# Atmospheric world models for infrastructure scenarios in Jamaica

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## Before the paper: the idea in plain language

Could we examine how a different development changes local conditions, or compare a prescribed storm crossing a city with one passing offshore? These are useful questions, but the answer depends on which physics the model actually represents.

**How it works, and why it matters**

The interactive example separates real historical inputs from two simple scenario models: surface heat storage and a prescribed wind vortex. Add buildings, move the track and inspect the equations.

**Value:** It makes the proposed planning use concrete and identifies what must be measured before a scenario can support a decision.

**Analogy:** A wind tunnel lets us ask a controlled question about an imposed flow. A visual model needs the same discipline about what is controlled, measured and left out.

## Abstract

We define a staged framework for using an atmospheric reconstruction in paired infrastructure and imposed-storm scenarios. A reduced surface-storage model and prescribed vortex provide executable conceptual examples. Their equations, units and limitations are explicit. Procedural buildings do not constitute a surveyed urban model, and the visual companion supplies no flood, damage or building-resolving forecast. The paper specifies the additional geometry, closures, observations, comparison methods and computational measurements required to establish planning value. This extension depends on the physical inference and verification developed in Papers 0–6.

# 1. Decision question and evidence boundary

The proposed atmospheric world model is intended to support controlled questions about place, forcing and infrastructure. A planner might ask how a coastal development changes heat storage, or how a prescribed storm circulation exposes Kingston differently from an offshore domain. Those questions require different physical models. A temperature forecast benchmark does not validate building aerodynamics, flood depth, damage or storm-track counterfactuals.

This paper defines a hierarchy: historical replay; uncertain atmospheric reconstruction; imposed-forcing sensitivity; coupled intervention experiments; and externally validated impact analysis. Only the first and a small analytical sensitivity are implemented in this visual companion. The three-dimensional buildings are procedural geometries, not a surveyed Kingston inventory. Their value here is to expose the data and closures needed to turn an attractive scenario into a falsifiable scientific experiment.

# 2. State, intervention and causal interpretation

Let x be the atmospheric state, b the building and surface descriptors, f the large-scale forcing, and η the unresolved-process parameters. A transition or continuous evolution model maps these quantities to a trajectory. An intervention modifies b while retaining a paired forcing and uncertainty draw. The resulting model difference is conditional on the equations and assumptions; it is not automatically the causal effect in the real city.

$$\frac{d\mathbf{x}}{dt} = \mathcal{F}(\mathbf{x}, \mathbf{b}, \mathbf{f}; \eta), \quad \Delta Y = Y(\mathbf{x}[\mathbf{b}_1, \mathbf{f}, \eta]) - Y(\mathbf{x}[\mathbf{b}_0, \mathbf{f}, \eta]). \tag{1}$$

Y must be defined in advance: for example, a degree-hour exposure or an area-mean temperature. Paired experiments reduce forcing differences; they do not remove structural error.

Use the same background trajectory, random-number stream, observation treatment and integration window for the paired runs. Report both runs and their difference. If a changed surface alters circulation beyond the domain, lateral conditions held fixed become a limitation. A large urban intervention may require an expanded coupled domain rather than a local correction. Surface heat, humidity, momentum and roughness exchanges must enter the appropriate budgets.

# 3. A deliberately reduced surface-temperature sensitivity

The implemented thermal demonstration is an anomaly budget per unit surface area. It uses the archived hourly shortwave input as a prescribed forcing. Surface heat capacity, albedo, anthropogenic heat and a linear exchange coefficient are

chosen scenario parameters. The anomaly is initialised at zero and is not calibrated to urban observations. It illustrates the direction and timescale of a simple storage process, rather than estimating Kingston's urban heat island.

$$C_s \frac{d\vartheta}{dt} = (1-\alpha)S_{\downarrow} + Q_A - h\vartheta, \quad \vartheta(0) = 0.$$

(2)

Cs: J m^-2 K^-1; S↓ and QA: W m^-2; h: W m^-2 K^-1. ϑ is a constructed surface anomaly, not observed 2 m air temperature.

$$\vartheta_{n+1} = e^{-h\Delta t/C_s}\vartheta_n + \frac{(1-\alpha)S_n + Q_A}{h}(1 - e^{-h\Delta t/C_s}).$$

(3)

Exact update for constant hourly forcing, positive h and Cs. This avoids an unstable explicit step when parameters change.

The illustrative land uses Cs=2×10⁶ J m^-2 K^-1 and α=0.20; the illustrative ocean uses Cs=2×10⁸ and α=0.06. Both use h=15 W m^-2 K^-1. Development fraction β adds QA=30β W m^-2. These values define a transparent sensitivity experiment. Evaporation, longwave exchange, canopy air, wall orientation, shading and atmospheric feedback are omitted. The plotted quantity must therefore remain a scenario anomaly.

## 4. Prescribed storm exposure versus a storm simulation

The vortex mode prescribes an axisymmetric tangential speed profile with maximum Vmax at radius R. A translating centre crosses the display domain. Moving the track offshore changes geometric distance, not hurricane formation or intensity physics. The pressure readout is a dynamic-pressure proxy from a prescribed wind, and excludes drag coefficients, gust factors, pressure coefficients, debris and structural response.

$$V(r) = V_{\max}\frac{r}{R}\exp\left(1 - \frac{r}{R}\right), \quad V(0) = 0, \qquad q_d = \frac{1}{2}\rho V^2.$$

(4)

r and R use the same distance unit. qd is in Pa when ρ is kg m^-3 and V is m s^-1. The profile is an idealised scenario, not a fitted Hurricane Beryl model.

The maximum follows by differentiating a e^(1−a): d/da=e^(1−a)(1−a), so the peak is at a=r/R=1. Squaring the speed explains why doubling V quadruples the dynamic-pressure proxy. The demonstration does not predict building damage. Adding blocks to the scene shows exposure geometry; they do not alter this prescribed flow. A building-resolving extension would need an appropriate CFD or urban-canopy model and measured validation data.

**Observation**A hypothetical hurricane crossing Kingston and one passing over the sea are different imposed tracks. Neither animation establishes the probability of that track or a real damage estimate.

## 5. Data and model requirements for an urban extension

| Required input | Physical role | Validation needed |
|---|---|---|
| Surveyed footprints, heights and terrain | Geometry, flow obstruction, shading and surface area | Coordinate, height and coverage checks; independent survey where possible |
| Roof/wall properties, land cover and vegetation | Radiation, storage, evaporation and roughness | Property uncertainty; local flux and temperature observations |
| As-issued wind, pressure, rain and ocean/boundary fields | Initial and lateral forcing | Time provenance, common support and held-out events |
| Drainage, soil, bathymetry and water levels | Runoff, inundation and coastal interaction | Independent flood depths and discharge; separate solver |
| Stations, profiles and flux observations | Atmospheric and surface verification | Quality control, siting, uncertainty and assimilation lineage |
| Infrastructure inventory and response models | Exposure, vulnerability and consequence | Engineering evidence; no inferred damage from animation alone |

A defensible sequence begins with an ocean-inclusive mesoscale reconstruction and independent withheld observations. Surface interventions follow only after budget closure and baseline skill are assessed. Building-scale effects require either calibrated parameterisation at regional scale or a nested high-resolution model with compatible boundary transfers. A hydrostatic mesoscale neural field cannot claim building-wake resolution by drawing smaller cubes.

## 6. Computational design and comparison

Local fields permit caching repeated background features and evaluating only the windows needed for a scenario. Shared parameters can reduce the number of independently trained networks, while a coarse communication level can transmit boundary information across the domain. These are implementation options, not measured speed claims. Record training and inference separately, including source retrieval, observation operators and posterior sampling. [1]

$$N_{\mathrm{vox}} = N_x N_y N_z N_t, \qquad C_{\mathrm{local}} \sim N_{\mathrm{active}}\, C_{\mathrm{field}} + N_{\mathrm{face}}\, C_{\mathrm{exchange}}. \tag{5}$$

These are bookkeeping estimates, not a hardware benchmark. Neural-field cost and interface iterations must be measured in the actual implementation.

Compare against an uncoupled local model, a global field, weak-constraint assimilation and an appropriate regional numerical baseline. Use the same observation window and forcing information. A useful result is an error–cost frontier, including memory and uncertainty quality. Reject a complexity increase when it yields no meaningful improvement in the target quantity. The current browser renderer is deliberately lightweight; its frame rate is unrelated to the cost of validated atmospheric inference.

## 7. Expected outcomes, regional benefit and limitations

The near-term goal is a source-auditable reconstruction experiment, not an operational urban digital twin. The next deliverables are an observation-support map, a known-truth sparsity benchmark, an interface ablation, a matched-compute comparison and a small real-event study. The expected benefit is better evidence about when the proposed coupling is informative. A null result may establish that a background bias, a missing process or insufficient observations dominates the architecture.

A later Jamaican planning application could compare heat-storage assumptions or stress-test infrastructure under explicitly prescribed events. Extension to other islands would test transfer rather than assume it. The global contribution would be an inspectable method and evidence on error propagation across coupled local representations. Decision value must be measured against a specified planning outcome and uncertainty threshold. Scientific-fiction inspiration motivates the questions; observations, equations and falsification determine the answers.

> **Literature update · 7 October 2026**The distinction between weather prediction and response to altered forcing is also emphasised in the recent Beucler et al. preprint. Climate claims require explicit forcing and stress tests outside the historical distribution. [2] Compare the closest literature.

## References and source lineage

Citations resolve to the shared numbered bibliography. The source-access register retains inherited and unappraised records separately. [3] [4] [1] [5]


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5. [5] Harder, P.; Hernandez-Garcia, A.; Ramesh, V.; Yang, Q.; Sattegeri, P.; Szwarcman, D.; Watson, C.; Rolnick, D. (2023). Hard-Constrained Deep Learning for Climate Downscaling. Journal of Machine Learning Research, 24(365), 1–40. Included in the revised doctoral literature review; full-text and identity checks vary by source

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AI-assisted drafting, coding and source reconciliation. Author and supervisory review remain necessary before scholarly submission. No journal acceptance or completed PhD is asserted.