 2. Results of a case study with a sensitivity analysis of predicted urban growth for the city of Valledupar (Colombia) in 2050, given three different policies for the maximum population capacity, which are shown across the different rows. The first column illustrates the hypothetical maximum population capacity maps without taking into account any of the protected areas. The second column shows hypothetical maximum population capacity maps taking into account the protected areas. The third column shows the population distribution (number of people in each square region of 100 m x 100 m). The fourth column shows the binary urban footprint, where white represents urban areas and black represents non-urban areas.

Flexibility as a critical component of an effective urban growth framework.

Cities have different data, sets of growth drivers, environmental risks, protected areas, and growth dynamics. Furthermore, they have financial and technical limitations, which affect the feasibility of doing a complex urban-growth modelling exercise. A flexible data-driven framework that can improve as more information becomes available, is therefore superior to a fixed and constrained rule-based model.

Beyond traditional input variables such as terrain slope, road infrastructure, protected areas, and urban built-up areas, the framework can also include variables that affect urban growth, which policymakers can influence. Such variables include the master plan, the maximum population capacity across the city, and others. By assessing the simulation results of different policy-based scenarios using the framework, policymakers can adjust their decisions to achieve the desired outcome (see Figure 2). The key variables that the framework uses come from the Global Human Settlement Program (Schiavina et al. 2019) that provides a spatial resolution of about 250m x 250m, and the Landsat program (Routledge 2019) that provides a spatial resolution of about 30m x 30m. With those key variables and other auxiliary data, the framework works at an intermediate spatial resolution of 100m x 100m. Once new data sources with better spatial resolution become available the framework will be able to provide output at a finer spatial scale without requiring changes to its internal structure.

Image: Medellín at night depicting high-rise buildings and the urban footprint spreading through the mountains

The framework was tested in Valledupar, a city in northeastern Colombia by using different policy scenarios (see Figure 2). For the first policy scenario, we used a constant maximum population capacity map of 20,000 people/km^2 and we find that such policy promotes densification. For the second policy scenario, we reduced the maximum population capacity radially outwards from the city centre using the same initial value as before and we find that this new policy promotes a fairly symmetric expansion of urban footprint. For the third policy scenario, we set the maximum capacity close to values of the population distribution in 2015, but introduced the planned expansions areas of the city with a small capacity of 6,000 people/km^2 and then we notice how this last policy triggers a quick urbanisation process, changing completely the city's original compact shape. According to the simulations, by 2050 the total urban areas for the three scenarios would oscillate among 44, 47, and 56 km^2 respectively, while the average values of the urban population density (i.e. total urban population divided by the total urban area) will oscillate among 13,162, 12,530 and 9,599 people/km^2, respectively for each scenario. From these results, we can conclude that the shape of the future urban growth in Valledupar is strongly influenced by the specific selection of the maximum population capacity.

Policy makers must understand how the footprint growth will change over time.

When a city's urban footprint is properly modelled and understood, it can be controlled more easily. Having a policy-sensitive framework for making urban-footprint growth predictions helps urban planners and policymakers find an ideal balance between strengthening the economy, improving the social conditions of citizens, and preserving the environment. For instance, protecting green areas in a central district reduces future building areas, but improves the local quality of life of the citizens and contributes to fighting climate change. Using evidence-based planning, policymakers and stakeholders can take the necessary actions to maximize the benefits of agglomeration and minimize the adverse impacts of urban growth, while effectively planning the required infrastructure and services for the community.

Further reading

PEAK Urban programme. (2018). The past, present, and future of urban footprint growth of Latin American cities.

Project: Read more online - **https://www.peak-urban.org/project/past-present-and-future-urban-footprint-growth-latin-american-cities**

Video: **https://youtu.be/k91MdLxLSiU**

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About us

The PEAK Urban programme aims to aid decision-making on urban futures by:

1. Generating new research grounded in the logic of urban complexity;

2. Fostering the next generation of leaders that draw on different perspectives and backgrounds to address the greatest urban challenges of the 21st century;

3. Growing the capacity of cities to understand and plan their own futures;

In PEAK Urban, cities are recognized as complex, evolving systems that are characterised by their propensity for innovation and change. Big data and mathematical models will be combined with insights from the social sciences and humanities to analyze three key arenas of metropolitan intervention: city morphologies (built forms and infrastructures) & resilience; city flux (mobility and dynamics) and technological change; as well as health and wellbeing.

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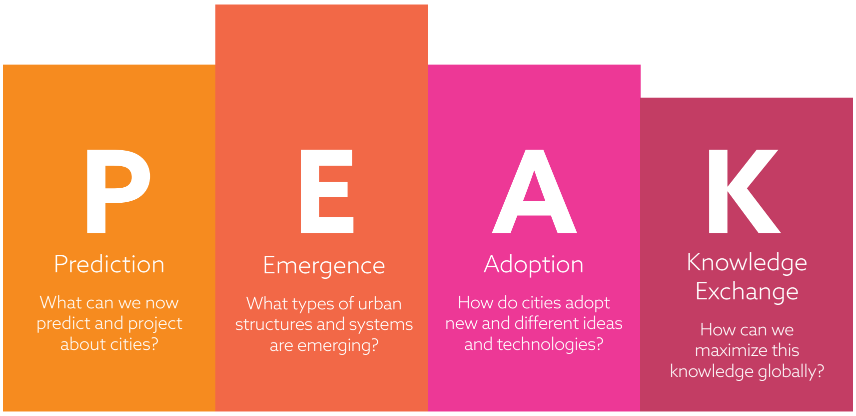
Our framework



The PEAK Urban programme uses a framework with four inter-related components to guide its work.

First, the sciences of **Prediction** are employed to understand how cities evolve using data from often unconventional sources.

Second, **Emergence** captures the essence of the outcome from the confluence of dynamics, peoples, interests, and tools that characterize cities, which lead to change.

Third, **Adoption** signals to the choices made by states, citizens and companies, given the specificities of their places, its resources and the interplay of urban dynamics resulting in changing local power and influence dynamics.

Finally, the **Knowledge** component accounts for the way in which knowledge is exchanged or shared and how it shapes the future of the city.

PEAK Urban is managed by the Centre on Migration, Policy and Society (COMPAS)

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