Cities, Urban Digital Twins and Weather/Climate Extremes

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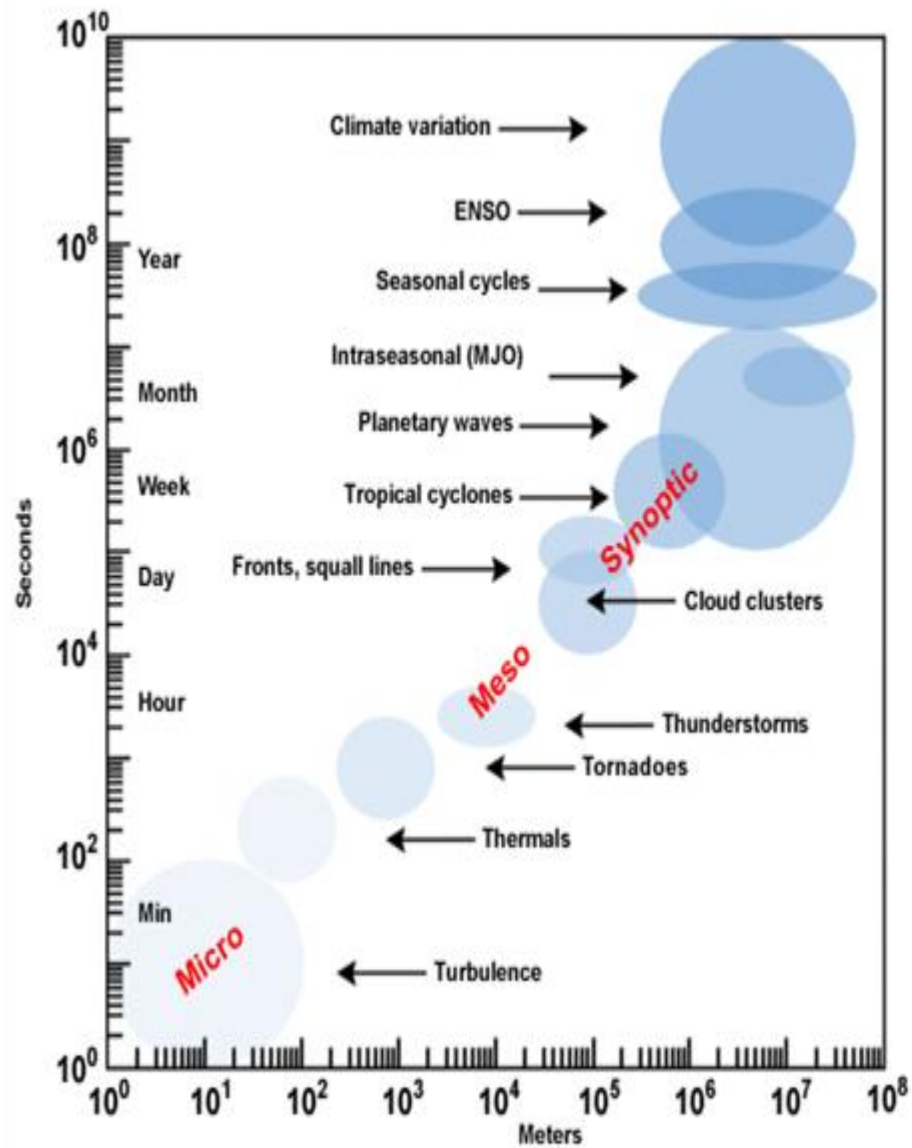
STIPMEX and Prediction of Monsoon weather Extremes

Sessions XII: ***AI/ML in Weather prediction***

Chair: Dr. E. N. Rajagopal, Co-chair: Dr. C. Gnanaseelan,

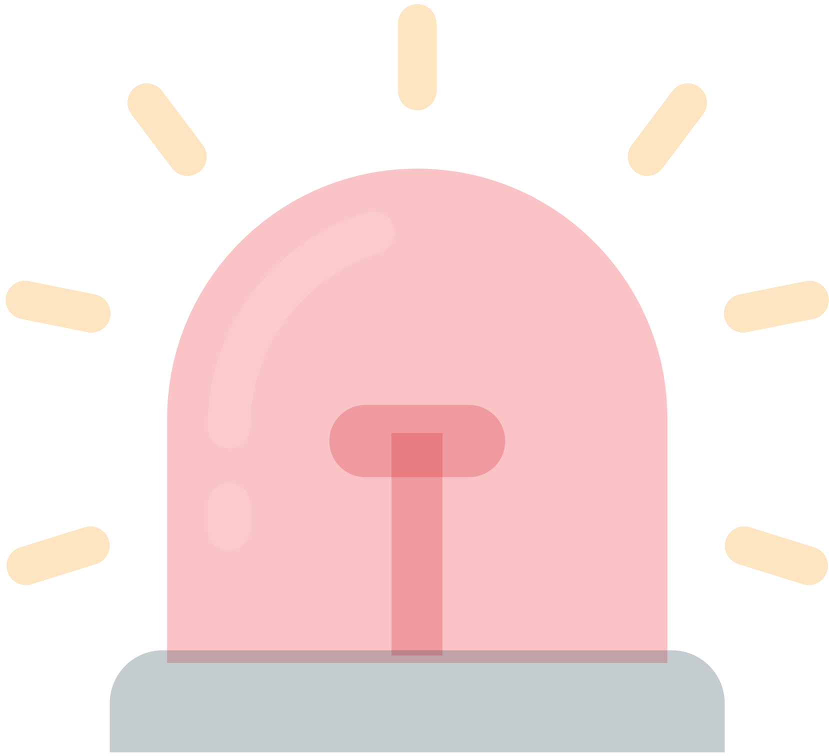
Most weather and climate research is useful but not readily usable and needs some interface/ processing

- **Complexity of Climate Extremes:** Multiscale
- Influenced by multiple physical and biological factors that interact in complex ways
- Physical/dynamical laws have constraints due to inherent assumptions
- Challenging to analyze using traditional methods
- → Opportunity in this limitation



Cities have a weather and climate emergency!

- **Increase in the extremes; city needs to prepare for eventualities**
- **Disadvantaged communities greatly challenged in "bouncing back"**
- **Infrastructure investments and response plans underway**
- **Many funding agencies, foundations looking for city-based solutions**
- **Next IPCC Special Report will be @ Cities**



Cities are exposed to heat, floods, lightning, hail, freeze, +++ impacts – This is well known

The impacts are disproportionately higher than for non-city regions – also known/ emerging

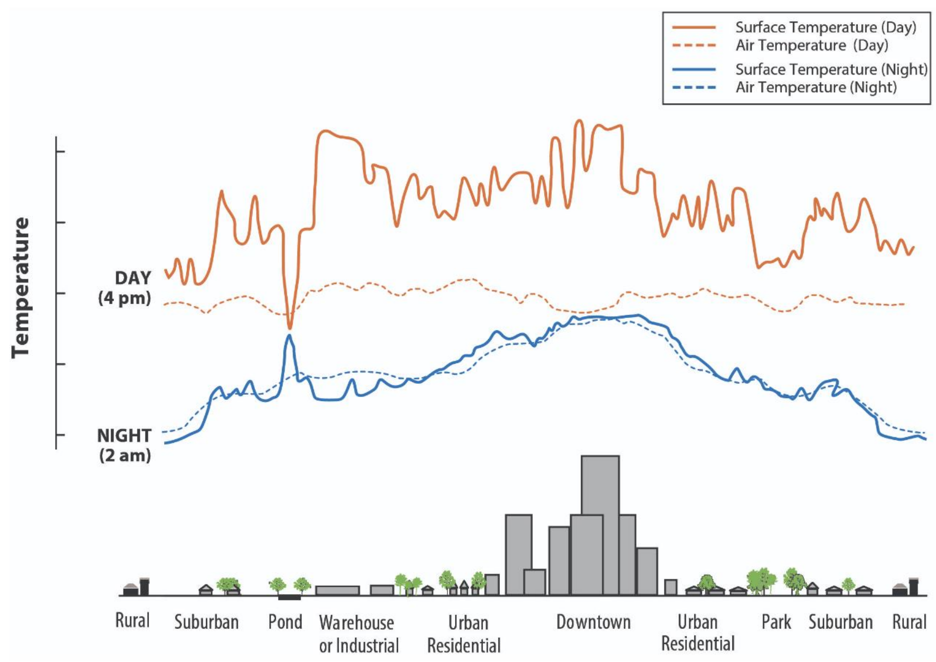
Do cities contribute to or create these weather and climate extremes?

Urban Heat Islands Can Be Deadly, and They're Only Getting Hotter

How built-up cities and higher temperatures threaten human health.

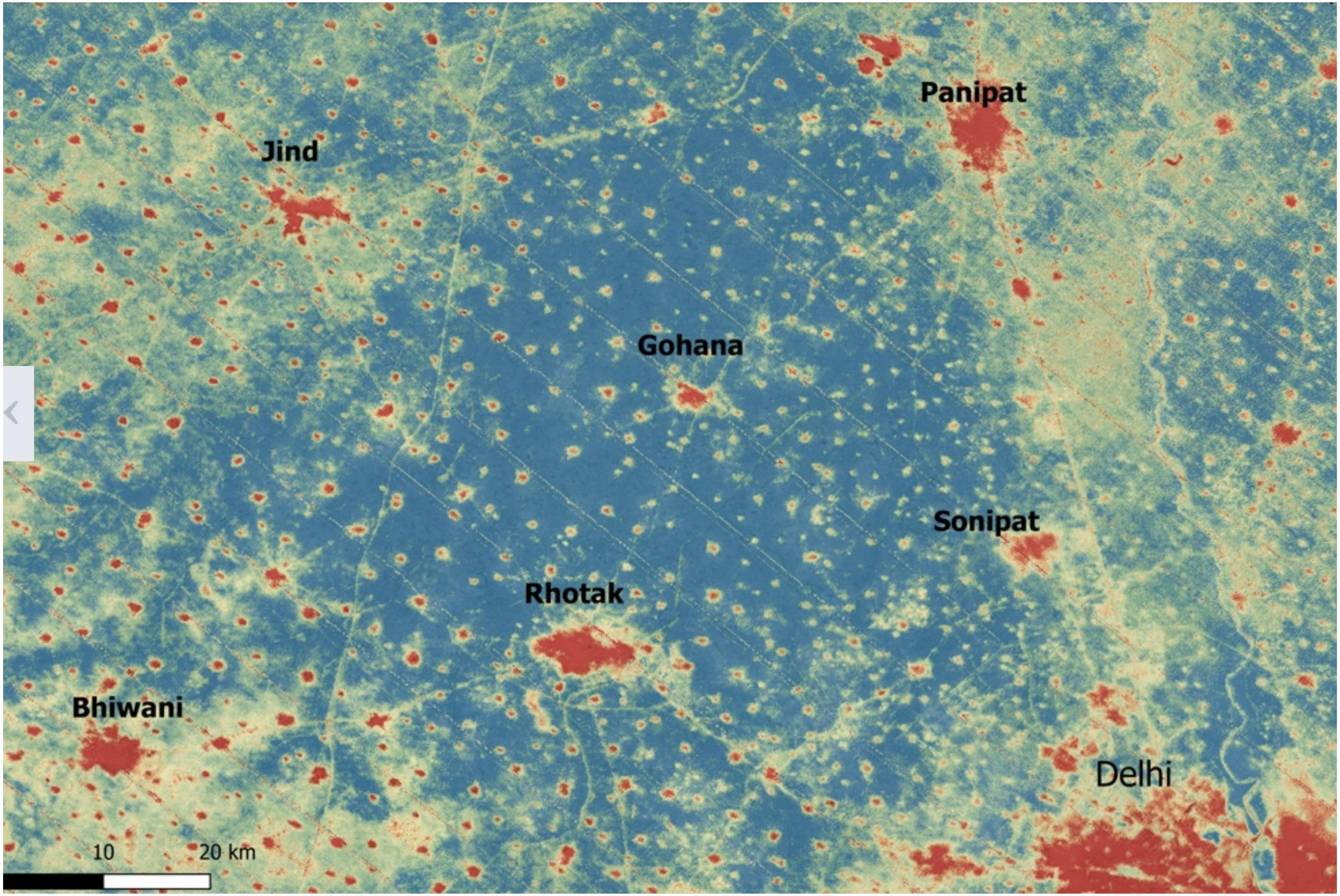
GETTY IMAGES

Heat Island Effect Diagram

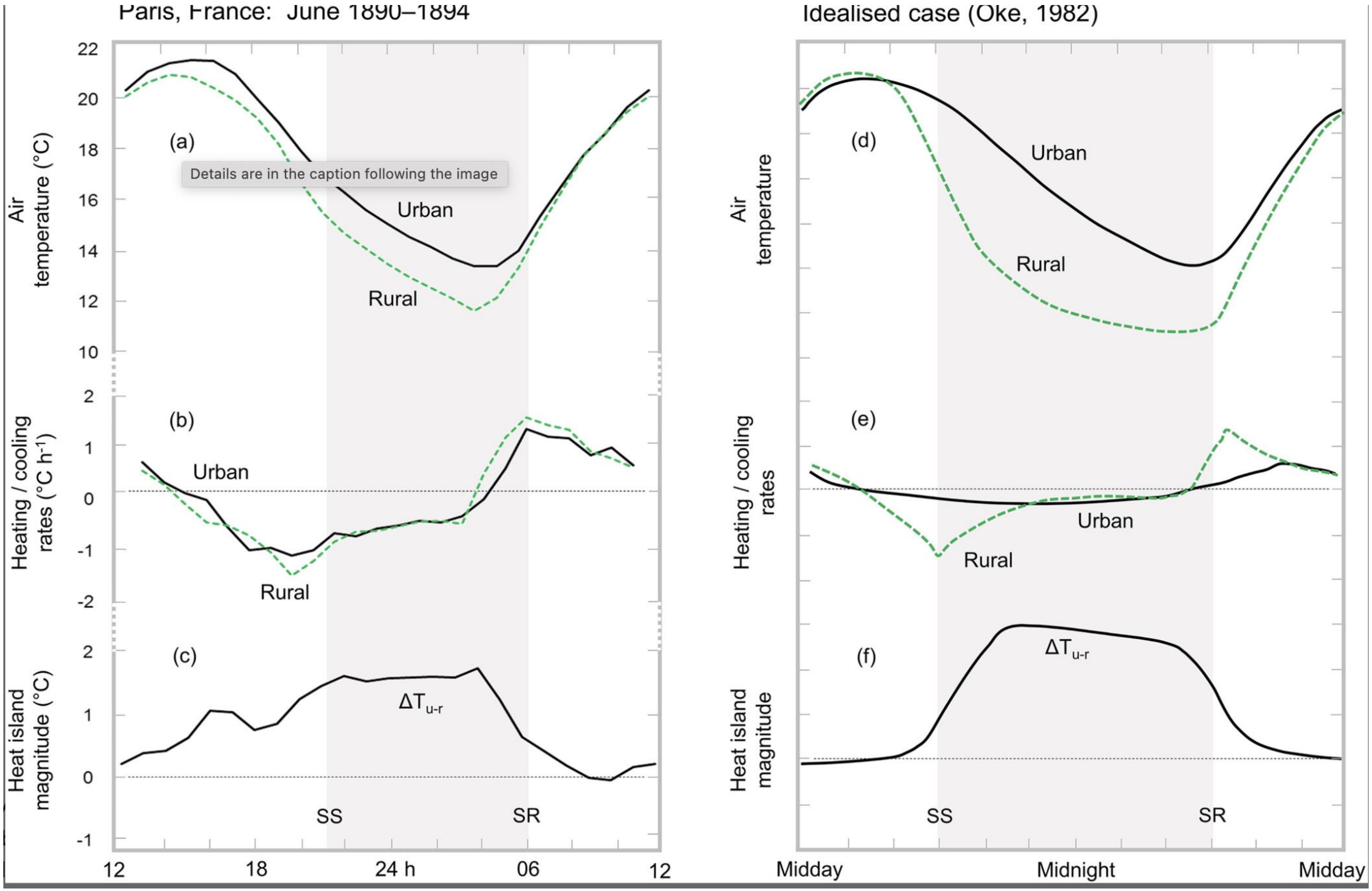


Surface temperatures vary more than atmospheric air temperatures during the day, but they are generally similar at night. The dips and spikes in surface temperatures over the pond area show how water maintains a nearly constant temperature day and night because it does not absorb the sun's energy the same way as buildings and paved surfaces. Parks, open land, and bodies of water can create cooler areas within a city. Temperatures are typically lower at suburban-rural borders than in downtown areas.

https://www.epa.gov/heatislands/learn-about-heat-islands

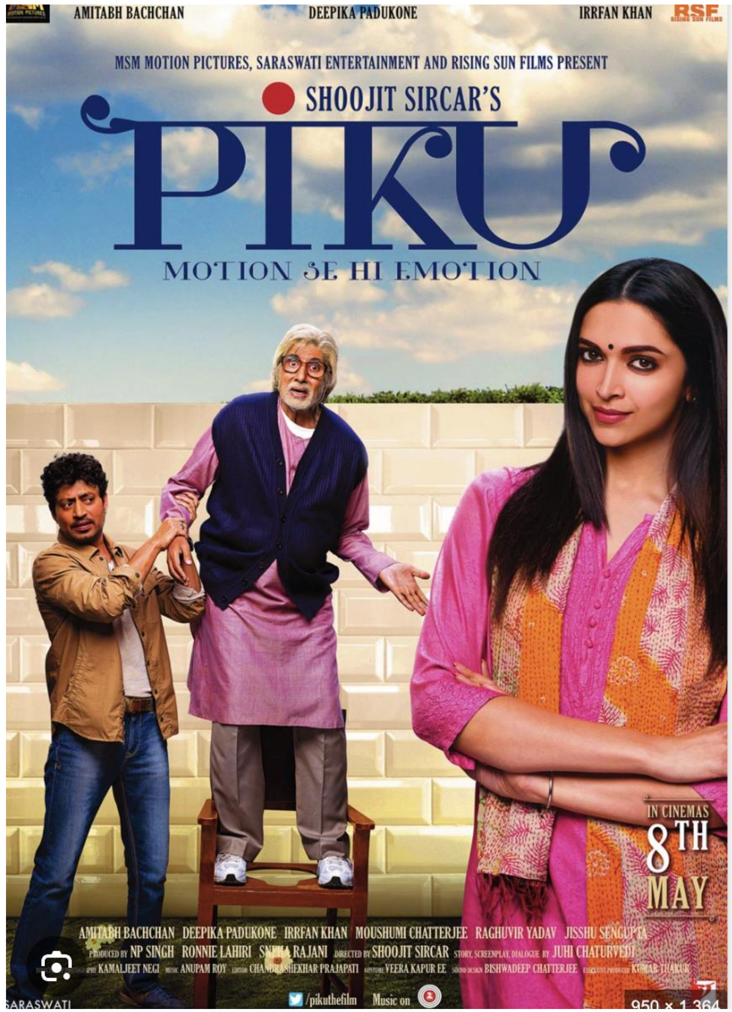


NASA's ECOSTRESS instrument made this image of ground temperatures near Delhi (lower right), around midnight on May 5. The urban "heat islands" of Delhi and smaller villages peak
102 degrees Fahrenheit (39 degrees Celsius) while nearby fields were about 40 degrees Fahrenheit cooler. Credit: NASA/JPL-Caltech



Stewart, I.D., et al 2021. Time evolution of the surface urban heat island. *Earth's Future*, *9*(10), p.e2021EF002178.

“High Temperature is a symptom of an underlying condition”



City Impacts Scale Beyond UHI (temperature)

Thermal effects (UHI) easier to detect.

1. Cause and effect co-located.
2. Results are consistent i.e. urbanization effect if increase in temperature
3. How to detect and represent UHI is relatively standardized (UHI or SUHI from satellite; Tu – Tr (some reference)

Urban Convection, Rainfall effects are highly nonlinear.

1. The effect can be over the city, downwind, upwind, or splitting around the city.
2. Impacts are nonlinear i.e can increase or decrease rains
3. Studies have used adhoc/ “erroneous” reference points in trying to show urban effect (treating rainfall as temperature field and ignoring dynamics)
4. No standard approach to used in showing the effect on rainfall.

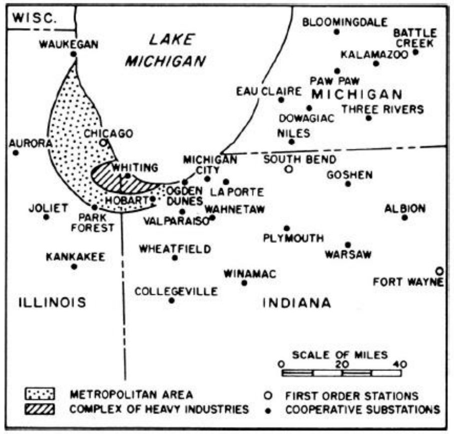


FIG. 1. Location of weather stations.

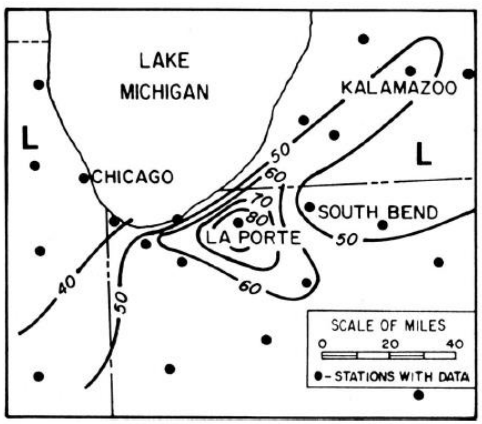


FIG. 8. Number of hail days in an average 20-yr period.

the La Porte weather anomaly— fact or fiction?

Stanley A. Changnon, Jr.
Illinois State Water Survey, Urbana

1970s "LaPorte Rainfall Anomaly" – (LaPorte is a small town ~ 50 miles downwind of Chicago) – Fact/Fiction? Instrument error? True Process?

1973 METROMEX Large Field experiment – St. Louis. Popular outcome " ~15-20% increase in rainfall downwind"

Work by Lowry, Landsberg provide summaries of urban rainfall changes and approaches

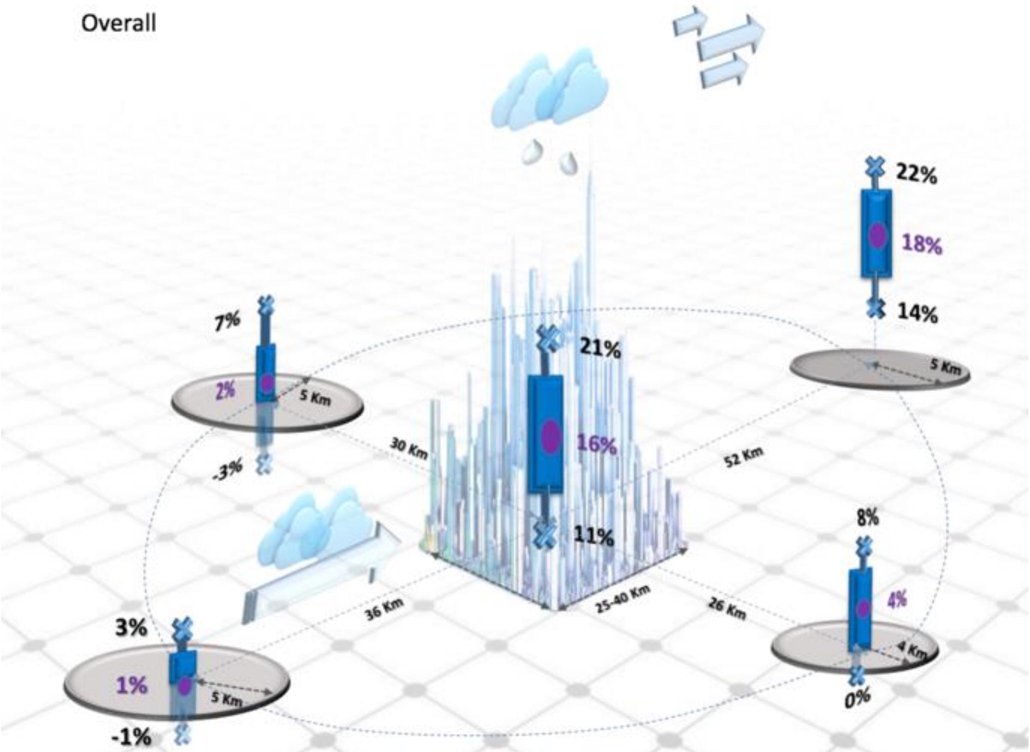
1990s-2000 – Bob Bornstein Project Atlanta, NYC – highlighting splitting of thunderstorms around City

- 2000 Jt. Urban Experiment – OKC; Niyogi et al. OKC paper (urban – rural soil moisture gradient) Niyogi, D., Holt, T., Zhong, S., Pyle, P.C. and Basara, J., 2006. Urban and land surface effects on the 30 July 2003 mesoscale convective system event observed in the southern Great Plains. *Journal of Geophysical Research: Atmospheres*, *111*(D19).
- 2005 Marshall Shepherd Earth Interactions Review paper highlighted the METROMEX from satellite rainfall perspective (confirmed findings; widely cited)
- 2005 Mumbai Heavy rains – 37 inches in 24 hrs – exceptional localized heavy rain; north heavy; south @3- 5 inches (2008 Lei et al. explicit analysis of urban representation on simulation)
- @2005 Beijing studies – IUM, BUBBLEX, SURFx – Miao, Bornstein, Grimmond, …(Zhong, Niyogi, Gonzalez, ….), BAMS paper
- 2010 – Atlanta studies (Shepherd; Mote; Stallin etc) – rainfall change; convection change; increase lightning, flood risks,..
- Shepherd, Niyogi – Atlanta Tornado NASA study (https://www.wired.com/2009/03/urbanstorm/)
- Kishtawal India climatology in follow up to a Science paper that Monsoon rainfall showing climatic increase in extremes; reanalyzed the data and showed the increase is only over urban grids (verified using TRMM as well as data used in Science paper)– (Kishtawal, C.M., Niyogi, D., Tewari, M., Pielke Sr, R.A. and Shepherd, J.M., 2010. Urbanization signature in the observed heavy rainfall climatology over India. International journal of climatology, 30(13), pp.1908-1916.) --
- 2011 – Niyogi et al. Indianapolis work- not case study but climatology of summer thunderstorms; objective image detection technique convection detection; 2X distance; control/reference point approach -(Niyogi, D., Pyle, P., Lei, M., Arya, S.P., Kishtawal, C.M., Shepherd, M., Chen, F. and Wolfe, B., 2011. Urban modification of thunderstorms: An observational storm climatology and model case study for the Indianapolis urban region. Journal of Applied Meteorology and Climatology, 50(5), pp.1129-1144.)
- @2012 NASA Interdisciplinary Science projects on urban climate – Geoff Henebry (USGS) and NSSL/NOAA team – radar and satellite products to analyze urban effects

- Parallel studies on aerosol effects on storm dynamics (UHI, roughness issues)
- 2007 – van den Heever and Cotton study – urban aerosols and convection
- 2011– Miao, IUM studies urban aerosols and dynamics
- 2010 – Danny Rosenfeld, Steiner, Jiwen Fan, … continued studies
- 2012 National Academies study – Urban meteorology
- 2018 NASA Interdisciplinary Sciences project on Urban Rainfall - Shepherd, Niyogi et al. (ongoing); Fei Chen, Niyogi et al. (modeling ongoing)
- 2022 DOE Urban Integrated Fields – Austin/ Southeast Texas, Baltimore, Chicago, and Phoenix region – each studying UHI and urban rainfall (and air quality/climate)
- ~2021-24 RDP Paris Olympics

Meta-analysis of urbanization impact on rainfall modification

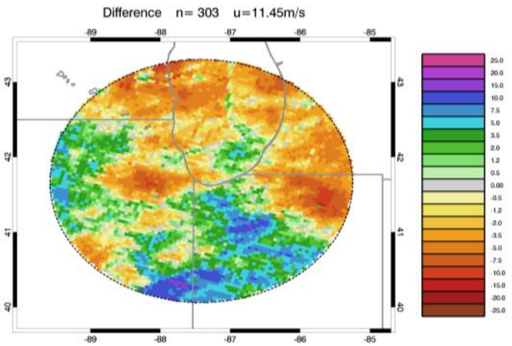
Jie Liu & Dev Niyogi ; *Scientific Reports,* **9**,
Article number: 7301 (2019) https://www.nature.com/articles/s41598-019-42494-2



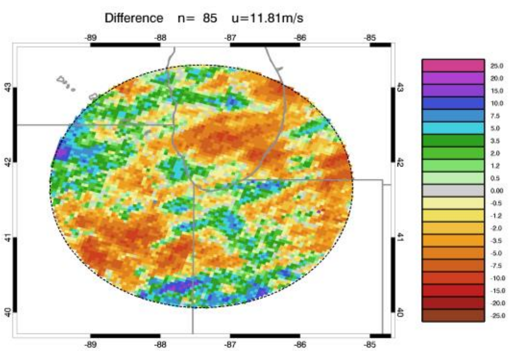
- Urbanization modifies rainfall, such that mean precipitation is enhanced by
- 18% downwind of the city,
- 16% over the city,
- 2% on the left and 4% on the right with respect to the storm direction.
- The rainfall enhancement occurred approximately 20–50 km from the city center.
- Rainfall increases not only downwind of the city but also over the city.

Chicago/ La Porte Rainfall analysis
(Reassessment with new knowledge and technology
urban heating and urban pollution affect downwind rainfall)

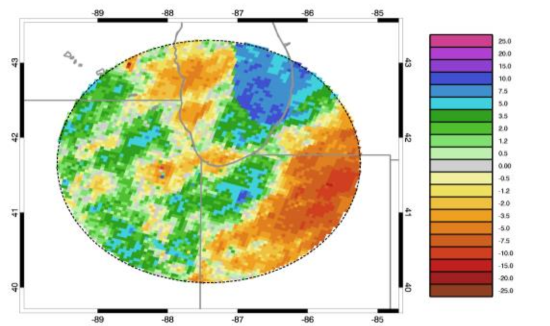
NW to SE moving → STRONG anomaly



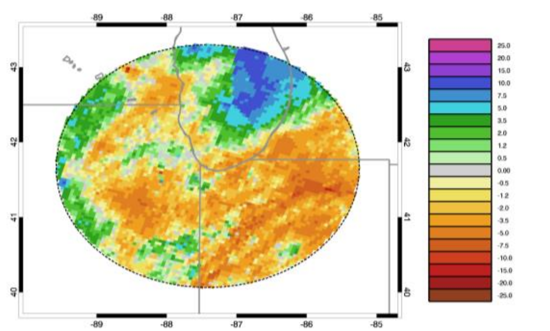
W to E moving → weaker anomaly



SW Wind Weekday → Anomaly present



SW Wind Weekend → NO ANOMALY



- 25km city size (Schmid and Niyogi); seems valid
- City shape matters (circular prone to amplification; triangular prone to deflect)
- Not just for weak synoptic features (even hurricane rainfield simulations affected by urban representation/urbanization)
- Not just flat terrain even under topographic influence – urban representation affects rainfall simulations (Long Yang paper GRL; Freitag paper GRL)
- Urbanization may be delaying convection in diurnal sense (climatologically)
- Possible UHI threshold for whether storm will cause more rain over city or down
- Aerosol effects are important but model seem to (surprisingly) capture rain effects even when aerosols are not included
- Early work on soil moisture fields in rural areas affecting urban thunderstorm being redone (seeing good signal)

Are Urban heat and Urban rainfall selectively/ geographically occurring or is it noted globally?

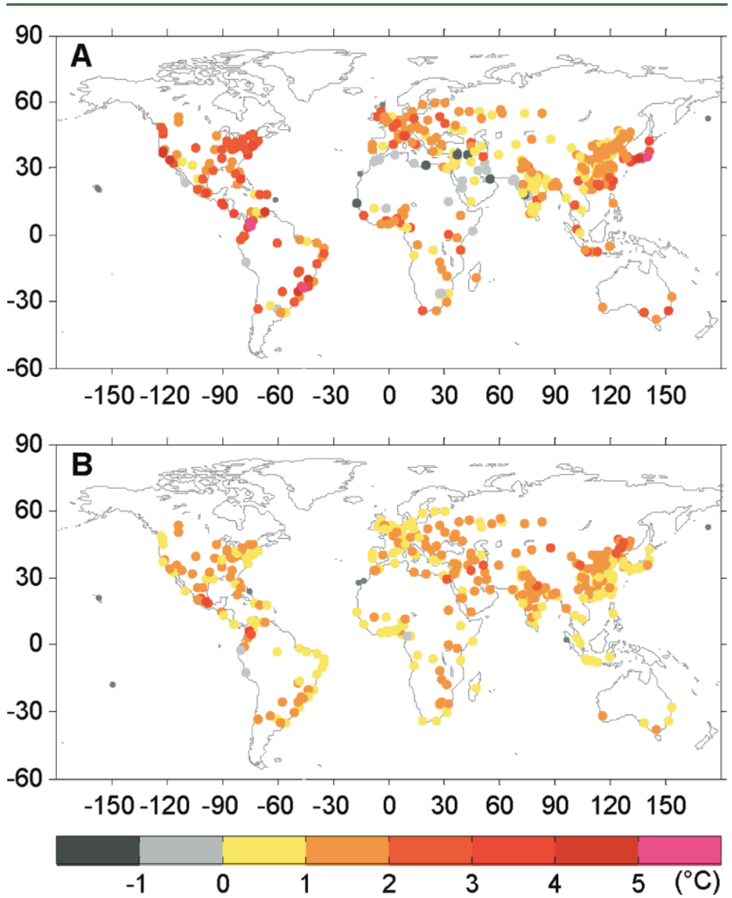


Figure 2. Spatial distribution of (A) annual mean daytime SUHII (°C) and (B) annual mean nighttime SUHII (°C) averaged over the period 2003–2008 across 419 global big cities.

Peng, et al. "Surface urban heat island across 419 global big cities." *Environmental science & technology* 46.2 (2012): 696-703.

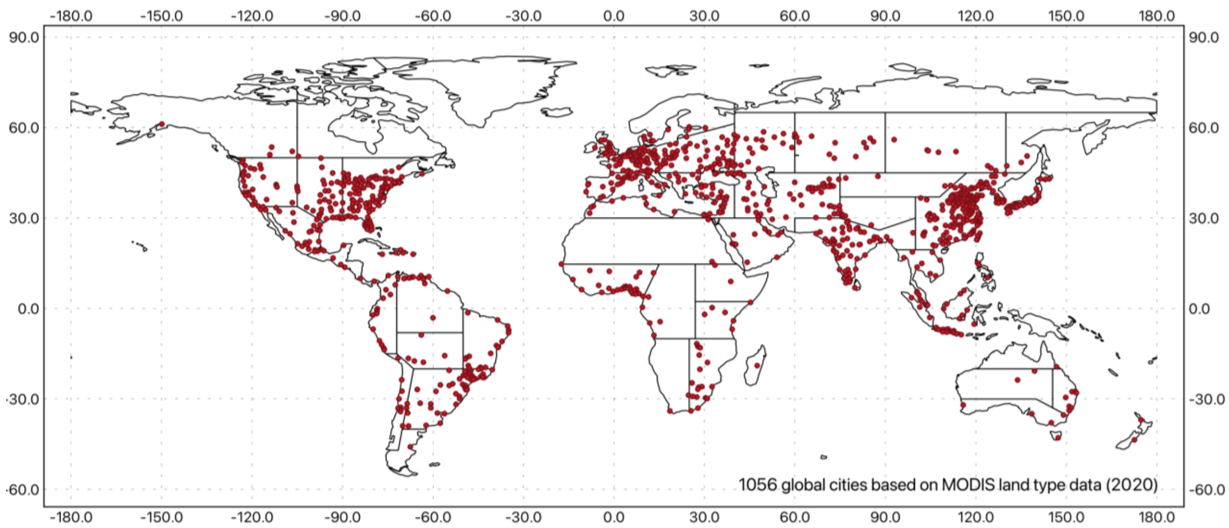
Table 1. Annual, Summer, and Winter Daytime and Nighttime Surface Urban Heat Island Intensity (SUHII, °C, Mean ± SD) across Six Continents (Africa, Asia, Europe, North America, South America, Oceania) Continents and the World[a]

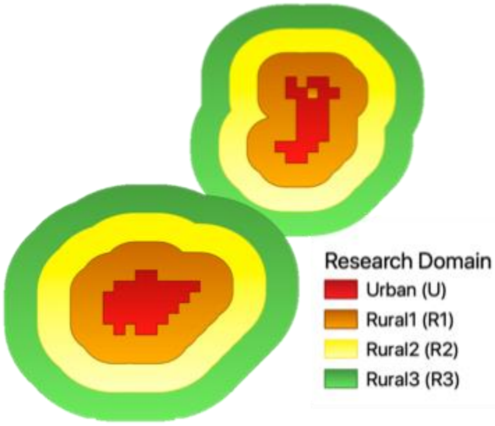
	Africa	Asia	Europe	North America	South America	Oceania	World
N	47	209	56	37	65	5	419
annual daytime SUHII (°C)	0.9 ± 1.1	1.2 ± 1.0	2.0 ± 0.9	2.3 ± 1.6	2.4 ± 1.0	1.5 ± 0.7	1.5 ± 1.2
annual nighttime SUHII (°C)	0.9 ± 0.5	1.1 ± 0.5	0.8 ± 0.4	0.9 ± 0.7	1.1 ± 0.5	1.0 ± 0.4	1.1 ± 0.5
summer daytime SUHII (°C)	1.0 ± 1.3	1.5 ± 1.3	2.1 ± 1.5	2.5 ± 1.6	3.0 ± 1.4	2.3 ± 1.2	1.9 ± 1.5
summer nighttime SUHII (°C)	0.7 ± 0.5	1.0 ± 0.5	1.0 ± 0.4	1.0 ± 0.7	1.3 ± 0.4	1.3 ± 0.4	1.0 ± 0.5
winter daytime SUHII (°C)	0.8 ± 1.2	0.9 ± 1.0	1.7 ± 0.4	2.2 ± 1.8	1.7 ± 1.1	0.8 ± 0.5	1.1 ± 1.2
winter nighttime SUHII (°C)	1.1 ± 0.5	1.2 ± 0.7	0.4 ± 0.4	0.9 ± 0.8	0.9 ± 0.7	0.8 ± 0.4	1.0 ± 0.7

Indian monsoon (Kishtawal et al. 2011); US heavy rain urbanization study (Singh et al. 2019 ERL); Global Urban Rainfall Modification study to appear in PNAS (Sui et al.); Long et al. in Nature Comm (2024 also global)

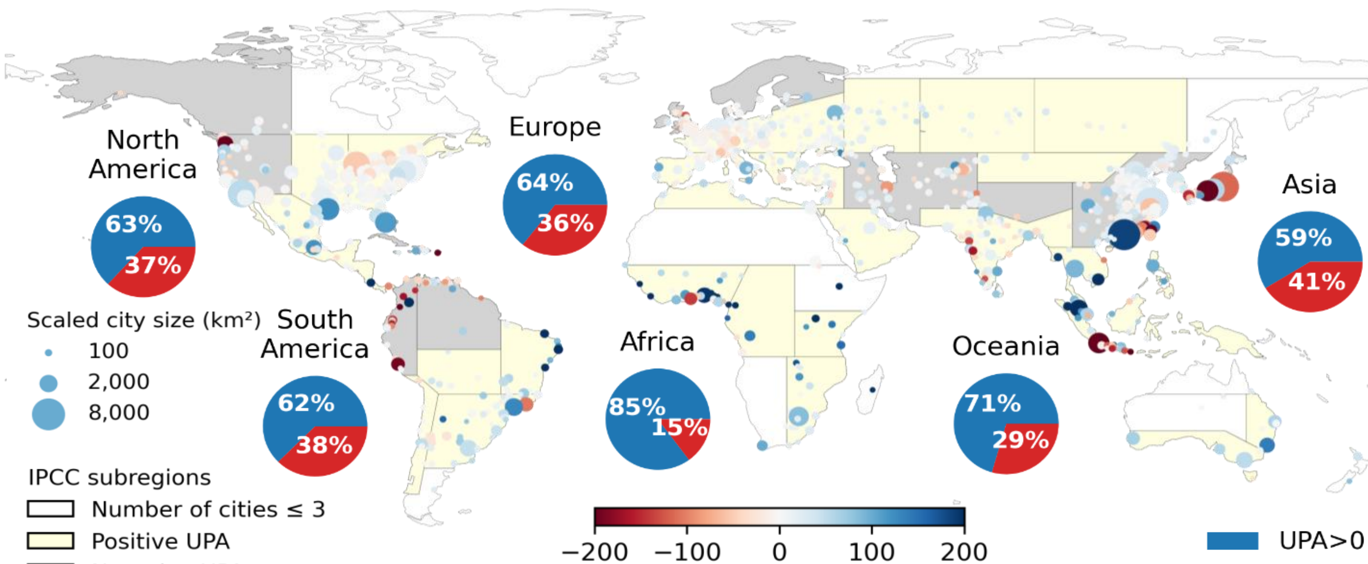
Over 1000 global cities

- 20-year precipitation data: 2001-2020
- Domain: 1 urban + 3 rural domains
- Urban precipitation anomaly (UPA) = $P_U - P_{R3}$





Urban Annual Precipitation Anomalies



(a) Urban annual precipitation anomaly (UAPA, mm/yr)

Impact factors: topography, local climate, and urbanization (population, UHI, and aerosol)

49 cities with millions of population: more annual precipitation in cities, larger extreme precipitation downwind of cities

- 63% of cities show urban wet islands (67% and 58% for large and small cities)
- 85% and 71% in Africa and Oceania; 60% in Asia

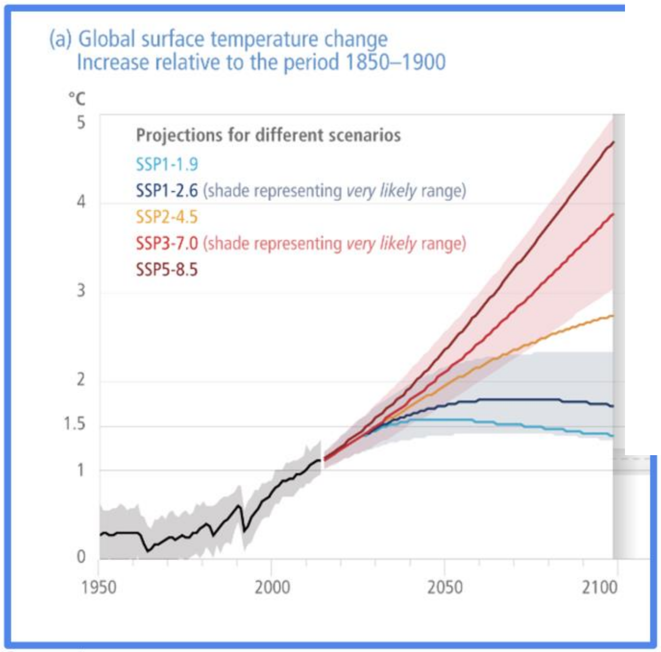
Extreme Cities

- 1. Do we need to represent cities in weather and climate models in order to better simulate the extremes over cities? Or even more broadly beyond the cities? i.e impact on city and impact from city on the thermal and dynamical (as well as chemical) environment in a model?

- 2. What are the level of details and explicit versus implicit representation needed? What feedbacks need to be ensured are appropriately represented?

- 3. Should models fields be downscaled from larger models? Or upscaled from neighborhood-scale/agent based models?

Climate Downscaling (coarse grid (100 km x 100 km) global information statistically brought to local scale (10km or finer) – This is top down and most common way of getting climate information



IPCC report
https://www.ipcc.ch/report/ar6/wg2/downloads/figures/IPCC_AR6_WGII_FigureSPM3abcde.png

CITY OF AUSTIN

FOR IMMEDIATE RELEASE
Release Date: Jun. 06, 2024
Contact: Shannon Stewart [**Email**]

As Austin braces for another hot season, the City's Offices of Sustainability and Resilience have published a suite of documents designed to help the community and City departments understand and prepare for the impacts of rising temperatures. These documents include the updated Climate Projections for the Austin area, the 2024 Summer Outlook, and the Heat Resilience Playbook.

"As we move into summer, we must acknowledge the increasing temperatures affecting our community," said Zach Baumer, Austin's Chief Sustainability Officer. "These documents provide essential science-based information to help our City departments and community members understand the climate impacts affecting Austin now and in the future — and how we can address them."

UT-City Climate CoLab
The Climate Projections and Summer Outlook were developed through the **UT-City Climate CoLab**, a collaborative effort between the City's Offices of Sustainability and Resilience and researchers at the University of Texas at Austin. Established in 2023, the CoLab is the first city-specific climate collaborative globally, linking City officials and climate scientists to develop Austin-specific climate data, tools, and assessments.

"Austin has experienced a series of weather extremes in recent years, from droughts and heat waves to heavy rain events and deep freezes," said Dev Niyogi, Professor of Earth and Planetary Sciences at the Jackson School of Geosciences, and part of UT's Planet Texas 2050 grand challenge. "The City and community members are deeply invested in understanding and preparing for future changes in our climate. The UT-City Climate CoLab represents a significant step in linking scientific advances with practical city needs and educational opportunities to develop effective climate solutions and resilience."

Climate Projections for Austin
The latest **Climate Projections for Austin** indicate that climate change will lead to hotter summers with more frequent heatwaves and fewer cold spells. Rainfall projections are highly uncertain, but the amount of rainfall in our area is expected to remain relatively unchanged. As the climate shifts, we can anticipate more extreme weather, more climate variability, and a slight increase in windy days. Temperatures above 110°F, once rare, are expected to become more common.

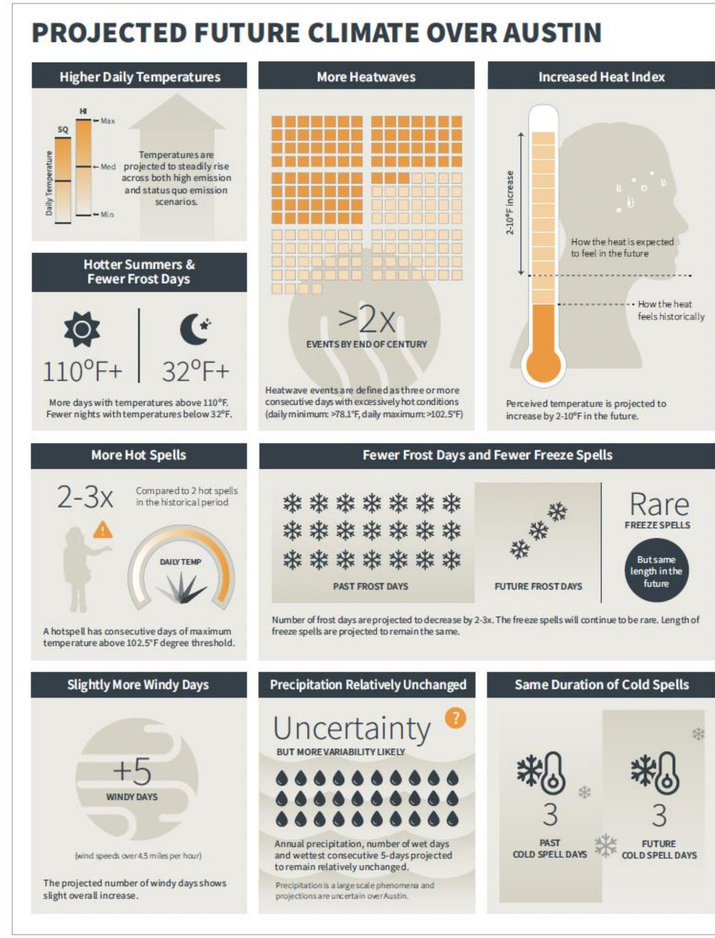
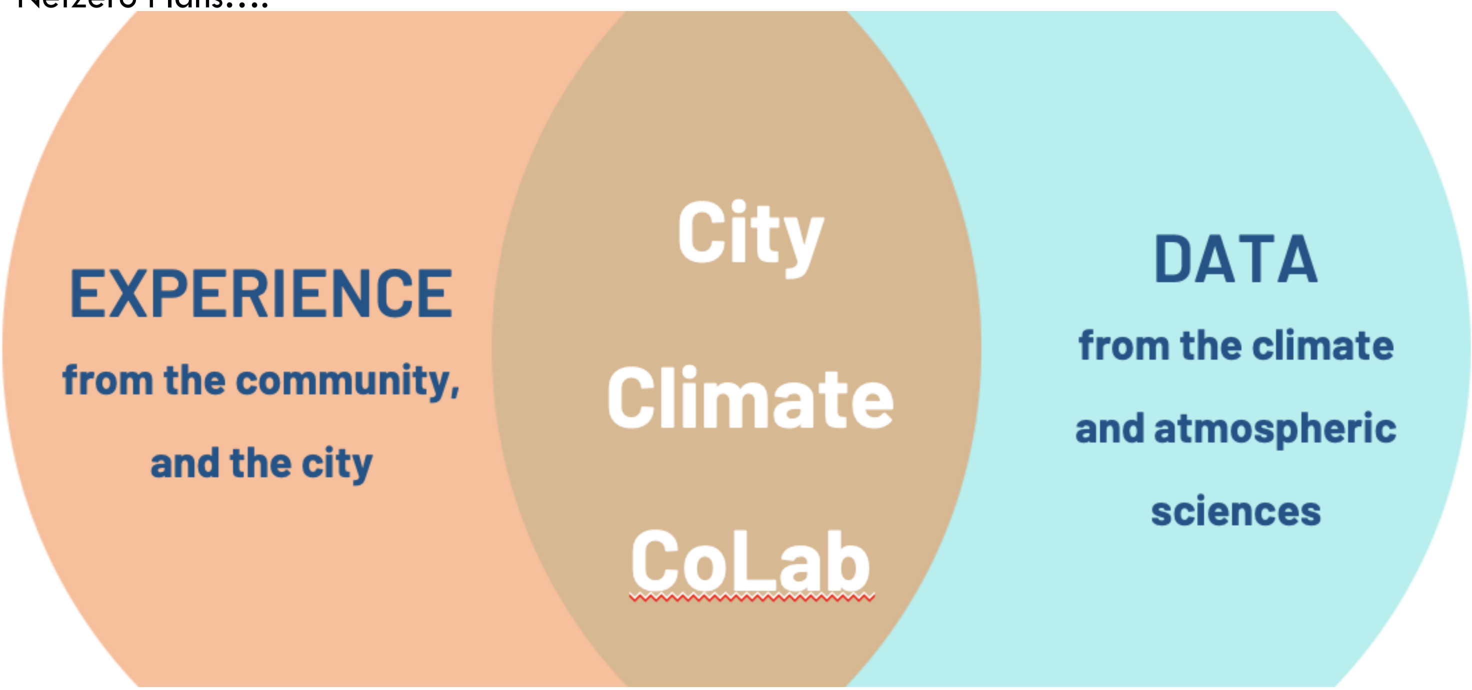


Figure 1 Summary of climate projections over Austin, Texas based on high and status quo emissions scenarios.

Many applications require hectometer/ hyperlocal scale datasets

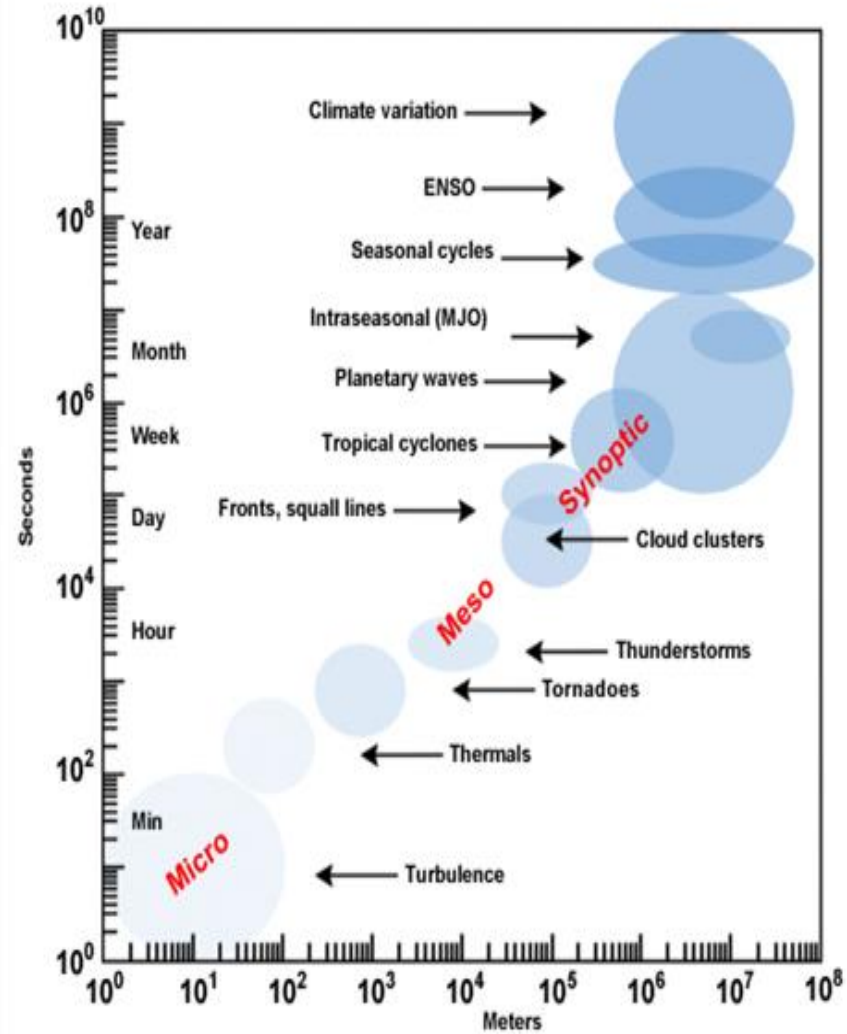
Water Availability (Water Future 2040)
Wind gusts/ loads/Impacts
PMPs
Building Energy Use, Emissions
Flood Risk Mapping and Modeling
Heat health studies
Heat Shelters/tree planting
Adaptation Strategies
Netzero Plans….



City Climate – emulators, DTs, dynamic models

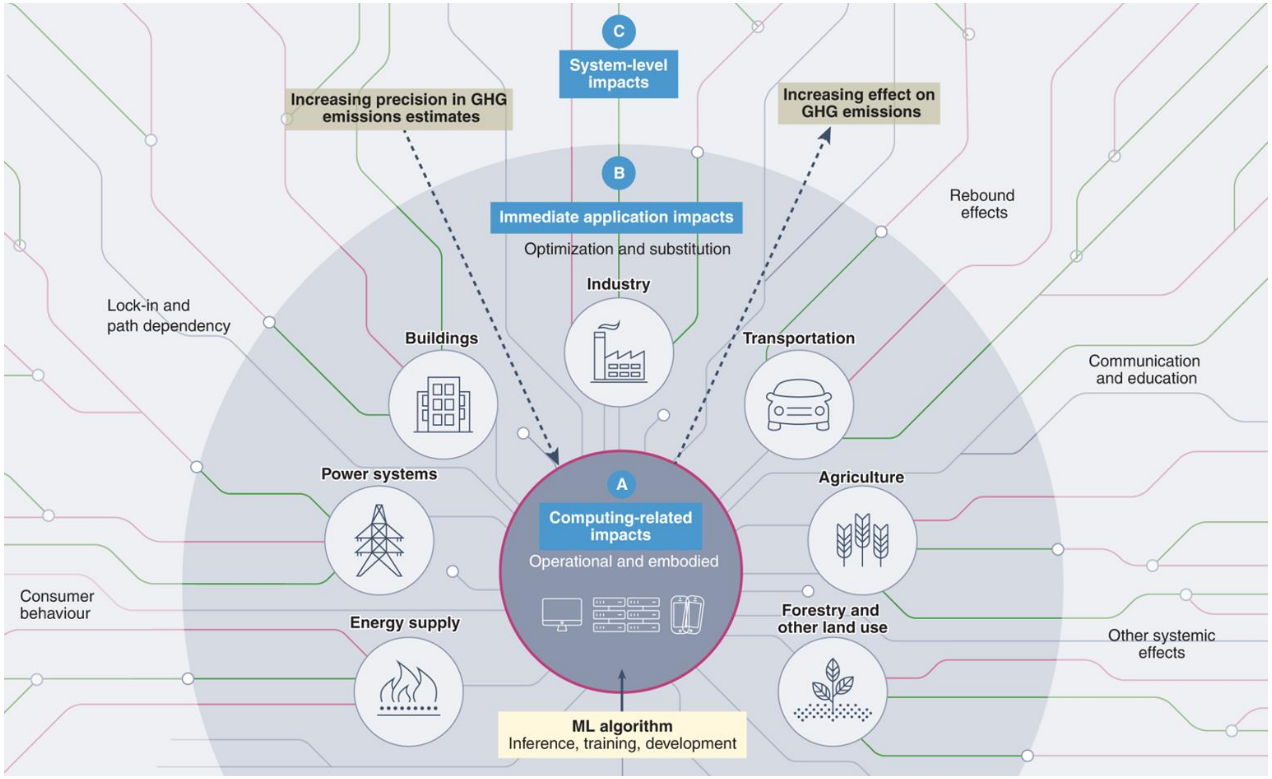
Recall: Most weather and climate research is useful but not readily usable and needs some interface/ processing
This is especially true for cities

- **Complexity of Climate Extremes**: Multiscale
- Influenced by multiple physical and biological factors that interact in complex ways
- Physical/dynamical laws have constraints due to inherent assumptions
- Challenging to analyze using traditional methods
- → Opportunity in this limitation
- (DOE US Gulf Coast Digital Twin project @UT Austin: E3SM, WRF, ADCIRC, hydraulics scaling) "Multiphysics Simulations and Knowledge discovery through AI/ML" : MUSiKAL



Importance of machine learning for climate

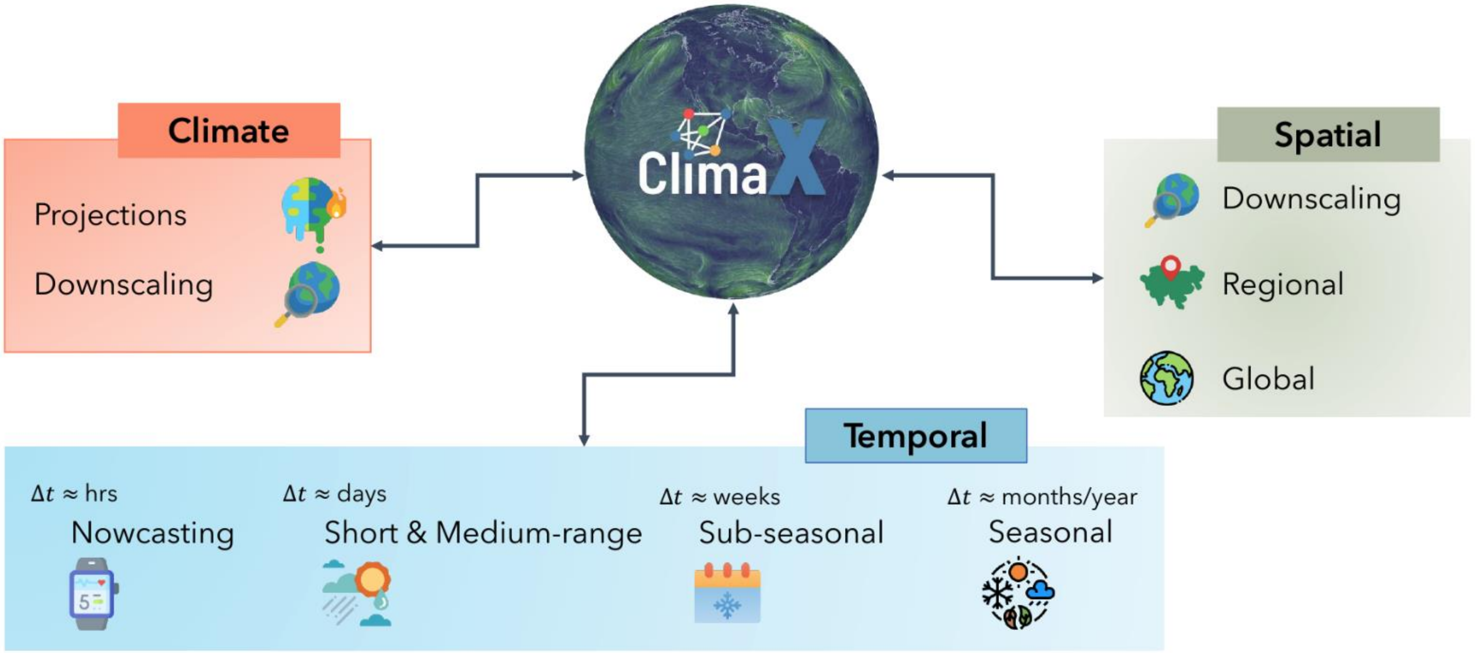
- **Real-world Applications:** From predicting extreme weather events to modelling long-term climate trends, ML algorithms have proven their worth in various real-world applications.



Kaack, L.H., Donti, P.L., Strubell, E., Kamiya, G., Creutzig, F. and Rolnick, D., 2022. Aligning artificial intelligence with climate change mitigation. Nature Climate Change, 12(6), pp.518-527.

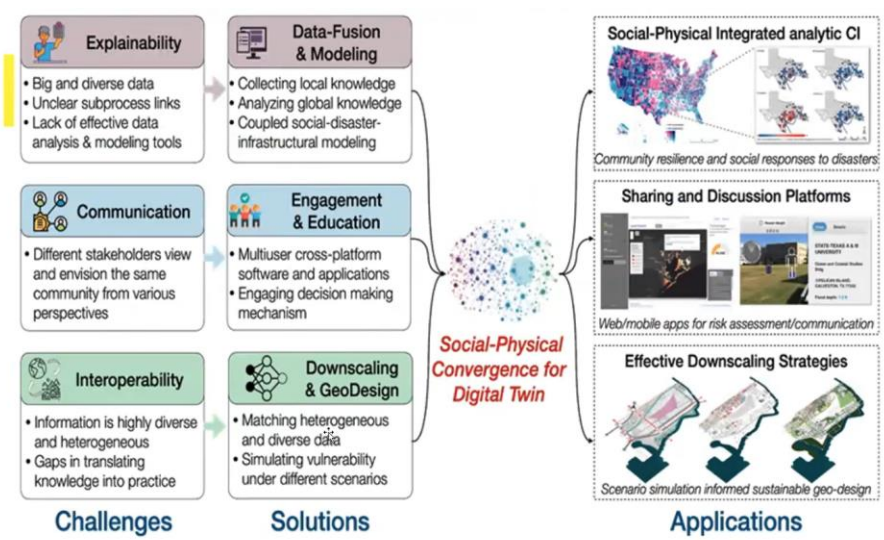
ClimaX

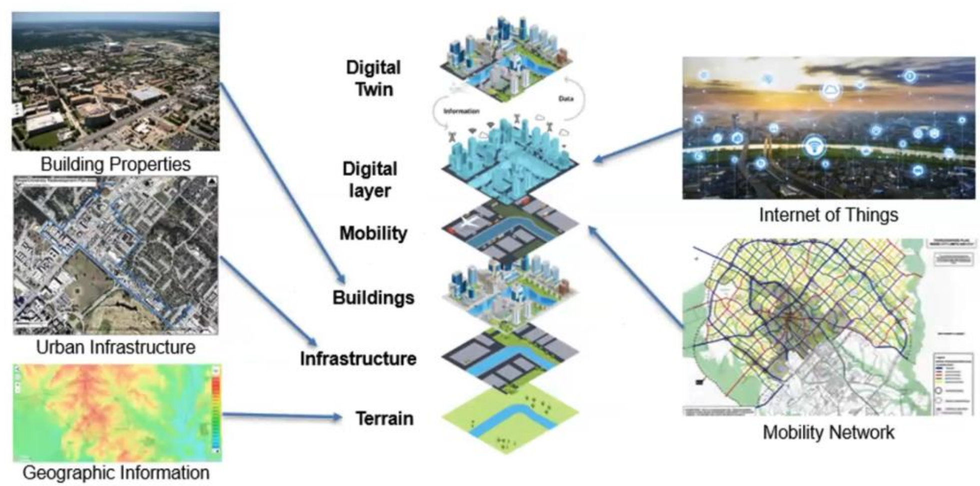
- A suite of capabilities, including weather forecasting with results competitive to Integrated Forecasting System (IFS)
- Data is pretrained with a combination of Observational Data, Indirect Measurements (eg. Satellite Data) & Climate Model Simulations (eg. CMIP6)
- Many such emulators/DTs available (eg Fourcastnet, Pangu-Weather,…)



Human Centered Digital Twin –

- Incorporates real-time and historical data of human dynamics and urban infrastructure.
- Fusion of data derived from terrain, infrastructure, buildings, IoT sensors and placed in a combined database.





Atmospheric Urban Digital Twin

Many definitions

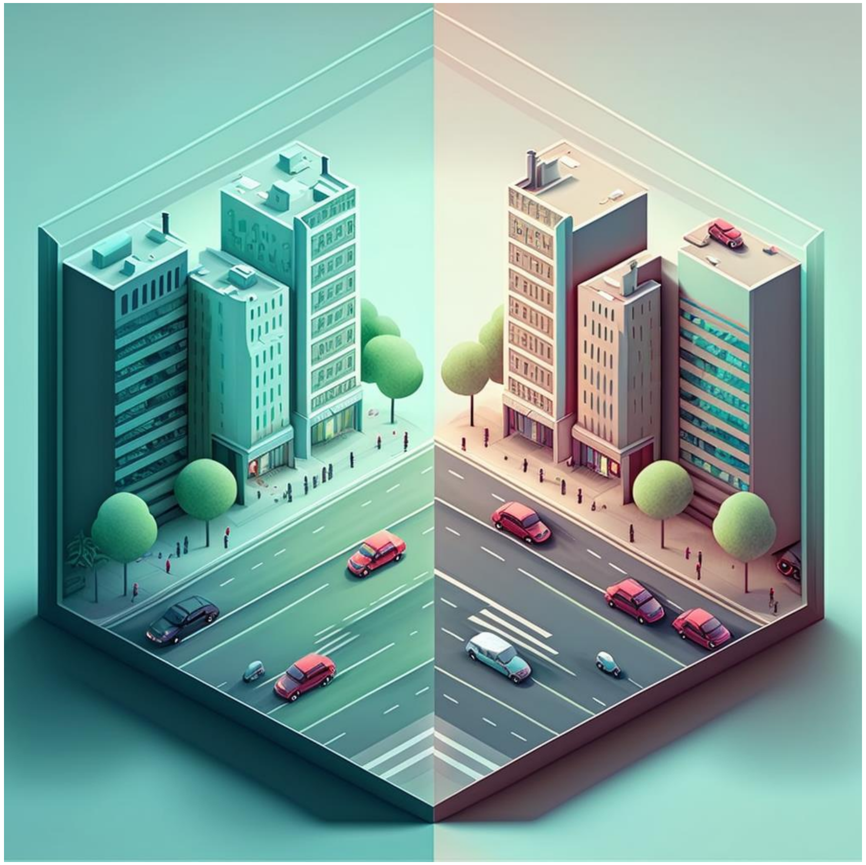
Virtual replica of a city, replicating its physical properties, systems, and processes digitally.

Twins could serve as a dynamic, real-time model of the city, allowing for simulation, analysis, and prediction of urban phenomena.

Infrastructure, geographic layers well captured

Need dynamical processes

(NSF international Workshop upcoming; also WCRP Lighthouse Activity on Digital Earth - participate in this subactivity)

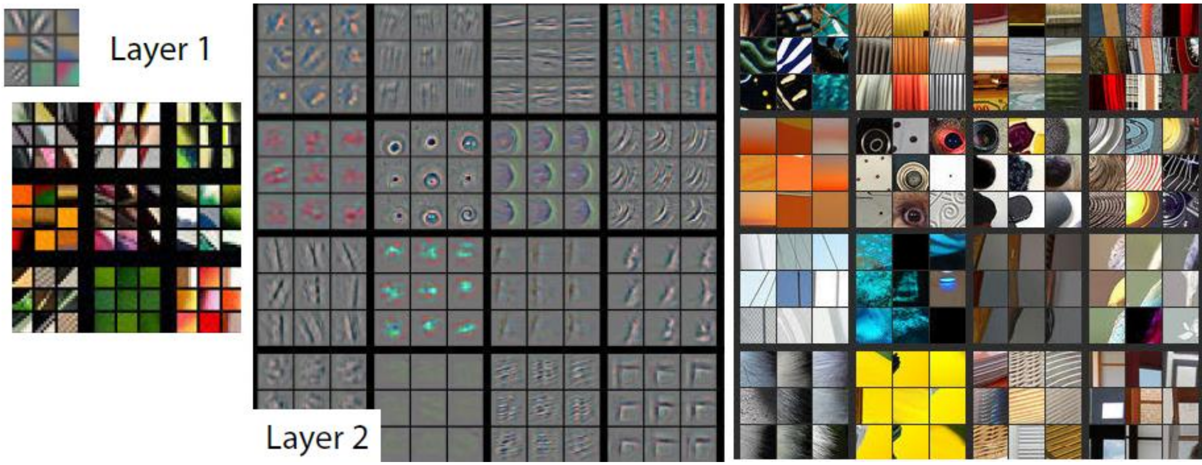


Defining Atmospheric Urban Digital Twins

- Speed (1000x, 10,000x,…)
- AI/ML approaches embedded
- End-user or decision (could also be input to a model)
- Integration
- Scalability

Rao, Y., Redmon, R., Dale, K., Haupt, S.E., Hopkinson, A., Bostrom, A., Boukabara, S., Geenen, T., Hall, D.M., Smith, B.D. and Niyogi, D., 2023. Developing Digital Twins for Earth Systems: Purpose, Requisites, and Benefits. *arXiv preprint arXiv:2306.11175*.

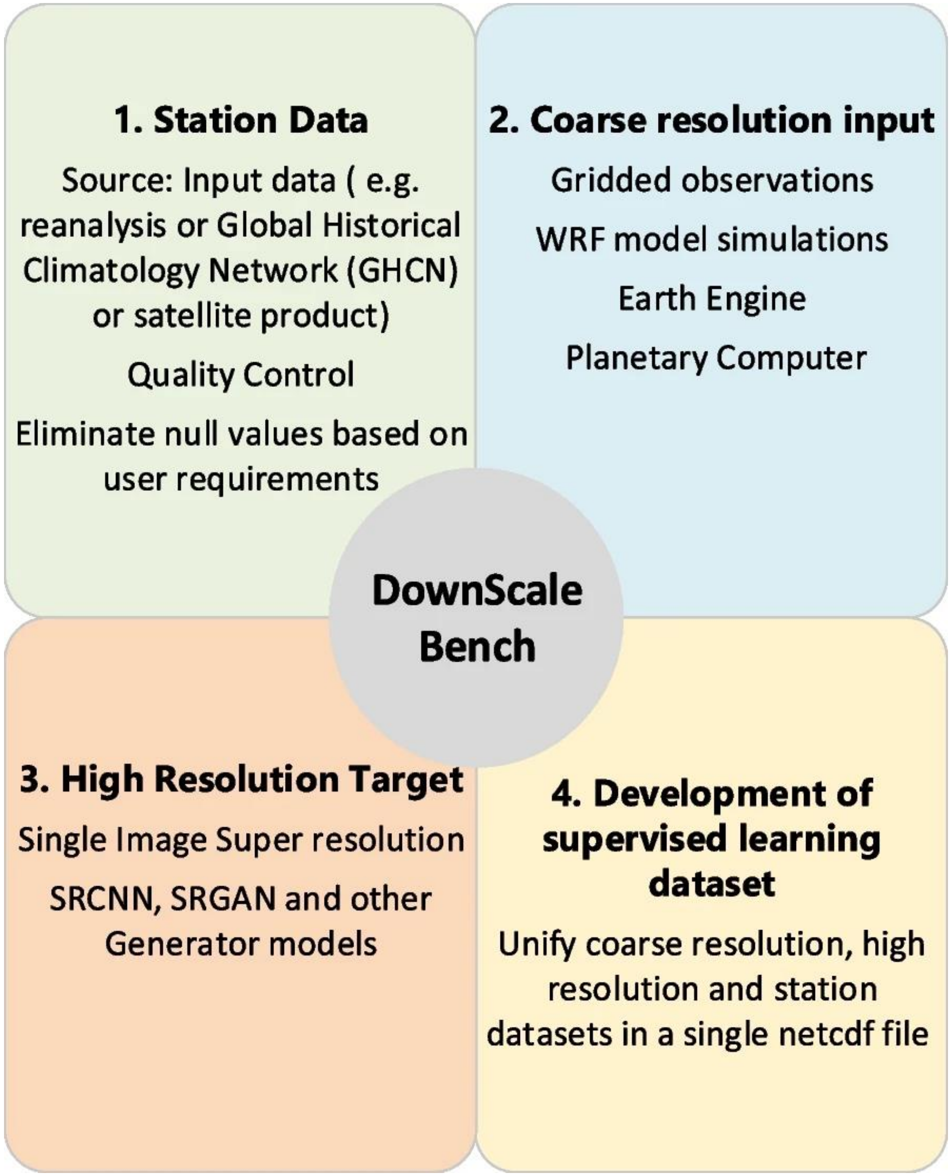
ML for high resolution (urban) downscaling



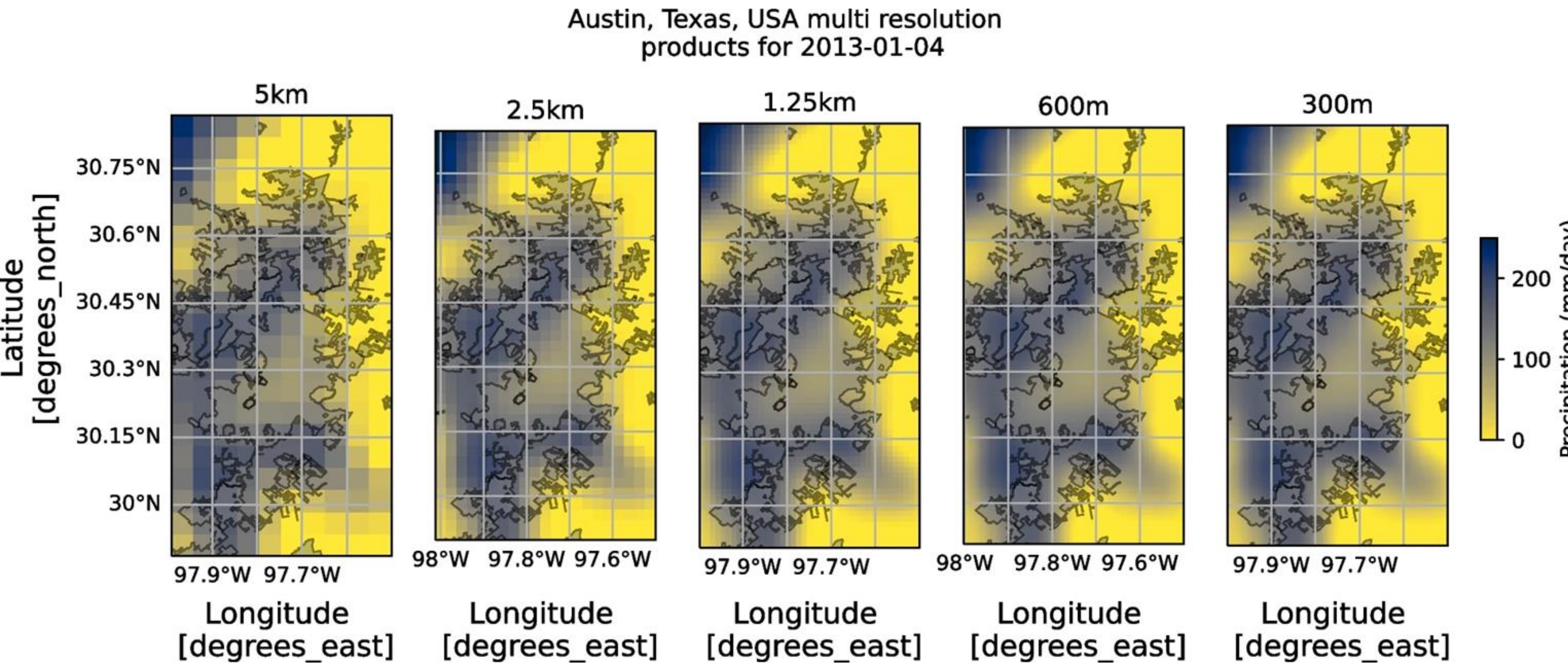
1Vision algorithm advances
2 Super resolution image
3 Data Convolution (extraction)

Zeiler, M.D. and Fergus, R., 2014. Visualizing and understanding convolutional networks. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I 13 (pp. 818-833). Springer International Publishing.

DownScaleBench for developing and applying a deep learning based urban climate downscaling



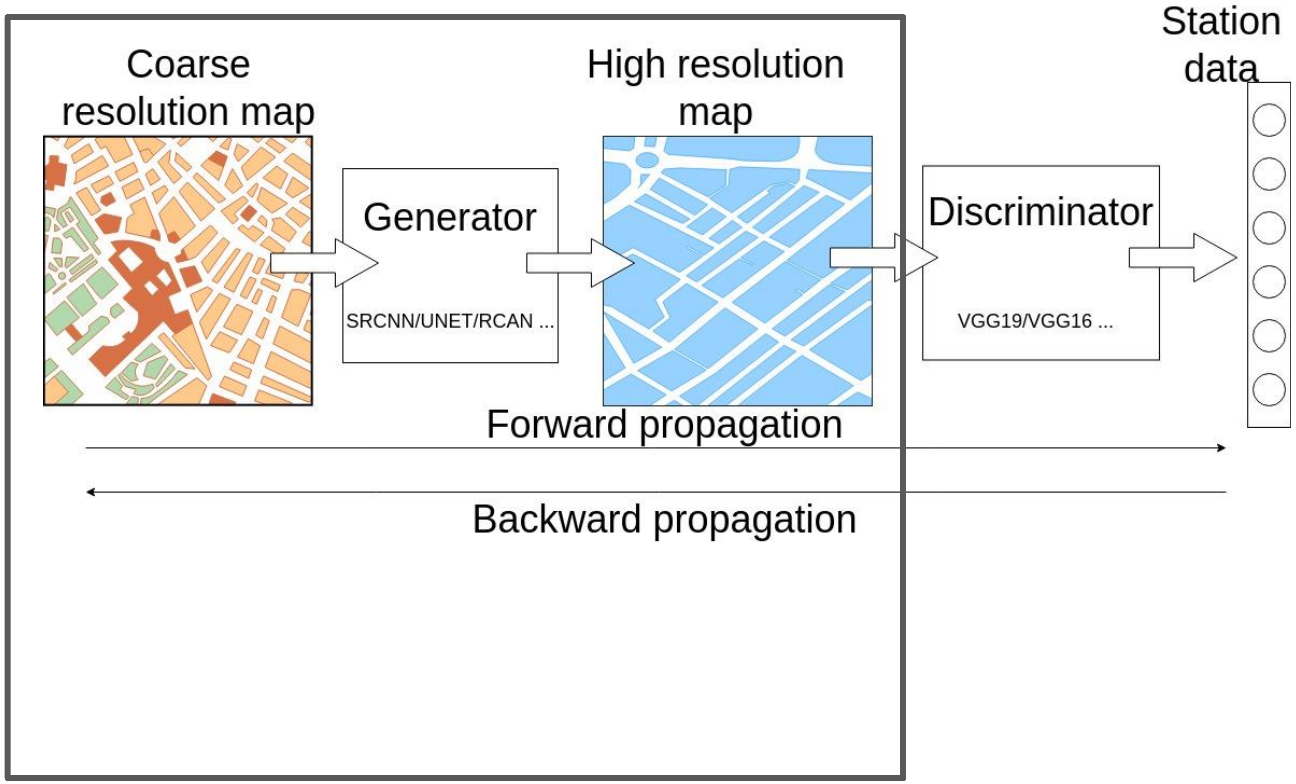
Singh, M., Acharya, N., Jamshidi, S., Jiao, J., Yang, Z.L., Coudert, M., Baumer, Z. and Niyogi, D., 2023. DownScaleBench for developing and applying a deep learning based urban climate downscaling-first results for high-resolution urban precipitation climatology over Austin, Texas. Computational Urban Science, 3(1), p.22.



SRCNN based downscaling

Singh, M., Acharya, N., Jamshidi, S., Jiao, J., Yang, Z.L., Coudert, M., Baumer, Z. and Niyogi, D., 2023. DownScaleBench for developing and applying a deep learning based urban climate downscaling-first results for high-resolution urban precipitation climatology over Austin, Texas. Computational Urban Science, 3(1), p.22.

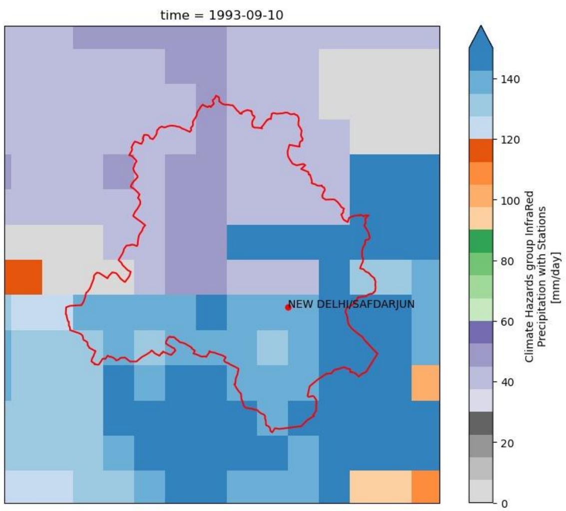
MeteoGAN for urban digital twins



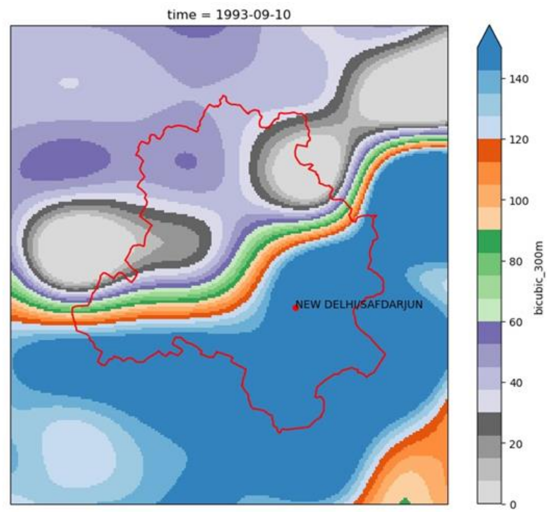
First results from MeteoGAN over New Delhi, rainfall case

1993-09-10

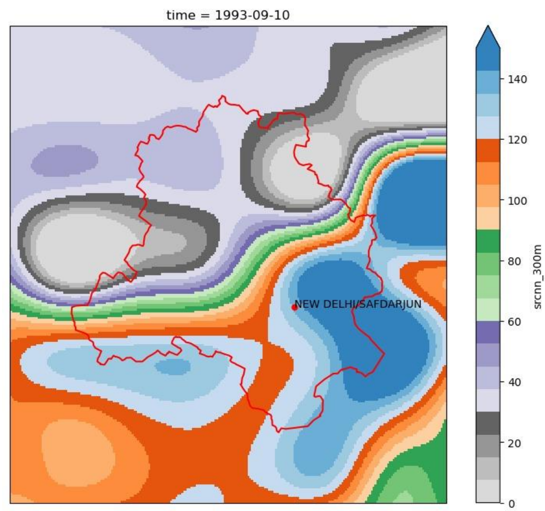
CHIRPS (5 km)



Bicubic (300 m)



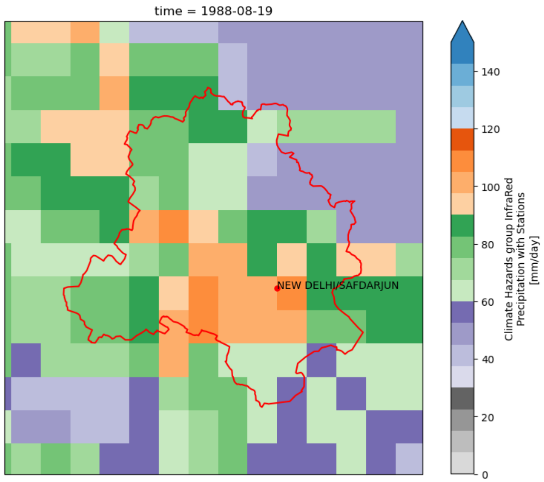
MeteoGAN (300 m)



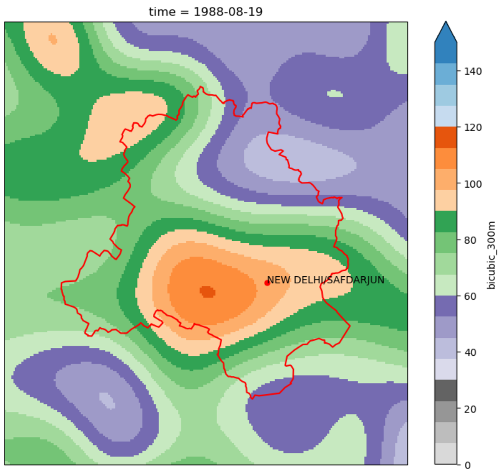
First results from MeteoGAN over New Delhi, rainfall case

1988-08-19

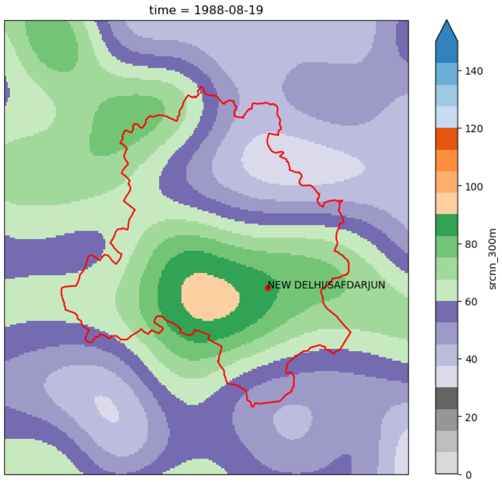
CHIRPS (5 km)



Bicubic (300 m)

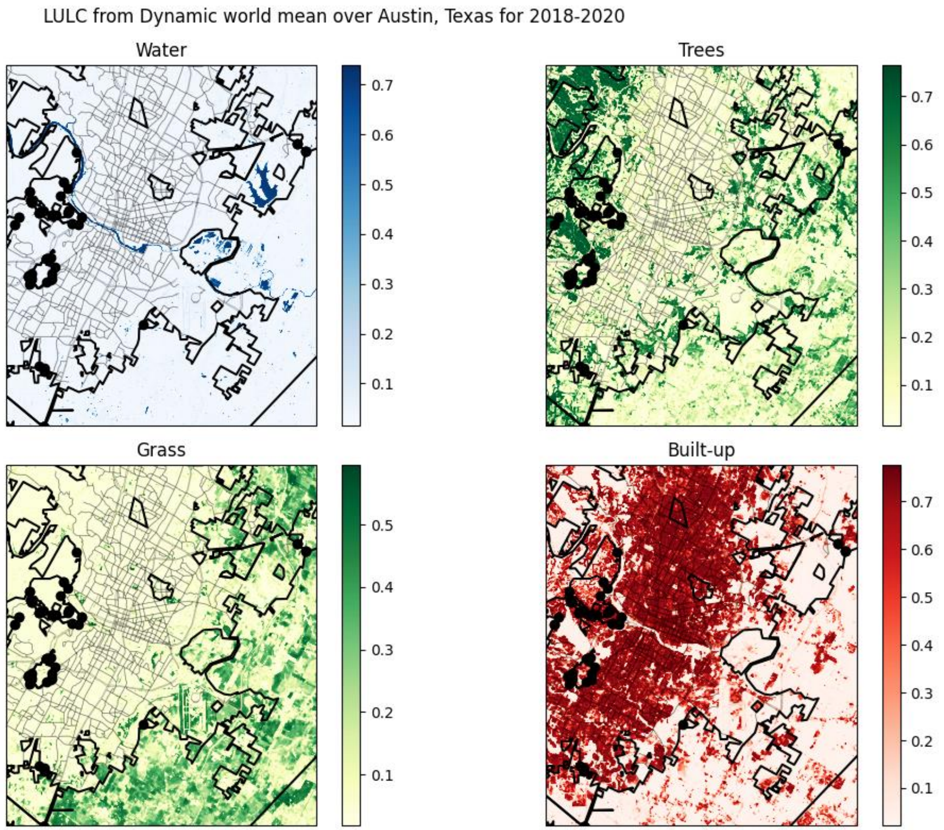


MeteoGAN (300 m)

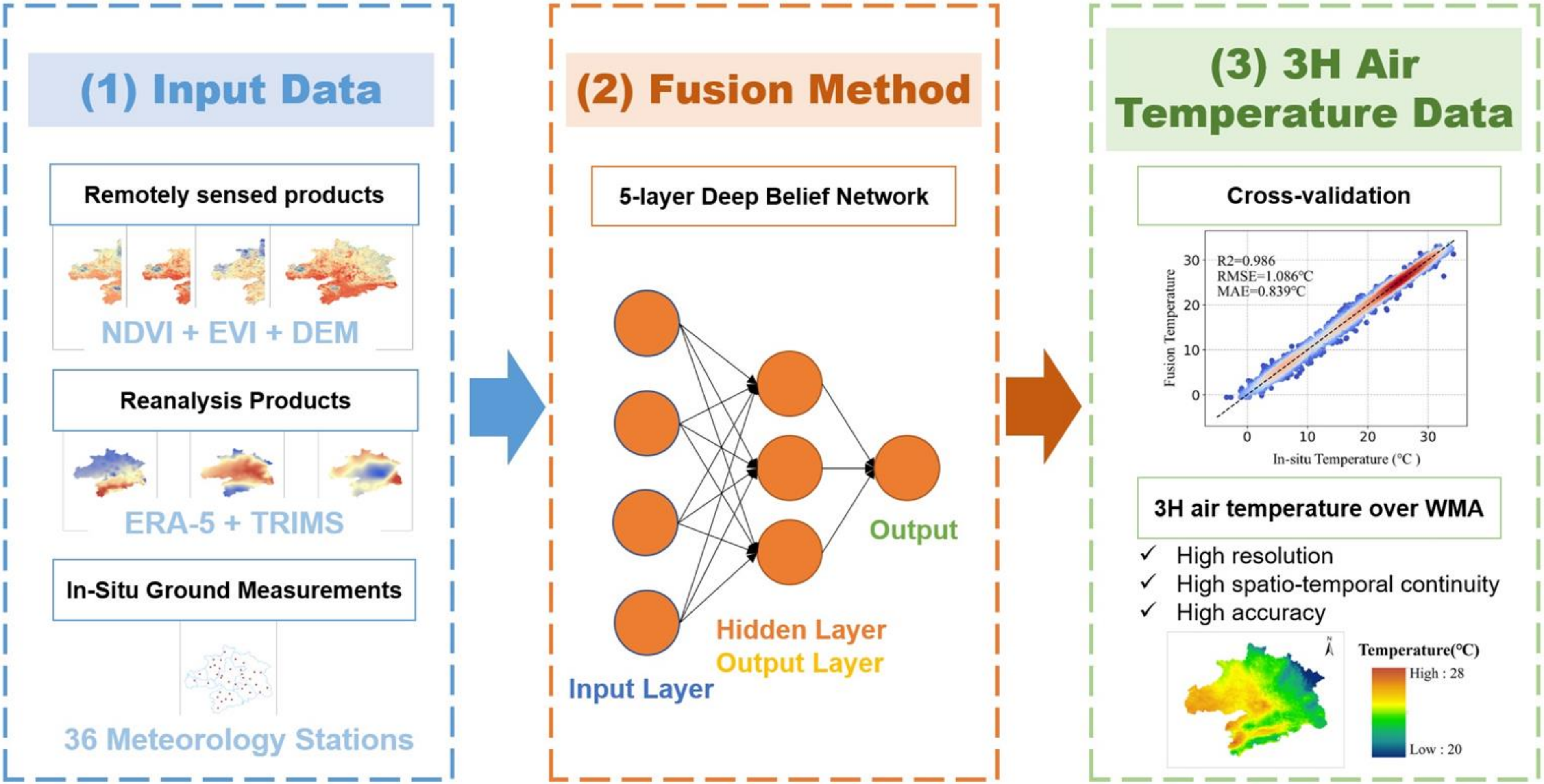


Further improvements to MeteoGAN

Incorporating physics in boundary conditio



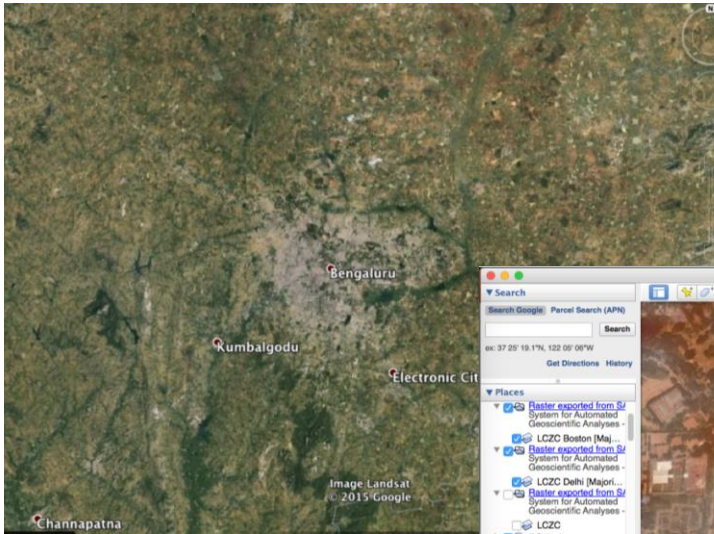
Including Physics in Models

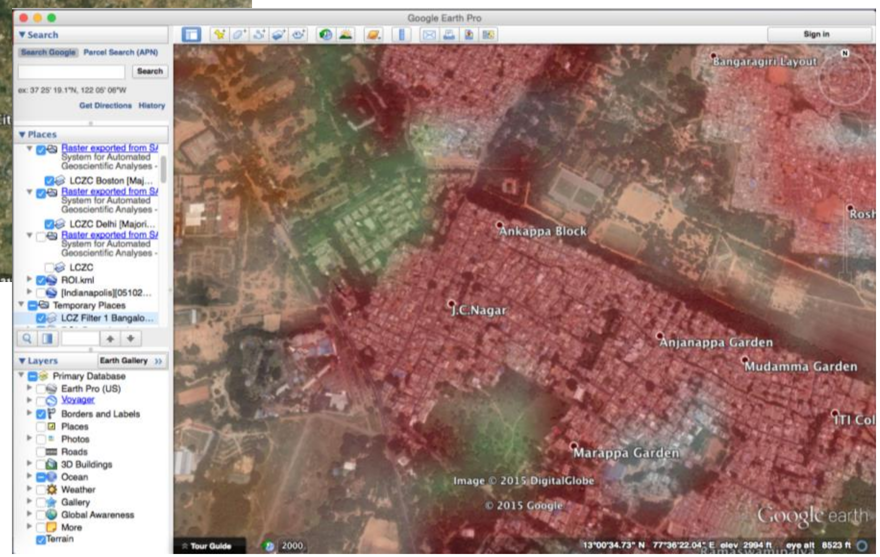


Zhang, X., Huang, T., Gulakhmadov, A., Song, Y., Gu, X., Zeng, J., Huang, S., Nam, W.H., Chen, N. and Niyogi, D., 2022. Deep learning-based 500 m spatio-temporally continuous air temperature generation by fusing multi-source data. *Remote Sensing*, *14*(15), p.3536.

Integrating AUDTs within Physics based models or using Physics-inspired ML approaches

WUDAPT urban data for weather models





Google Earth, Open Street Maps and Landsat Imagery based reclassification of Cities, with Local Survey and Verification, and Rendering. Map released to broader community.

Patel, P., Karmakar, S., Ghosh, S. and Niyogi, D., 2020. Improved simulation of very heavy rainfall events by incorporating WUDAPT urban land use/land cover in WRF. *Urban Climate*, 32, p.100616.

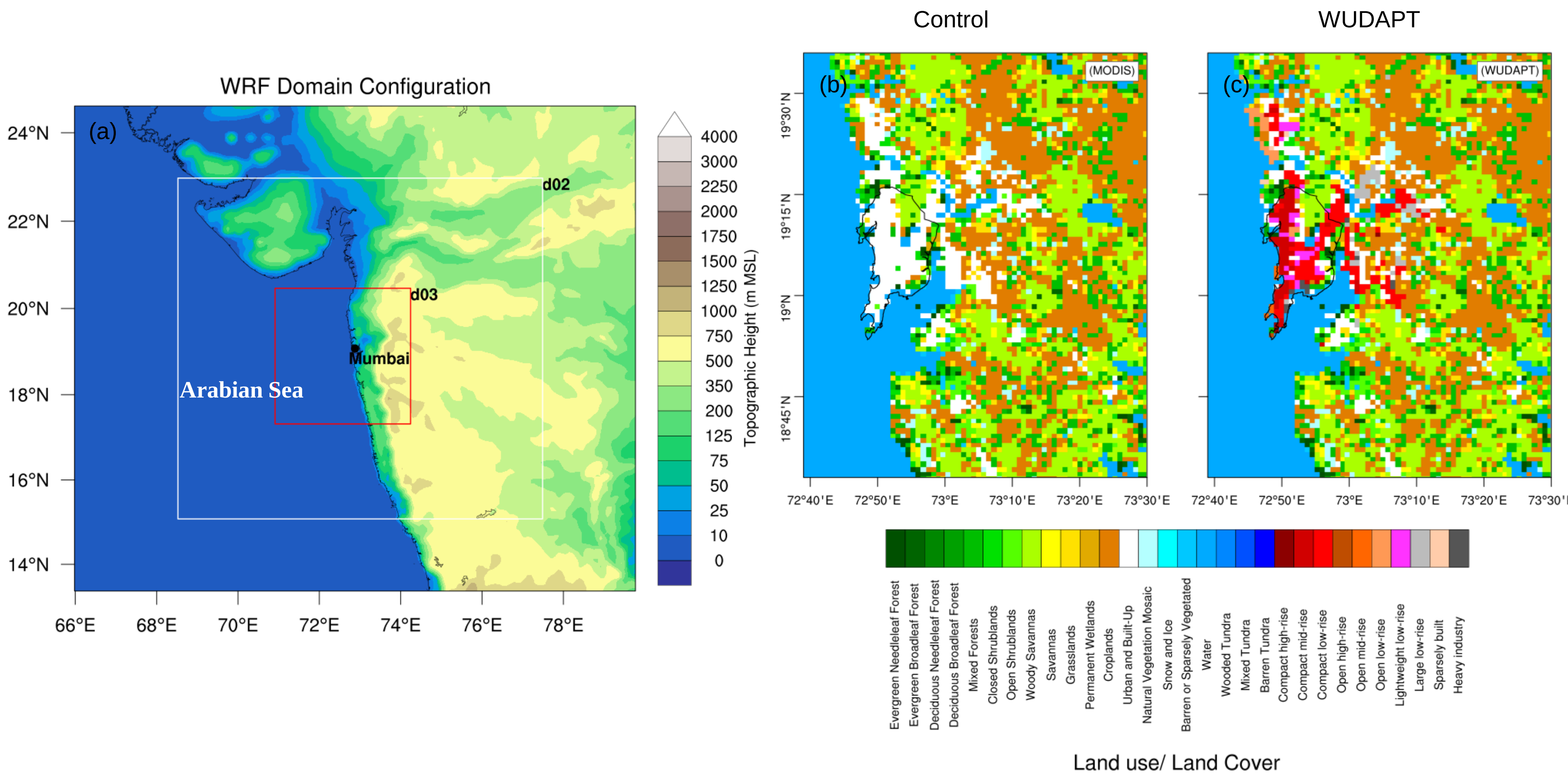
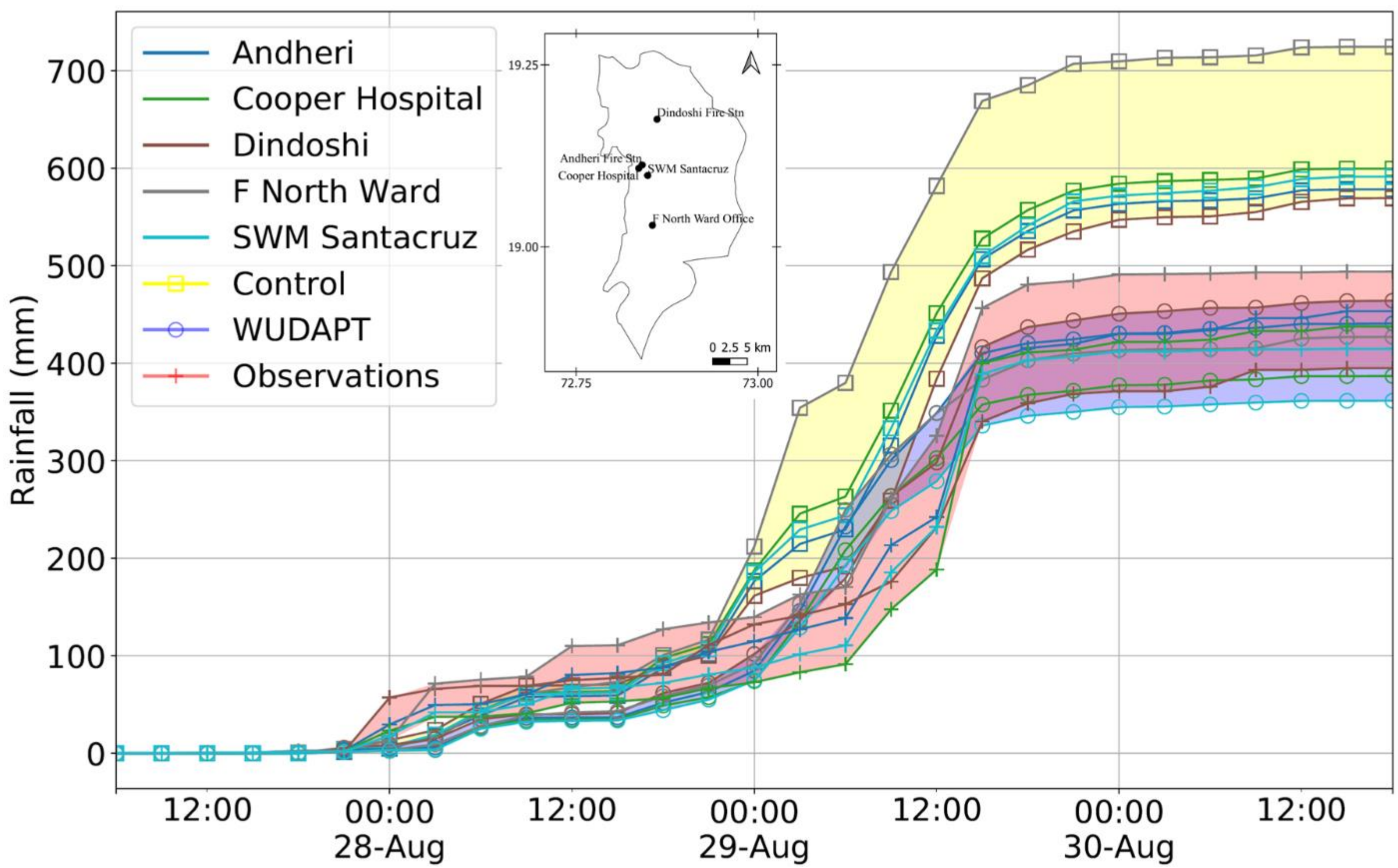
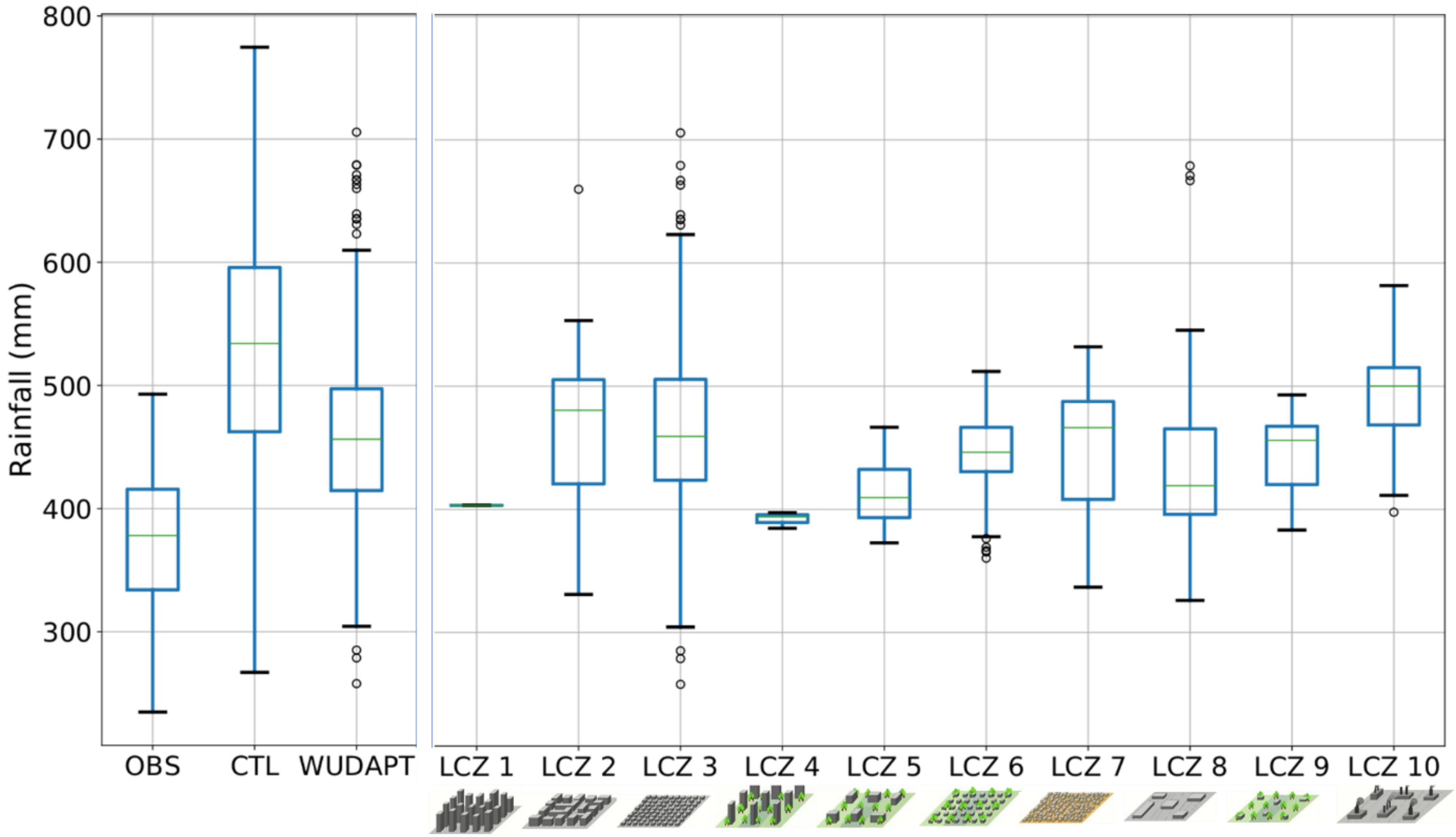
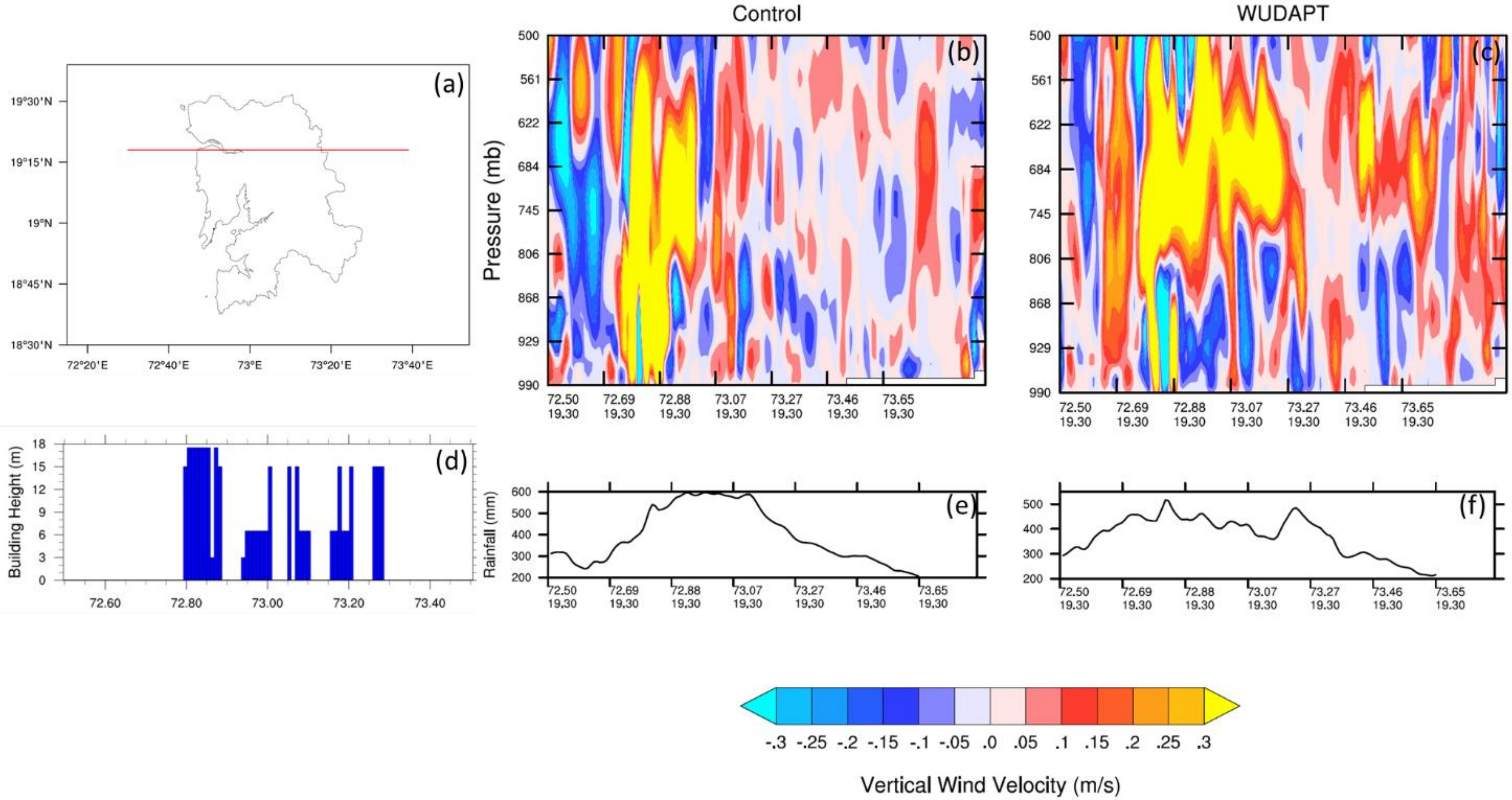


Figure 1: (a) Domain configuration of WRF (b) Land use/ land cover for control (MODIS) and including LCZ classes (WUDAPT) Black line represents the study area.



Andheri
Cooper Hospital
Dindoshi
F North Ward
SWM Santacruz
Control
WUDAPT
Observations
Rainfall (mm)
0
100
200
300
400
500
600
700
12:00
00:00
28-Aug
12:00
00:00
29-Aug
12:00
00:00
30-Aug
12:00
19.25
19.00
72.75
73.00
Dindoshi Fire Stn
Andheri Fire Stn
SWM Santacruz
Cooper Hospital
F North Ward Office
0 2.5 5 km


800
700
600
500
400
300
Rainfall (mm)
OBS
CTL
WUDAPT
LCZ 1
LCZ 2
LCZ 3
LCZ 4
LCZ 5
LCZ 6
LCZ 7
LCZ 8
LCZ 9
LCZ 10

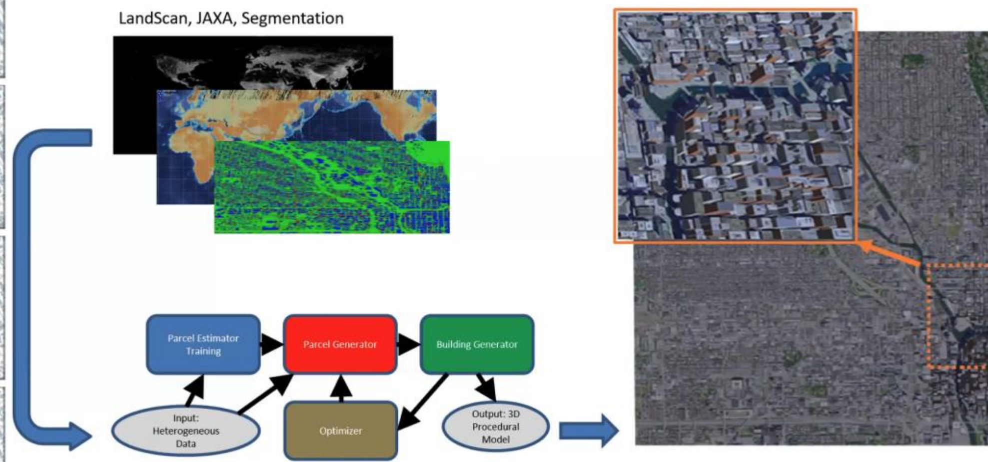


Control
WUDAPT
(a)
(b)
(c)
(d)
(e)
(f)
19°30'N
19°15'N
19°N
18°45'N
18°30'N
72°20'E
72°40'E
73°E
73°20'E
73°40'E
Pressure (mb)
500
561
622
684
745
806
868
929
990
72.50 19.30
72.69 19.30
72.88 19.30
73.07 19.30
73.27 19.30
73.46 19.30
73.65 19.30
Building Height (m)
18
15
12
9
6
3
0
72.60
72.80
73.00
73.20
73.40
Rainfall (mm)
600
500
400
300
200
-.3 -.25 -.2 -.15 -.1 -.05 .0 .05 .1 .15 .2 .25 .3
Vertical Wind Velocity (m/s)

Integrated AI Platform for Urban Computing

- **Highlights scarcity of data for urban models**
- Urban Artificial Intelligence to automatically build 3d models of cities from data available from all sources. (Incomplete but highly varied)

- Satellite images: generate cities from low-res



Patel, P., Kalyanam, R., He, L., Aliaga, D. and Niyogi, D., 2023. Deep learning-based urban morphology for city-scale environmental modeling. *PNAS nexus*, *2*(3), p.pgad027.

Aliaga, D., & Niyogi, D. (2024). Digitizing cities for urban weather: representing realistic cities for weather and climate simulations using computer graphics and artificial intelligence. *Computational Urban Science*, *4*(1), 8.

URBAN PROCEDURAL MODELING

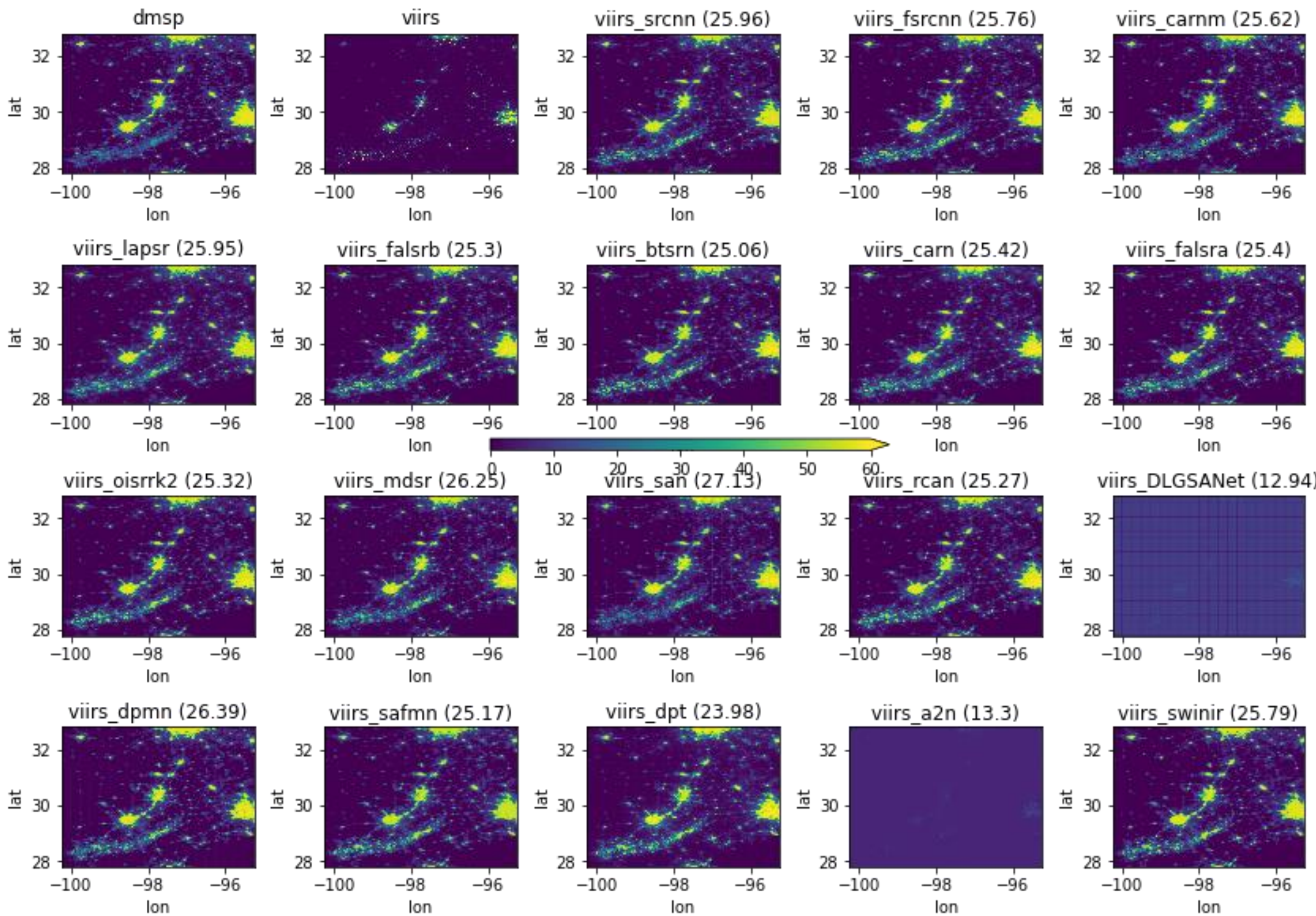
Dublin – 3D Urban Procedural Model

Dublin – 3D Google Earth

Content Design Example

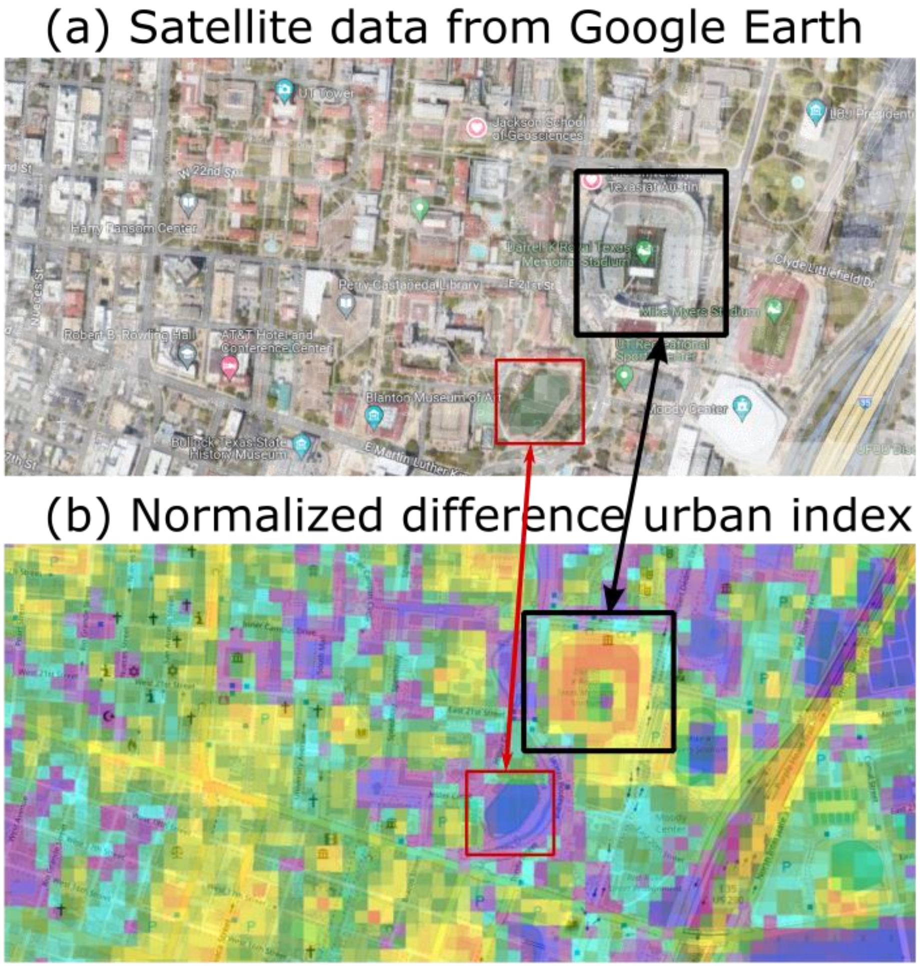
ClimateDownscaleSuite

VIIRS and DMSP continuity for night time light data transformation



manuscript in review

Long-term normalized difference urban index (NDUI) data time series for urban studies



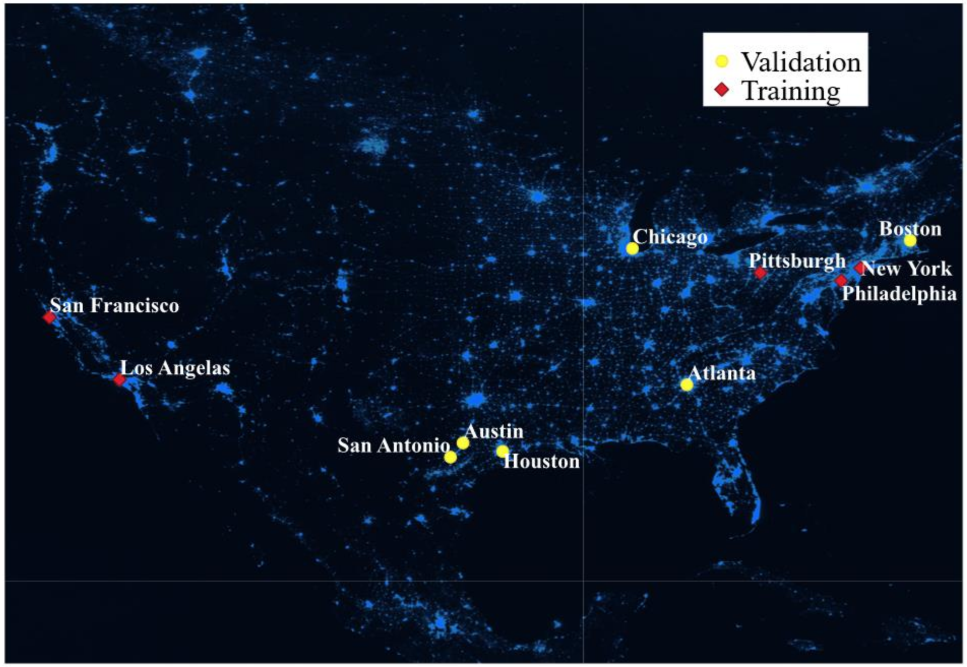
UT GLOBUS: UT- GLObal Building heights for Urban Studies at 1-meter resolution – A high-resolution urban building height digital twin

Inputs: ALOS 30-m, LCZ, population

Model: UNET

Target: USGS LiDAR 1-m building height

Ongoing development for 500 cities across the world

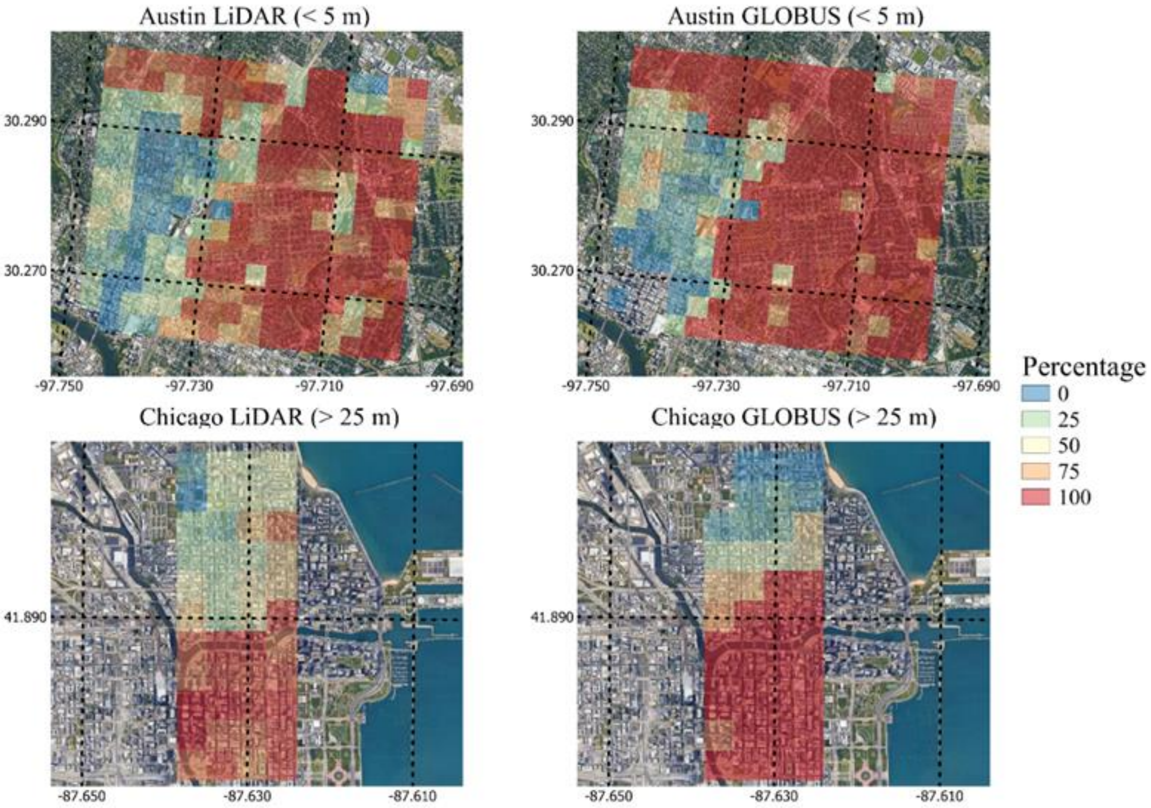


Harsh Kamath, Manmeet Singh, Lori Magruder, Zong-Liang Yang and Dev Niyogi
in revision with Scientific Data

https://arxiv.org/ftp/arxiv/papers/2205/2205.12224.pdf

UT- GLOBUS: Histogram of building heights

Similar statistics modelled by GLOBUS relative to LiDAR



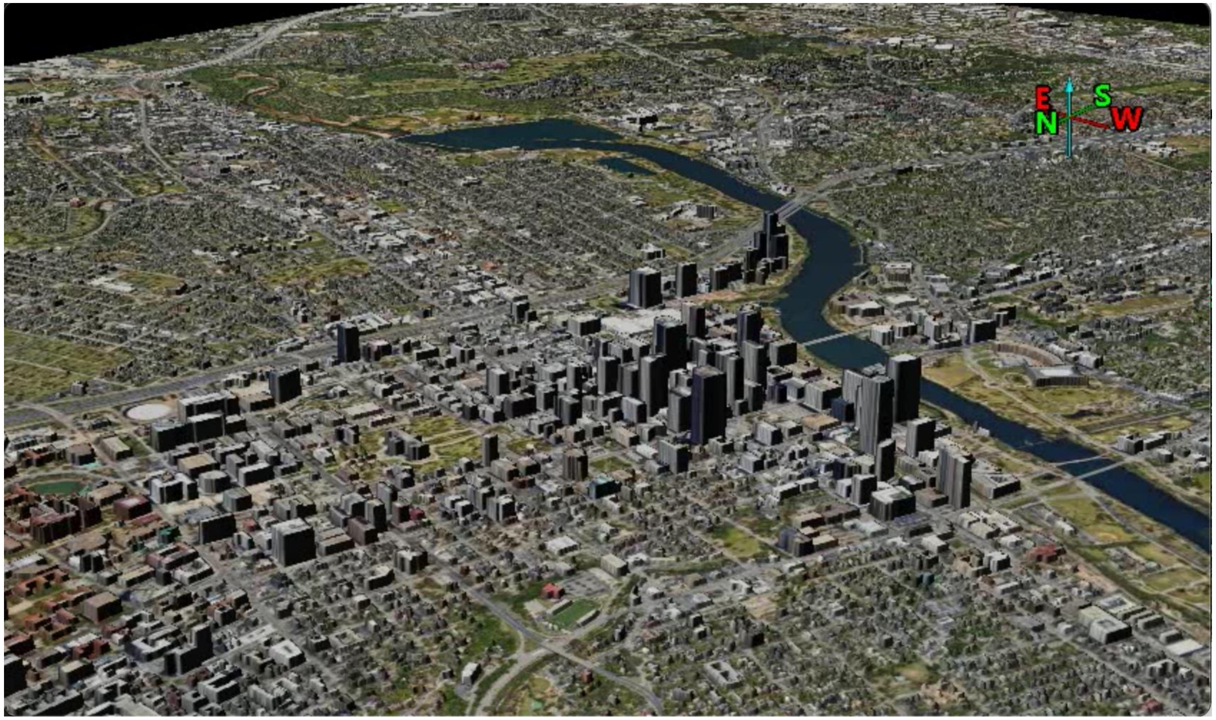
Harsh Kamath, Manmeet Singh, Lori Magruder, Zong-Liang Yang and Dev Niyogi

https://arxiv.org/ftp/arxiv/papers/2205/2205.12224.pdf

UT-GLOBUS Dataset

An Open-Source global cities dataset for building heights

- Uses open-source spaceborne satellite data.
- Employs machine learning approaches to predict building level information.
- Easily ingested in weather models.
- Used to calculate thermal comfort, model predictive output



TEXAS Geosciences
The University of Texas at Austin
Jackson School of Geosciences

TE(x)US LAB

GeoHealth HOME RESEARCH NEWS PEOPLE PUBLICATIONS JOIN US

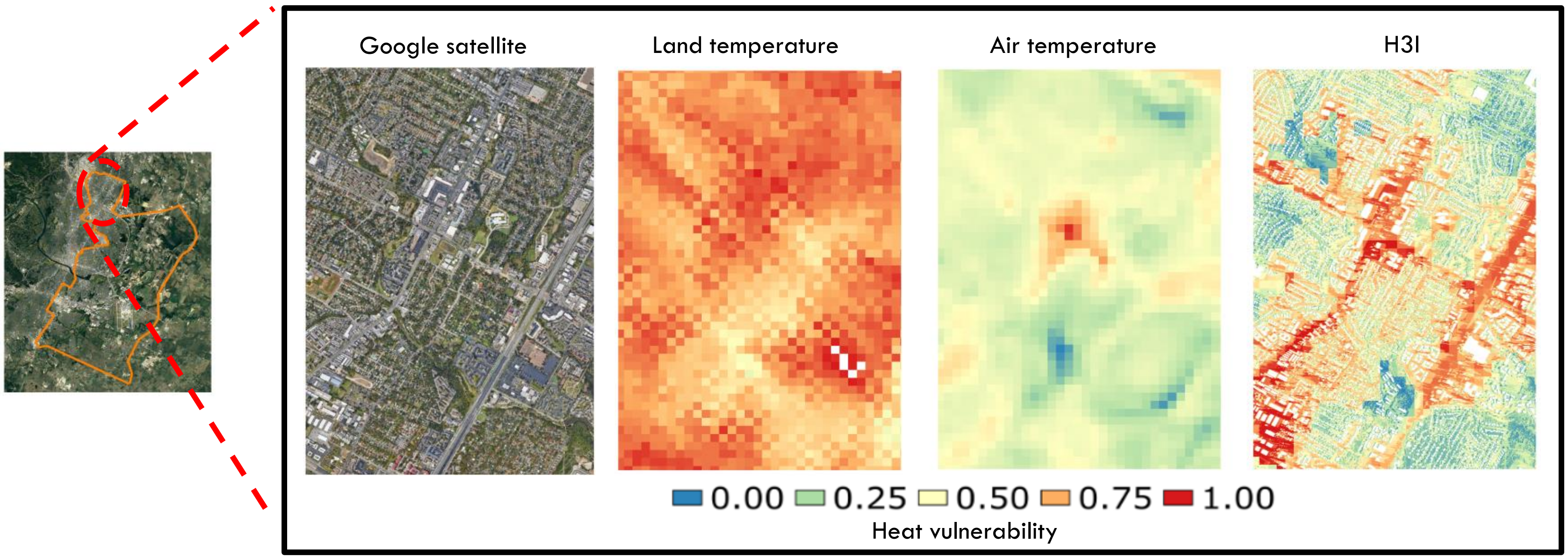
UT GLObal Building Heights for Urban Studies (UT GLOBUS)

There is a growing interest in modeling urban microclimate at finer scales to ensure a detailed representation of cities. Currently, while models have the capacity to simulate urban microclimate at city- and street- scales, the lack of detailed building information for model input often acts as a bottleneck. To tackle this issue, we introduce GLObal Building heights for Urban Studies (UT-GLOBUS), a level of detail-1 building dataset that utilizes open-source spaceborne data and a random forest model to predict building-level information. Model simulations with UT-GLOBUS shows that there is an improvement in the simulation of city-scale urban temperatures. Further, UT-GLOBUS can be used to inform environmental justice decisions for heat from street-scale modeling and to perform if-then analysis to test the efficacy of heat mitigation strategies.

Harsh Kamath

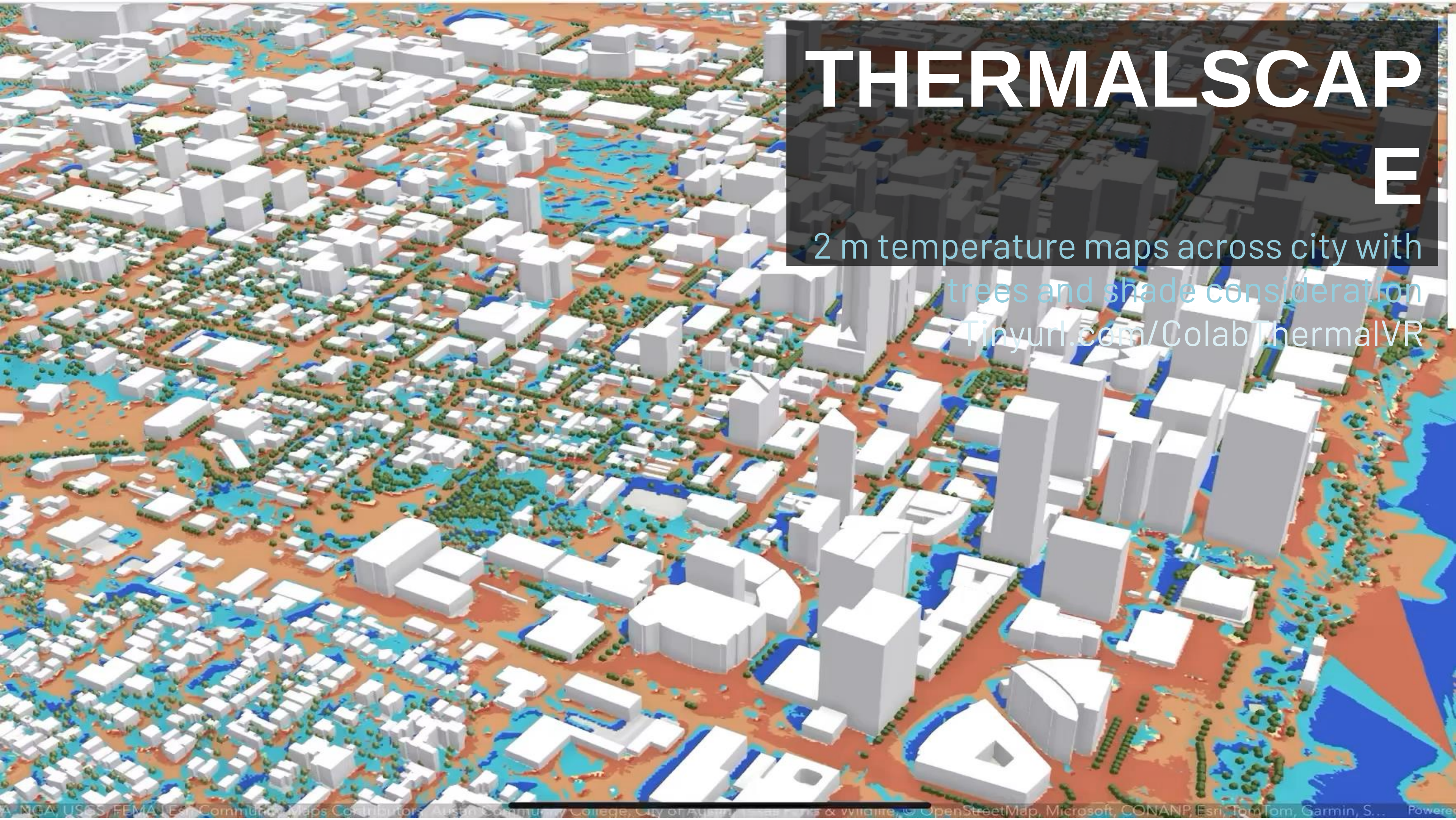
Open source, Build height data sets for cities globally (See https://texuslab.org/)

DT data for real world impacts - Human Heat Health Index (H3I)



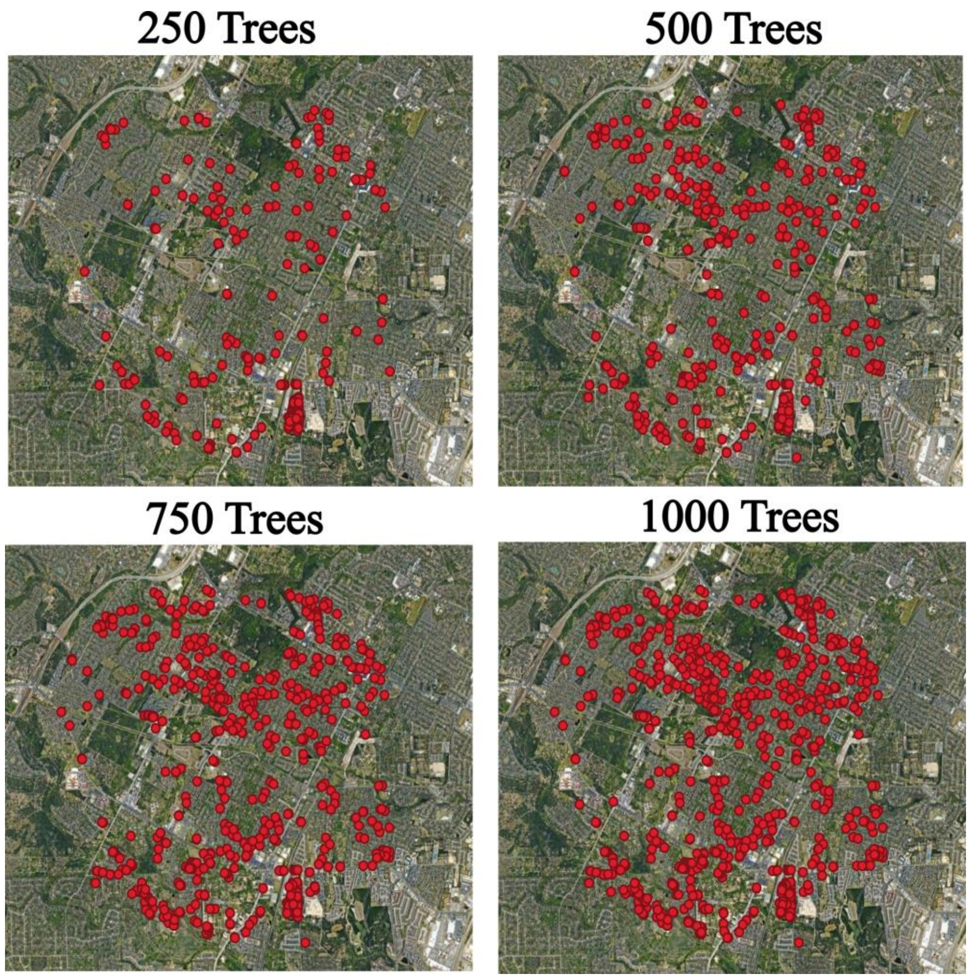
$$\mathrm{H3I} = \mathrm{SoVI} \times \sum_{time=\mathrm{i}} \{\max(\mathrm{UTCI_i} - 32), 0\} \times \mathrm{E_i}$$

Ref: H3I, Kamath, 2023


THERMALSCAPE
2 m temperature maps across city with trees and shade consideration
Tinyurl.com/ColabThermalVR

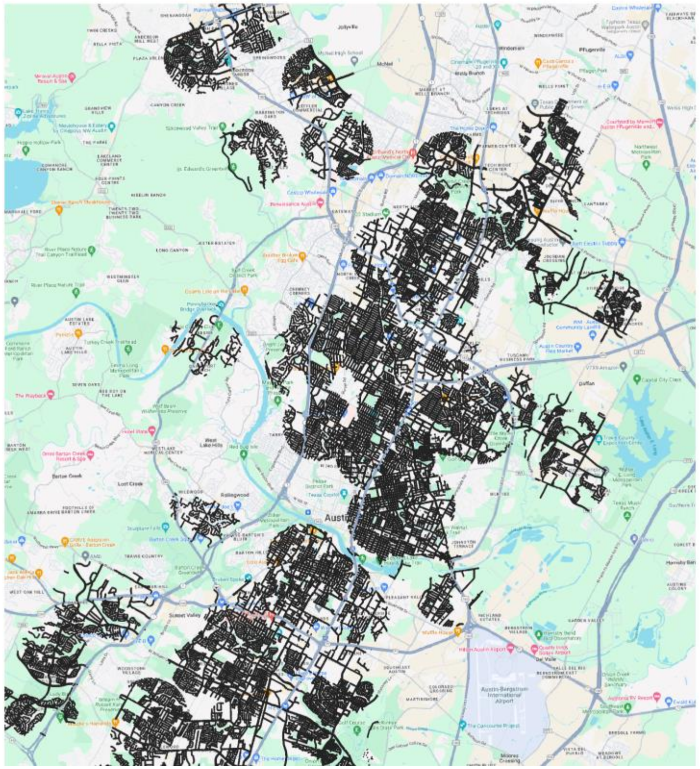
How to optimize urban tress for heat mitigation?

Within 2-mile buffer



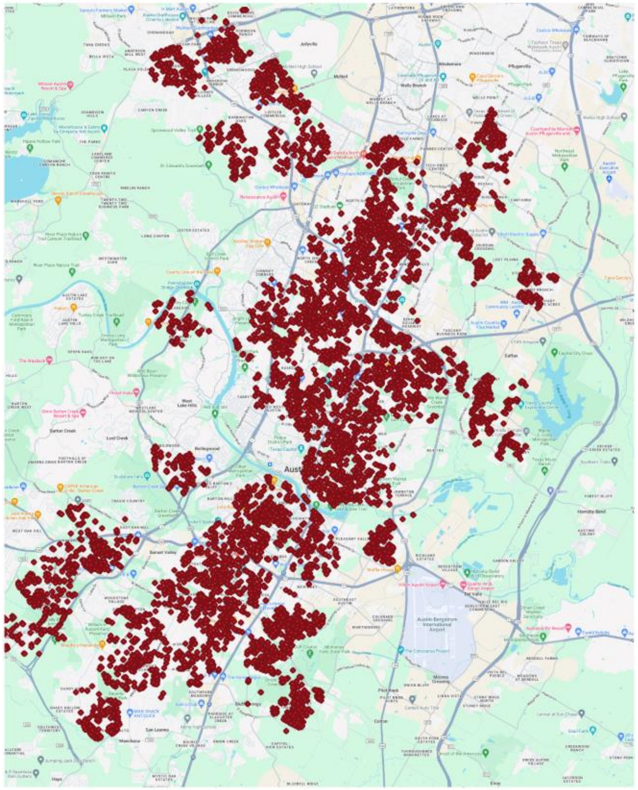
Austin open public spaces

Available public space



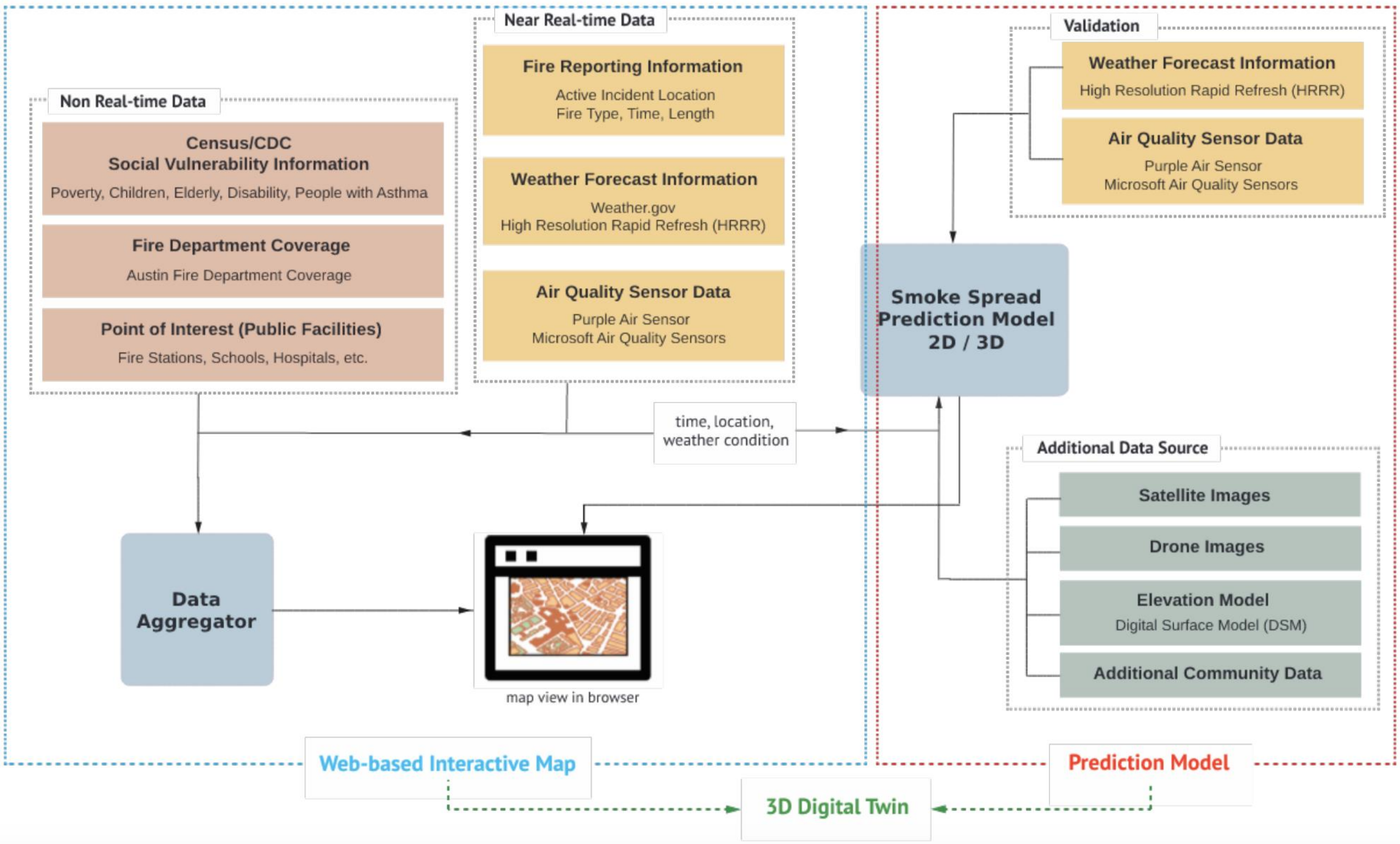
About 18,000 trees optimized

New tree locations

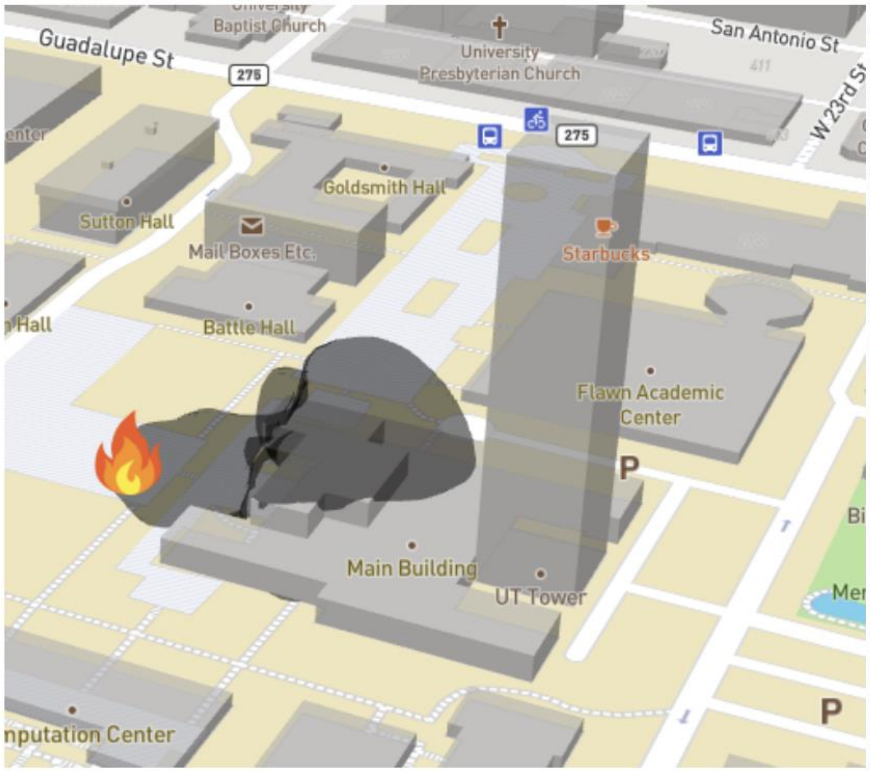


Fire and Smoke Digital Twin

Lewis, R. H., Jiao, J., Seong, K., Farahi, A., Navrátil, P., Casebeer, N., & Niyogi, D. (2024). Fire and smoke digital twin—A computational framework for modeling fire incident outcomes. *Computers, Environment and Urban Systems*, *110*, 102093.



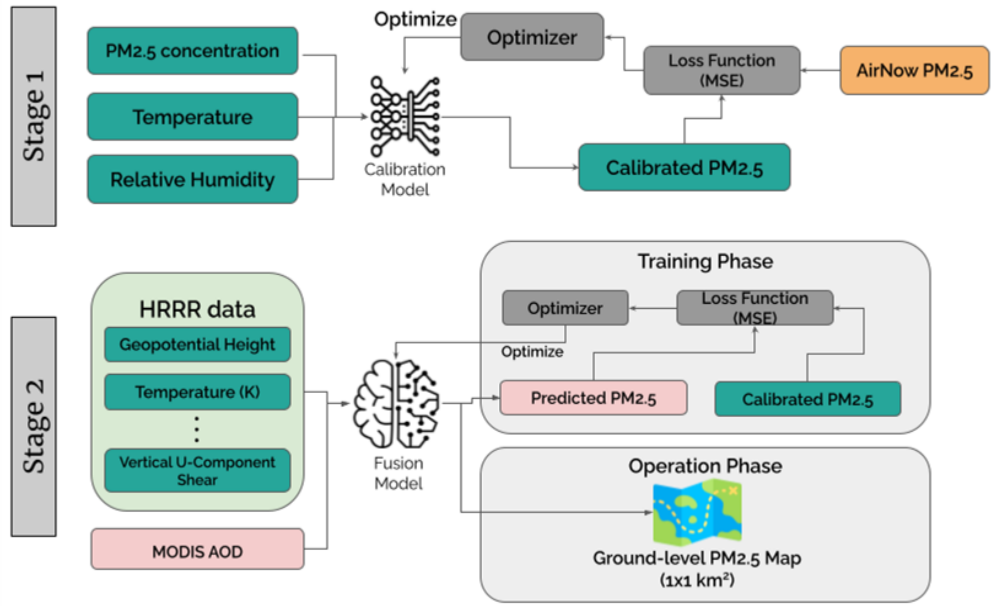
Fire and Smoke Digital Twin

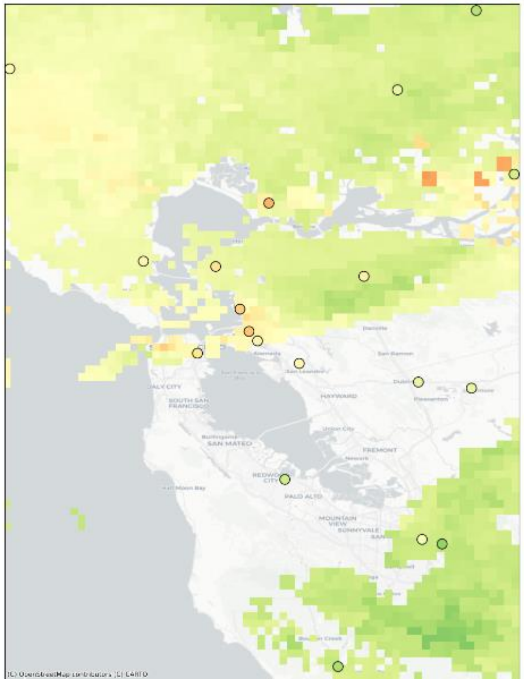


Lewis, R. H., Jiao, J., Seong, K., Farahi, A., Navrátil, P., Casebeer, N., & Niyogi, D. (2024). Fire and smoke digital twin–A computational framework for modeling fire incident outcomes. *Computers, Environment and Urban Systems*, *110*, 102093.

Air Quality Data Fusion

Combine multiscale, ground based and satellite remote sensing datasets over cities



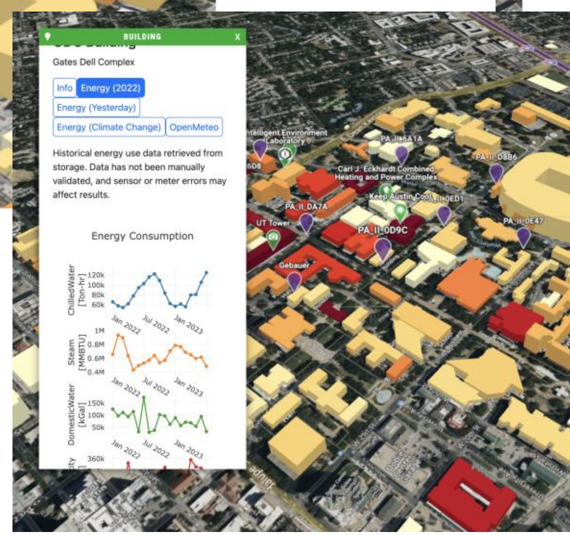


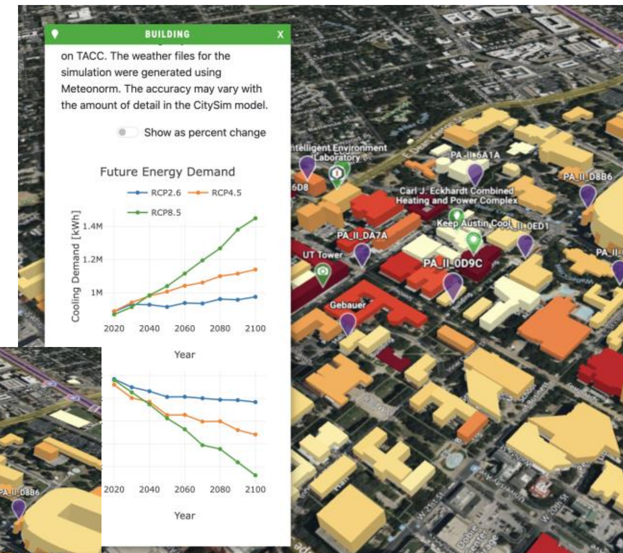
- Machine Learning can help fuse multiple remote sensing datasets into ground-level PM2.5 measurements.

CityTFT: Temporal Fusion Transformer for Urban Building Energy Modeling, TY Dai, D Niyogi, Z Nagy

Dai, T.Y., Dilsiz, A.D., Niyogi, D. and Nagy, Z., 2023, November. A Comparison of Different Deep Learning Model Architectures and Training Strategy for Urban Energy Modeling. In *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation* (pp. 316-317).

UTwin: A digital twin of the UT Austin campus, BuildSys23 Calvin Lin, TYDai, AD Dilsiz, D Crawley, D Niyogi, Z Nagy






Building Metadata
Built 2017
Laboratory: Research Laboratory
4,972
454,422 sq. feet
Chilled Water
Steam
View EER at UT Building Information
Climate Projection (RCP)
Future Energy Demand
Cooling Demand Prediction
Weather Forecast (Next 7 days)
Chilled Water (Next 7 days)
BUILDING
EER Building
Engineering and Education Research Center
Info
Energy (2022)
Energy (Yesterday)
Energy (Climate Change)
OpenMeteo
Energy Consumption
MOVE
ZOOM
TILT & ROTATE
VIEWPOINTS
CAMPUS ENERGY
BUILDINGS
OTHER FEATURES
WEB MAP SERVICES
INFORMATION
CONTENT
Campus Overview
Outdoor Air Quality
Building Layers
Chilled Water
Steam
Electricity
Additional Datasets
Flood Map
Transit Map
Census Blocks
Land Cover
Weather Radar
Hourly Avg PM2.5

UT City Climate Colab

Empower communities with climate data and tools

A framework for cities to build climate smart infrastructure (netzero, heat/health, fire, investments..)

Dev Niyogi[1] Allysa Dallmann[1], Marc Coudert[2], Zach Baumer[2], Patrick Bixler[1], Paola Passalacqua[1], Junfeng Jiao[1], Yang Zong Liang[1], Zoltan Nagy[1], Heidi Schmalbach[1]

1. The University of Texas at Austin
2. The City of Austin

utcitycolab.org

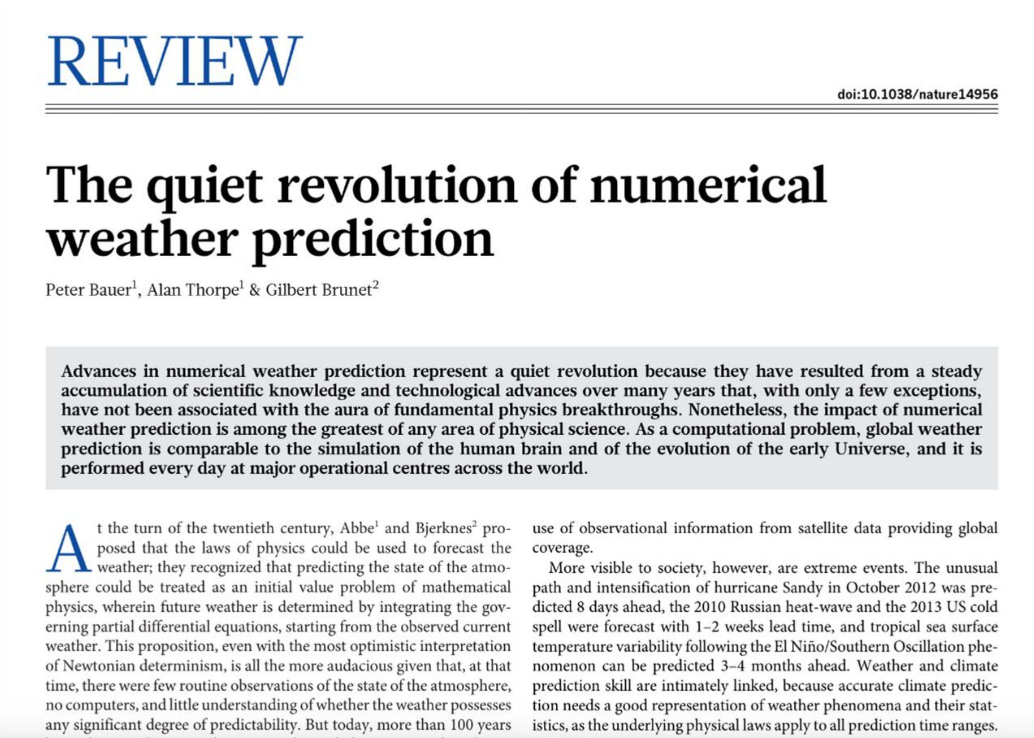
2. The City of Austin


HEAT MAPPING
Active Fire Incidents Map
08:00
LOCAL DATA
Temperature, Precipitation, Air Quality, Satellite, Transportation, and Infrastructure
Academia, City, Community Partnership
Community Feedbacks, Response, and Exposure to Extreme Weather and Climate
LIVED EXPERIENCES
Lived experiences combined with local data
INFORMED DECISIONS

Digital Twins, Cities and Wx/Climate Extremes

- Creating Scenarios with Decision Timelines
- Planning and Preparing for Various Outcomes
- Localizing datasets and products
- Emulators
- Input data for models (parameter values, gridded initial conditions)
- Education and training

Importance of Physics-Based Approaches



REVIEW

doi:10.1038/nature14956

The quiet revolution of numerical weather prediction

Peter Bauer[1], Alan Thorpe[1] & Gilbert Brunet[2]

Advances in numerical weather prediction represent a quiet revolution because they have resulted from a steady accumulation of scientific knowledge and technological advances over many years that, with only a few exceptions, have not been associated with the aura of fundamental physics breakthroughs. Nonetheless, the impact of numerical weather prediction is among the greatest of any area of physical science. As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe, and it is performed every day at major operational centres across the world.

At the turn of the twentieth century, Abbe[1] and Bjerknes[2] proposed that the laws of physics could be used to forecast the weather; they recognized that predicting the state of the atmosphere could be treated as an initial value problem of mathematical physics, wherein future weather is determined by integrating the governing partial differential equations, starting from the observed current weather. This proposition, even with the most optimistic interpretation of Newtonian determinism, is all the more audacious given that, at that time, there were few routine observations of the state of the atmosphere, no computers, and little understanding of whether the weather possesses any significant degree of predictability. But today, more than 100 years later, this paradigm translates into solving daily a system of nonlinear

use of observational information from satellite data providing global coverage.

More visible to society, however, are extreme events. The unusual path and intensification of hurricane Sandy in October 2012 was predicted 8 days ahead, the 2010 Russian heat-wave and the 2013 US cold spell were forecast with 1–2 weeks lead time, and tropical sea surface temperature variability following the El Niño/Southern Oscillation phenomenon can be predicted 3–4 months ahead. Weather and climate prediction skill are intimately linked, because accurate climate prediction needs a good representation of weather phenomena and their statistics, as the underlying physical laws apply to all prediction time ranges.

This Review explains the fundamental scientific basis of numerical

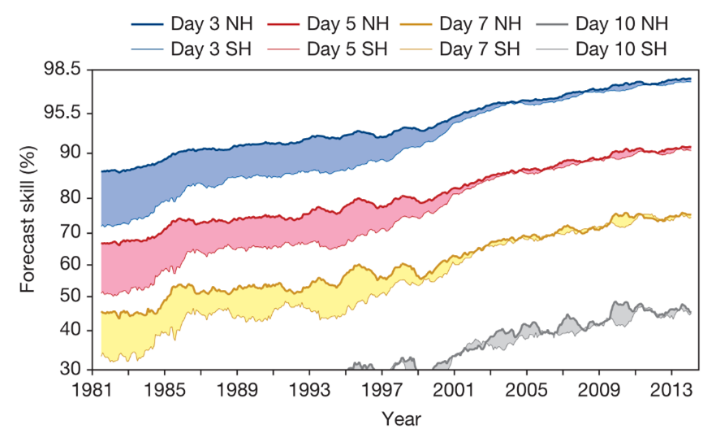


Figure 1 | A measure of forecast skill at three-, five-, seven- and ten-day ranges, computed over the extra-tropical northern and southern hemispheres. Forecast skill is the correlation between the forecasts and the verifying analysis of the height of the 500-hPa level, expressed as the anomaly with respect to the climatological height. Values greater than 60% indicate useful forecasts, while those greater than 80% represent a high degree of accuracy. The convergence of the curves for Northern Hemisphere (NH) and Southern Hemisphere (SH) after 1999 indicates the breakthrough in exploiting satellite data through the use of variational data[100].

Bauer, P., Thorpe, A. and Brunet, G., 2015. The quiet revolution of numerical weather prediction. *Nature*, *525*(7567), pp.47-55.