

Seeing Cities Clearly: How AI and Drones Are Rewriting the Urban Map

When the wildfires hit Los Angeles in early 2025, the response was swift—but not precise. Fire crews raced to neighborhoods where the flames had jumped containment lines, but no one could say for sure which buildings were occupied, which structures were commercial versus residential, or where vulnerable infrastructure might already be failing. The problem wasn't a lack of bravery or skill; it was a fundamental lack of information. Planners didn't know what information they were missing and where their information was inaccurate.

This data gap is a growing liability. The past decade has seen a consistent increase in the frequency and intensity of natural disasters. From the devastating wildfires that have swept through California and other parts of the American West to the powerful hurricanes battering the Gulf and Atlantic coasts, and the unpredictable tornadoes tearing through

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the Midwest, our cities are more vulnerable than ever. The [National Climate Assessment \(NCA\)](#)¹ and reports from the Intergovernmental Panel on Climate Change (IPCC) have made it clear: urban areas, with their dense populations and complex infrastructure, are on the front lines of a changing climate.

What if planners could collect, access, and analyze local data with regionally specific techniques? A new generation of AI-powered tools is offering just this, a path to a clearer, more resilient future for our urban spaces. Driven by recent research, these tools are rapidly advancing our ability to understand and prepare for the challenges of an era marked by heightened natural disasters. This article will explore how integrating AI with high-resolution aerial imagery and spatial data enables a granular, actionable view of the built environment,

¹ Update - August 2025: The 5th NCA Report was [removed](#) from its [primary location](#) by the Trump Administration in June 2025 but it can still be

found through [ESRI](#) and [NOAA](#) (for now). This marks a concerning step backwards in a field that holds so much potential.

revealing a new era of proactive urban planning and disaster resilience.

The Data Deficit: A Problem in Plain Sight.

Think of a city as a human body. Transportation networks function like the circulatory system, moving goods around a city, city workers maintain infrastructure and natural areas like an immune system, keeping the city healthy. Urban planners are like doctors for cities, but until very recently, urban planners have been working against serious obstacles in the form of data availability, accuracy, and timeliness. When a person is ill, doctors run diagnostics like blood work, X-rays, and MRI scans to find potential causes behind the symptoms they see. Yet, for years, cities have been trying to treat their ailments—traffic congestion, pollution, and vulnerability to climate disasters—without a full, accurate picture of their own internal workings.

For a long time, the best "diagnostic tools" available were outdated maps and manual surveys, a patchwork of inconsistent information. This is especially true for crucial details

like what a building is being used for. Open-source data, like OpenStreetMap, often lacks reliable information on building occupancy, which is critical for preparing for and responding to disasters. A team of data scientists led by Tom Narock, an associate professor at Goucher College, notes in their research that, "federal and local agencies have identified a need to create building databases to help ensure that critical infrastructure and residential buildings are accounted for in disaster preparedness and to aid the decision-making processes in subsequent recovery efforts." Despite this, the "free-form and optional nature" of this data means most buildings have no reliable occupancy type. Historically, this data has been deprioritized because it was very intensive to collect and use. New collection and analysis techniques stand to make collecting lots of data much easier, but cities still have unreliable baseline data. Collecting fresh baseline data needs to be a top priority.

A New Diagnostic Toolkit

To address this data deficit, a powerful suite of new technologies has emerged. The first is a process called remote sensing. Remote sensing is the first step in the diagnostic process for city planners assessing urban health and sustainability. It relies on data collection with drones and satellites equipped with multispectral cameras to perform non-invasive scans. These scans reveal far more than the human eye can see. A conventional camera captures what we see as visible light, but a drone with a multispectral camera can detect local issues like the subtle signs of a "sick" urban forest, just as an X-ray can reveal a fracture beneath the skin. Satellite data, meanwhile, acts like a full-body scan, giving a high-level view of the entire urban "organism" from above.

The data gathered from these "scans" is then analyzed by a specialized form of artificial intelligence called machine learning (ML). Machine learning involves using algorithms trained on massive datasets to recognize specific patterns. Like a medical specialist, ML

focuses on diagnosing specifics and making this information available to a primary care physician. It can't identify all of the issues, but each ML model can more quickly and reliably identify specific issues than a general model. For example, it can be trained to look at a remote sensing image of a building and, by analyzing its shape, size, and location, accurately classify it as a residential, commercial, or industrial structure. In the context of the research conducted by Dr. Narock's team, the ML model was trained to identify the building occupancy from a collection of different data points. In this case, creating a dataset of the number of people in an area and which buildings are likely occupied is critical for analyzing risk, assessing damage, and coordinating search-and-rescue efforts in the event of natural disasters. Similar work can be done to optimize traffic flow and inform the development of transportation networks.

Narock's team focused on creating a reliable building database by combining various open-source datasets, including OpenStreetMap, with ML models. This doesn't create new data out of thin air but

relies on computer pattern recognition to make educated guesses with new data. To understand the accuracy of these estimations, they needed to consider uncertainty and potential variability. To understand this, think about a doctor's diagnosis. In most cases, a doctor will never share a certain prognosis. Instead, they might say, "Based on diagnostics, we are 97% certain you have pneumonia and 70% certain that you will recover with no lasting issues." These percentages are the uncertainty or how confident the doctor is in the data, assessment tools, and situation as a whole. In the same way, the ML model gives a confidence rating for its predictions, helping planners know when the data is reliable and when it might be worth a closer, manual inspection or when a new model should be considered.

This process is not about replacing human judgment but enhancing it. Machine learning identifies telling patterns in cityscapes and hands a detailed report to the ultimate decision-makers, the planners and policymakers.

Data-Driven Solutions in Practice

Together, remote sensing and machine learning act as a powerful team to create a comprehensive picture of the urban environment. Planners can then compare these data to create a comprehensive treatment plan for the city or make fast decisions in reaction to a rapidly evolving situation. They can predict which areas are most at risk during a heat wave or where wildfire might spread based on the health of the urban forest and the types of buildings nearby. This allows a city to move from reactive treatment to proactive, preventative solutions.

The applications of AI-driven urban analysis are far-reaching. The toolkit created has interdisciplinary applications for managing a city's health. A 2024 study published in NPJ Urban Sustainability discusses how AI's integration into Earth observation is transforming urban analysis across five major categories, which collectively form a holistic diagnostic check-up for any city.

Land-use classification, for instance, goes beyond simple zoning. The AI can precisely map the city's "anatomy" — identifying where residential,

commercial, industrial, and green spaces actually are, not just where they are designated on a decades-old map. This provides the foundational knowledge for all other applications.

Disaster risk management is the direct result of this advanced diagnosis. By combining land-use data with real-time weather and climate information, the AI can predict which neighborhoods are most vulnerable to flooding, tornadoes, or wildfires, allowing for more strategic evacuation plans and resource deployment. This is a crucial step in aiding the "decision-making processes in subsequent recovery efforts" that Narock's research discusses.

Pollution monitoring provides a critical check of the city's "vital signs." Remote sensing can track airborne pollutants and identify urban heat islands, helping planners pinpoint areas that need intervention, such as new green spaces or updated building codes, to improve public health.

Built infrastructure identification is the recognition and categorization of specific structures, which is invaluable

for both proactive planning and sustainability-focused historic preservation. 3D modeling and UAV data allow for the precise identification of historic buildings, enabling the city to protect its past while planning for a resilient future.

Ecosystem assessment is the evaluation of the city's natural systems. This includes understanding the impacts of development on the environment surrounding an urban area as well as the health of urban parks and wildlife.

In 2023, a research team from the University of Tennessee used early versions of these tools to explore the viability of drone remote sensing for urban forest management. They conducted a case study in Knoxville, Tennessee, using a drone equipped with a multispectral camera to collect data on an urban forest. By combining this remote data with traditional field measurements, they were able to make key observations about the forest's health.

The researchers used various vegetation indices (VIs) — metrics that quantify how plants reflect different

wavelengths of light — to assess the health of the trees from the drone imagery. This allowed them to identify several areas of conservation concern, including a high proportion of overstory trees in decline, a significant presence of invasive species like Amur honeysuckle and kudzu, and a number of canopy gaps.

The implications of this study are immense. The team's findings indicate that drone remote sensing is a low-cost and efficient tool that can help city governments overcome the financial and personnel challenges of manual ground assessments. This technology allows for the efficient collection of data on a city's green infrastructure, which is vital for combating the urban heat island effect, improving air quality, and providing natural protection against flooding. Drones used in some of this work are financially attainable for even smaller municipalities, enabling a better standard of care for urban forests and eventually landscapes than would otherwise be possible for places limited by staff or resource availability.

Protecting the Past, Preparing for the Future

One of the most complex challenges facing urban planners is balancing the preservation of a city's history with the need for modern, sustainable infrastructure. This is not a simple choice between retrofitting an old building or demolishing it to build a new one. As Cornell researchers Dingkun Hu and Jennifer Minner explored in their review, UAVs and 3D modeling are crucial tools for historic preservation, allowing for highly detailed virtual models of historic sites. However, these historic areas are often more vulnerable to modern threats. A traditional, dense city center may be more walkable and resilient to extreme heat in some ways, but its older infrastructure may be ill-equipped to handle the intense rainfall of a modern hurricane, the ground-shaking of an earthquake, or support the fire barriers required to prevent urban wildfires from getting out of hand.

The AI-driven urban planning system can help navigate this paradox. By

combining historic data and 3D models with the latest vulnerability assessments, planners can create a strategy that protects a city's heritage while strategically modernizing for resilience. It can identify specific, high-risk structures that need retrofitting without mandating a complete overhaul of a historic neighborhood. This is a crucial step towards a future where we don't have to choose between preserving the past and protecting the future. The key in so much of the AI-informed urban planning is tailoring models to provide effective region or municipality-specific solutions. Previously, case-specific sustainability solutions would have required expensive consultants and lots of manual data collection, but with these tools, informed planners can keep much of this work in-house, reducing cost and increasing accessibility.

Challenges and the Future of Urban Planning

While this new diagnostic toolkit for cities is powerful, it is not without its limitations. Subsequent studies in [2023](#) and [2024](#) provide crucial context by

noting existing gaps and challenges. There is, for example, a general over-reliance on supervised learning, which involves lots of human guidance and intervention, while other AI modeling methods remain largely underexplored. Artificial intelligence is new and can be scary at times, but the AI industry has a tremendous following and inventor base, all but guaranteeing continued development. As more independent AI modeling matures, so will societal opinions on its use. In the meantime, further research can help clarify how AI should and shouldn't be used in sustainability science and urban planning. The inconsistency of open-source data also remains a significant challenge. These obstacles are not a reason for pessimism, but rather a guide for future research.

The journey toward a truly resilient and sustainable urban future is just beginning. By combining remote sensing's all-seeing eye with machine learning's diagnostic precision and more complex AI models' strategic insights, we are empowering planners, stakeholders, and residents to see their cities with

unprecedented clarity. Planners are now equipped with the tools to shift from merely reacting to disaster to actively planning for a future where our communities are not only smarter, but safer. Additional research on specific impacts of climate change on cities including the upcoming [IPCC Special Report on Climate Change and Cities](#) releasing March 2027 will further quantify the impacts of climate change supporting planners in their mitigation and avoidance efforts.

References

- Crimmins, A. R., et al. (Eds.). (2023). *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://repository.library.noaa.gov/view/noaa/61592>
- Fei, L., Yigitcanlar, T., Nepal, M., Nguyen, K., & Dur, F. (2023). Machine learning and remote sensing integration for leveraging urban sustainability: A review and framework. *Sustainable Cities and Society*, 96, 104653. <https://doi.org/10.1016/j.scs.2023.104653>
- Hersher, R. (2025, July 1). *The White House took down the nation's top climate report. You can still find it here*. NPR. <https://www.npr.org/2025/07/01/nx-s1-5453501/national-climate-assessment-nca5-archive-report>
- Hu, D., & Minner, J. (2023). UAVs and 3D city modeling to aid urban planning and historic preservation: A systematic review. *Remote Sensing*, 15(23), 5507. <https://doi.org/10.3390/rs15235507>
- Intergovernmental Panel on Climate Change (IPCC). (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [H. Lee & J. Romero (Eds.)]. IPCC. <https://www.ipcc.ch/report/ar6/syr/>
- Narock, T., Johnson, J. M., Singh-Mohudpur, J., & Modaresi Rad, A. (2025). Building occupancy type classification and uncertainty estimation using machine learning and open data. *Environmental Data Science*, 4, e10. <https://doi.org/10.1017/eds.2025.2>

Sestras, P., Roşca, S., Bilaşco, Ş., Şoimoşan, T. M., & Nedevschi, S. (2023). The use of budget UAV systems and GIS spatial analysis in cadastral and construction surveying for building planning. *Frontiers in Built Environment*, 9, 1206947.

<https://doi.org/10.3389/fbuil.2023.1206947>

Wavrek, M. T., Carr, E., Jean-Philippe, S., & McKinney, M. L. (2023). Drone remote sensing in urban forest management: A case study. *Urban Forestry & Urban Greening*, 86, 127978.

<https://doi.org/10.1016/j.ufug.2023.127978>

Weng, Q., Li, Z., Cao, Y., & Li, X. (2024). How will AI transform urban observing, sensing, imaging, and mapping? *npj Urban Sustainability*, 4, 50.

<https://doi.org/10.1038/s42949-024-00188-3>

ESRI. (2024). *National Climate Assessment Interactive Atlas*.

<https://nca-atlas-nationalclimate.hub.arcgis.com/>