Model-Based AI Applications in Urban Adaptation Analysis and Engineering

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Y. Jeffrey Yang, Ph.D., P.E. (EPA/ORD/WID/IWRB)
Heng Wei, Ph.D., P.E. (University of Cincinnati)

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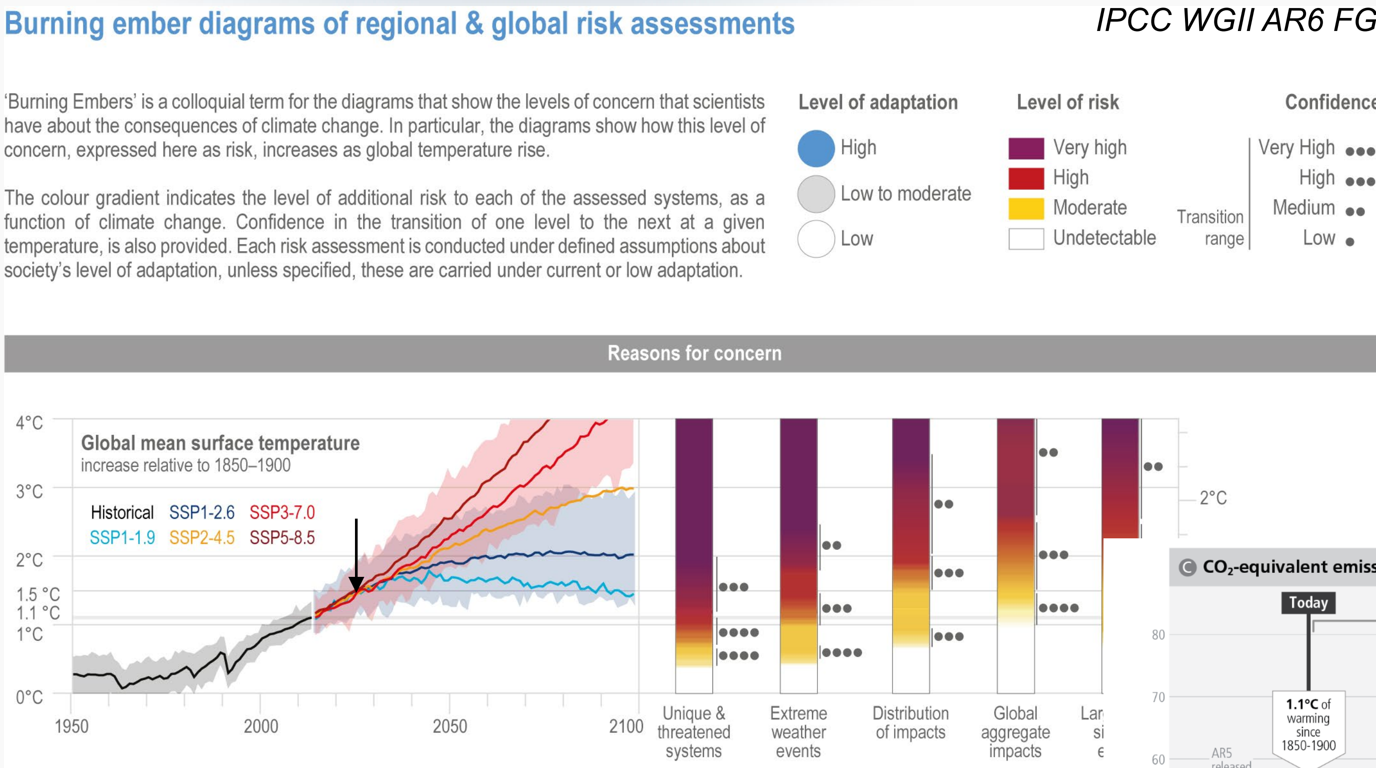
Agenda

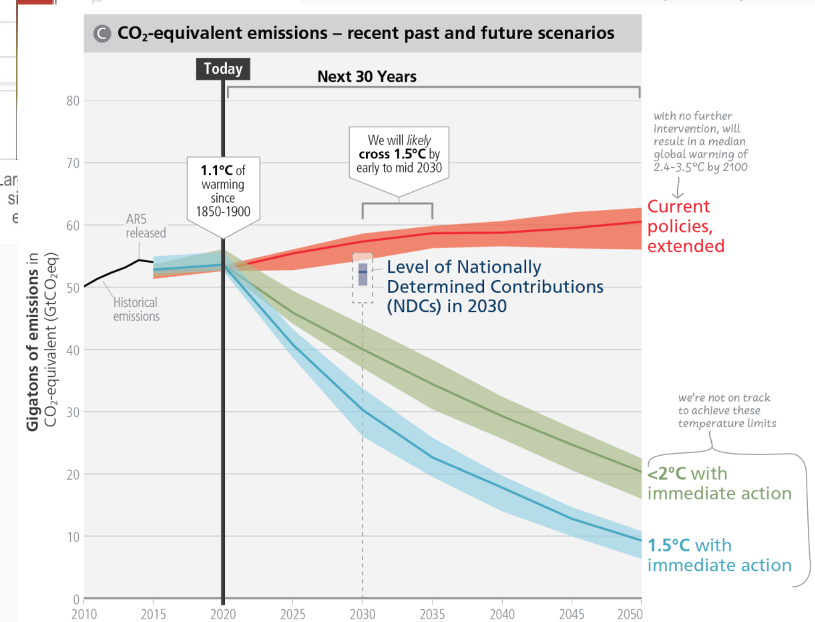
- Overview of AI-based applications in green-house gas (GHG) reduction and system resilience from urban transportation
- EPA's Smart Urban Design (SUD) platform with integrated model simulation as digital twins for urban infrastructure planning and engineering
- Two practical examples of AI-enabled simulation: Urban-wide GHG emission and project-level transportation optimization
- Summary and outlooks

Urban As GHG Sources

IPCC WGII AR6 FGD (2022)



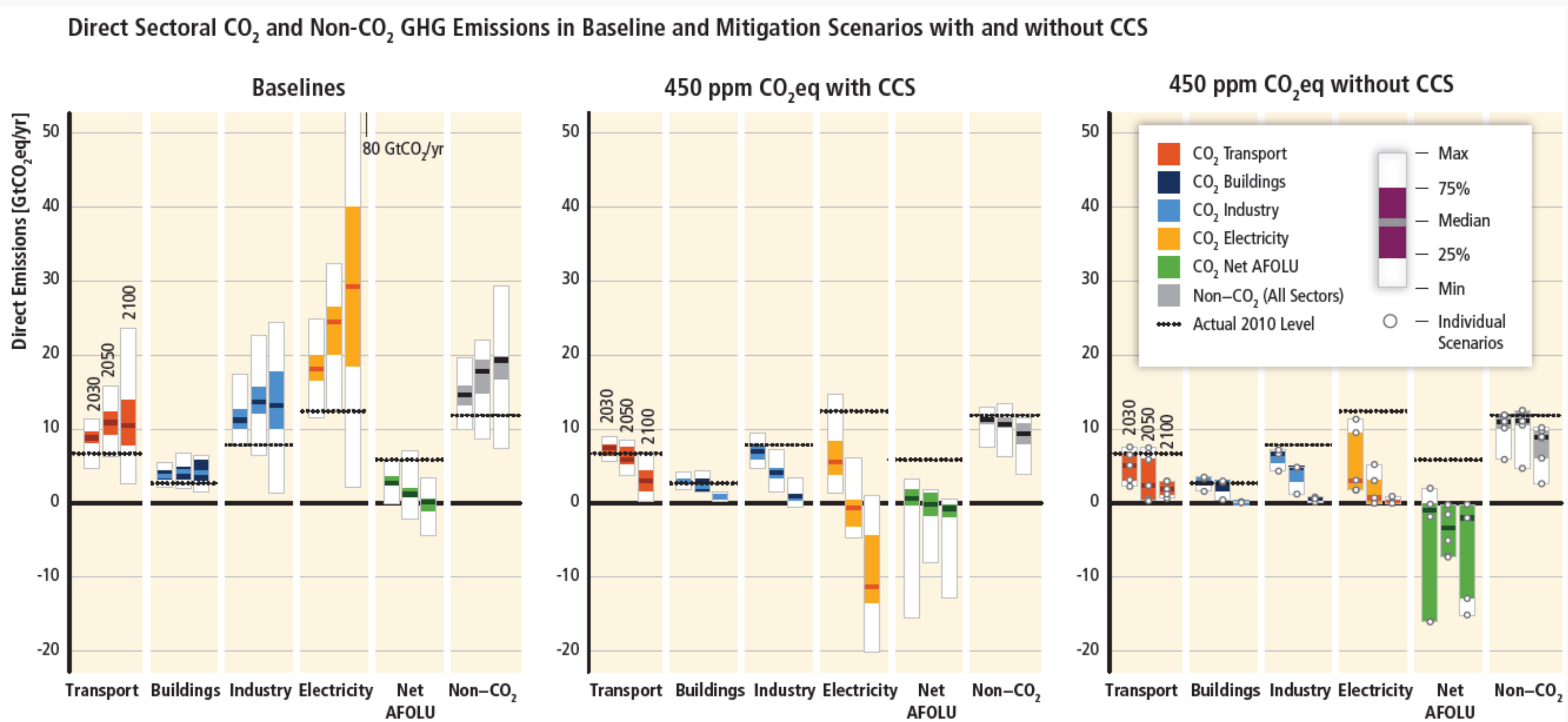
IPCC AR6 SPM (2022)



- Climate change is above 1.5°C now under current policy
- Immediate actions needed before 2030 to reduce GHG emission for the 1.5°C and <2°C scenarios
- Climate impact on urban systems and EJ communities cannot be overstated

Urban Systems and Climate Actions

- Urban transportation and water management are the two interrelated major infrastructure systems
- Land-based transportation is a major source of criteria pollutants (CP) and GHG emissions, and it is rapidly evolving (e.g., electrification, autonomous driving, mass transit, walkable communities, etc.)
- Transport sector has the third largest potential for GHG reduction and air pollution reduction as the co-benefit

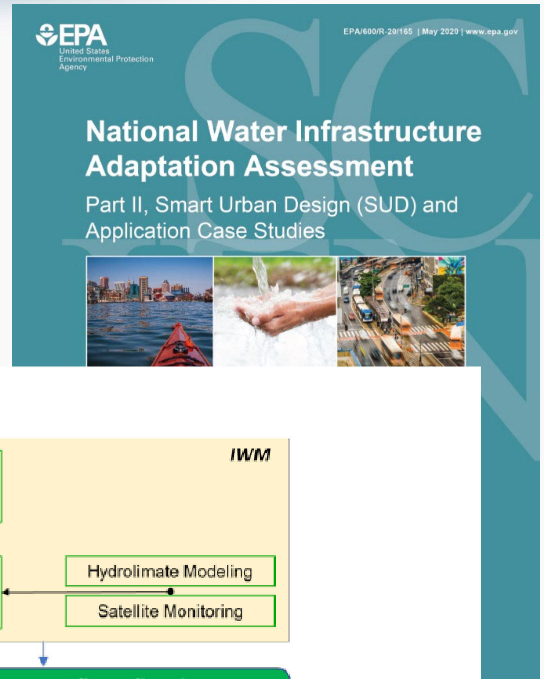


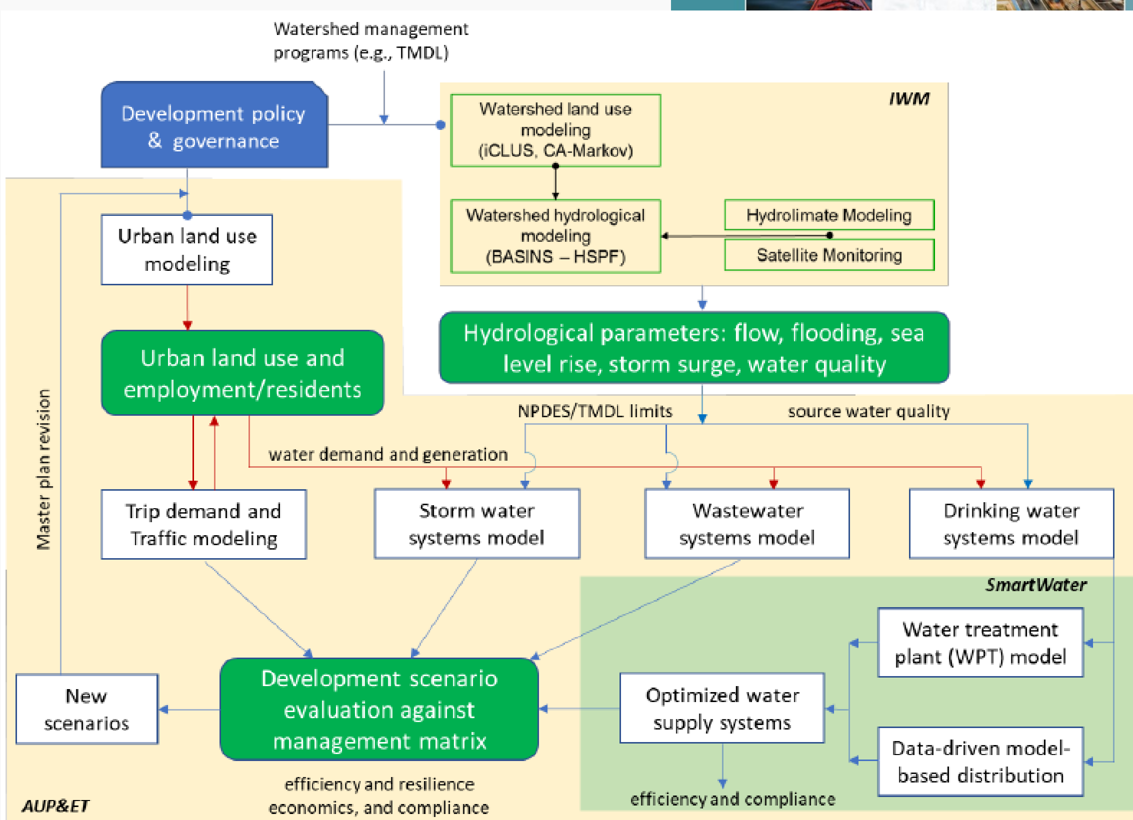
IPCC WG3 AR5 SPM (2022)

EPA Research on Urban Adaptation - Smart Urban Designer (SUD) tools

Adaptive Urban Planning and Engineering Tool (AUP&ET) is a digital twin for decision-making support

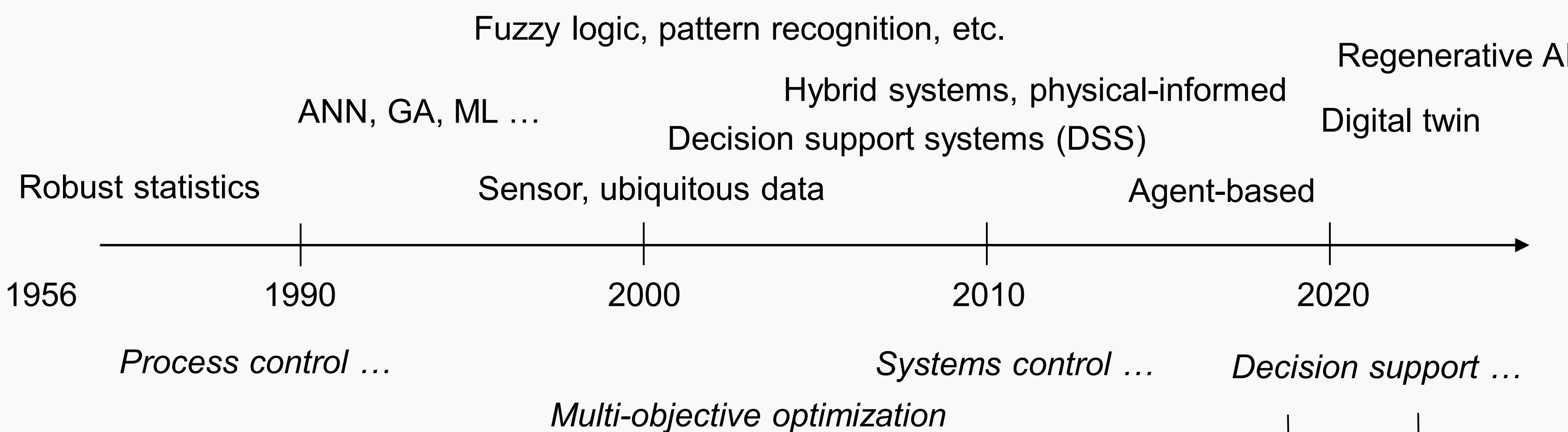
EPA (2020)





- SUD tools include Integrated Watershed Model (IWM), AUP&E, and SmartWater systems.
- AUP&ET simulates urban infrastructure systems for transportation, water, wastewater and stormwater planning and management.
- Considers both climate resilience and mitigation co-benefits in system construction and operations.
- AI-enabled model-based system performance simulations for scenario analysis.
- AUP&ET for transportation: Air Impact Relating Scenario-based Urban Setting and Transportation Asset (Air-SUSTAIN)

AI Role as Objective-specific



Project-level adaptive management (CV in traffic flow)

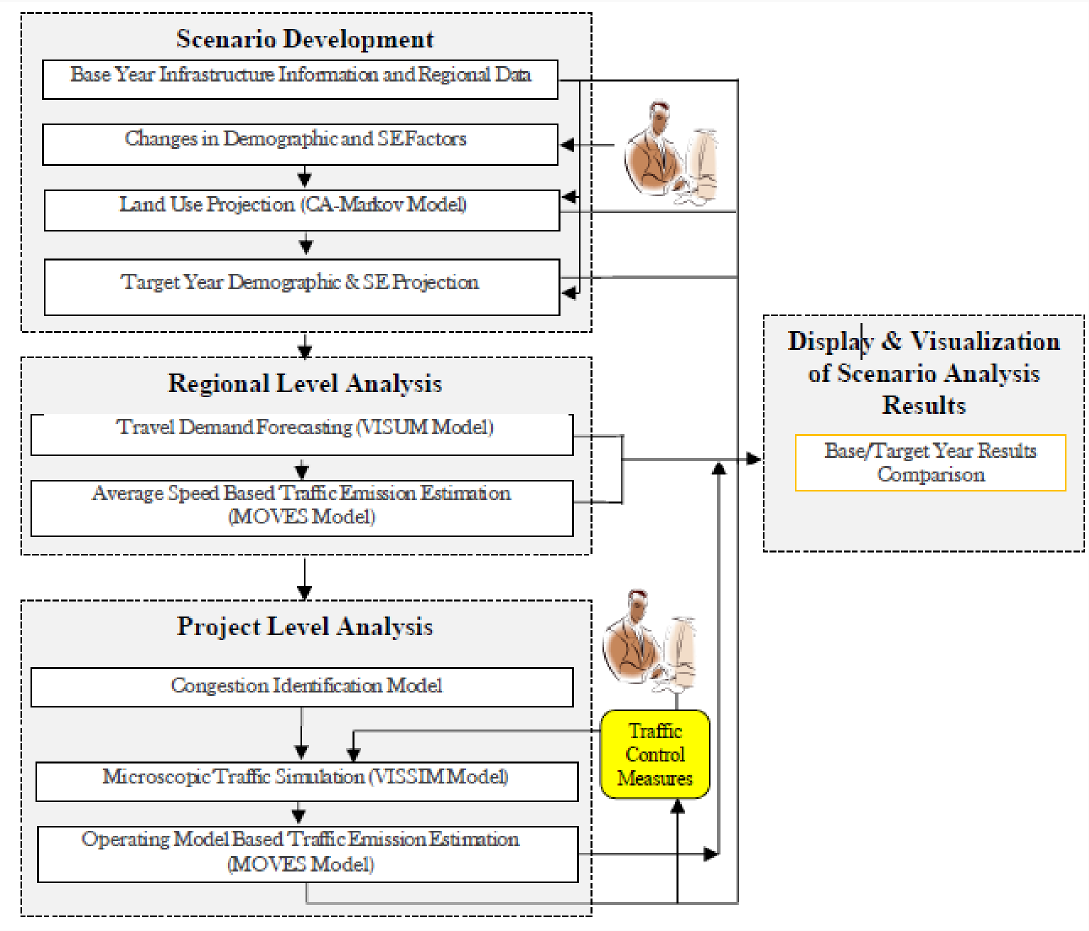
Regional-level adaptive planning (efficiency, GHG, EJ)

Henk van Zuylen (2012) in Transportation Res. Circular No.E-C168

"A general distinction between "ordinary" computer systems and AI is **the complexity of the AI computer systems**, including" the complexity of AI program, the algorithms, and the physical processes.

Engineering applications of AI.. are more on **"weak" AI**, the computer applications that deal with **limited application areas**… and seem to be **some intelligent features**…"

AI in Urban Planning and Engineering



Transportation simulations using Air-SUSTAIN

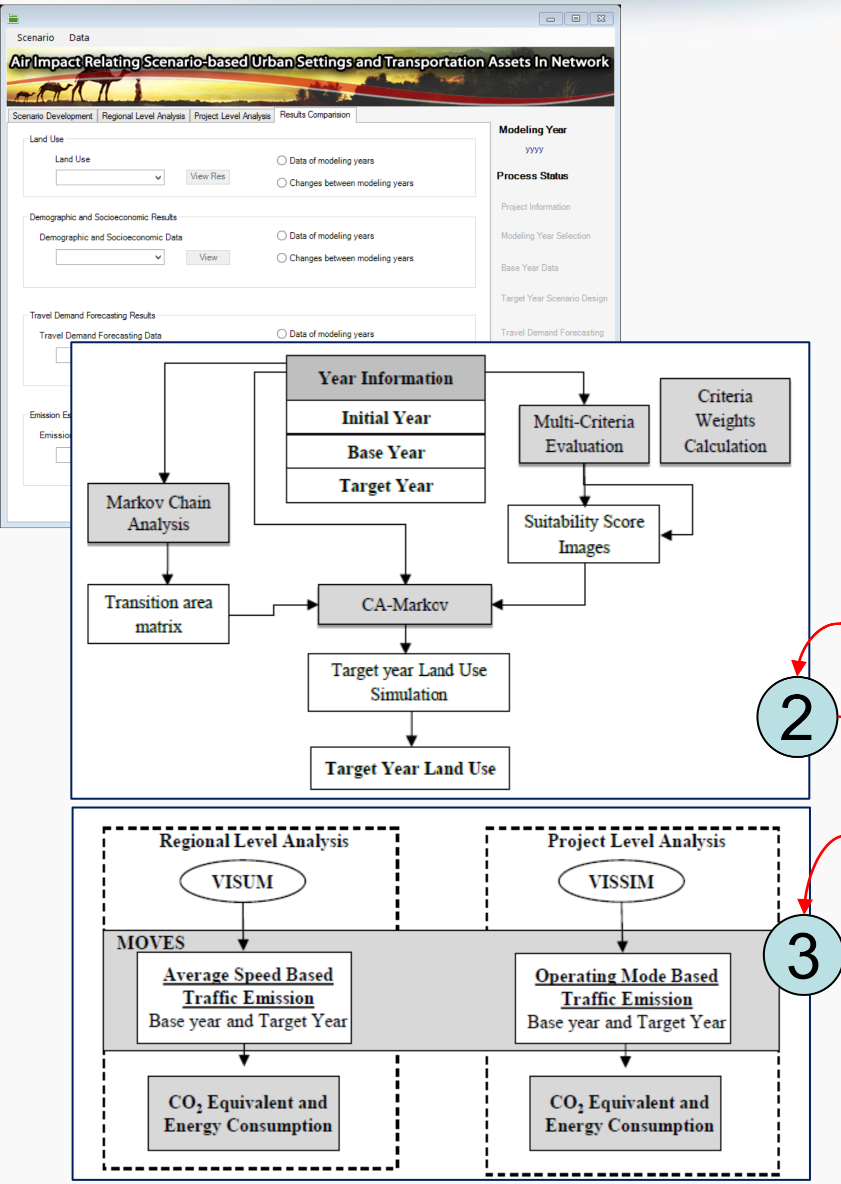
- Complex and integrated model simulations as digital twins for regional-level and/or project-level analysis
- Scenario developments for climate, land use, demographic projections with uncertainties
- Physics-informed AI in scenario development and model parameterization

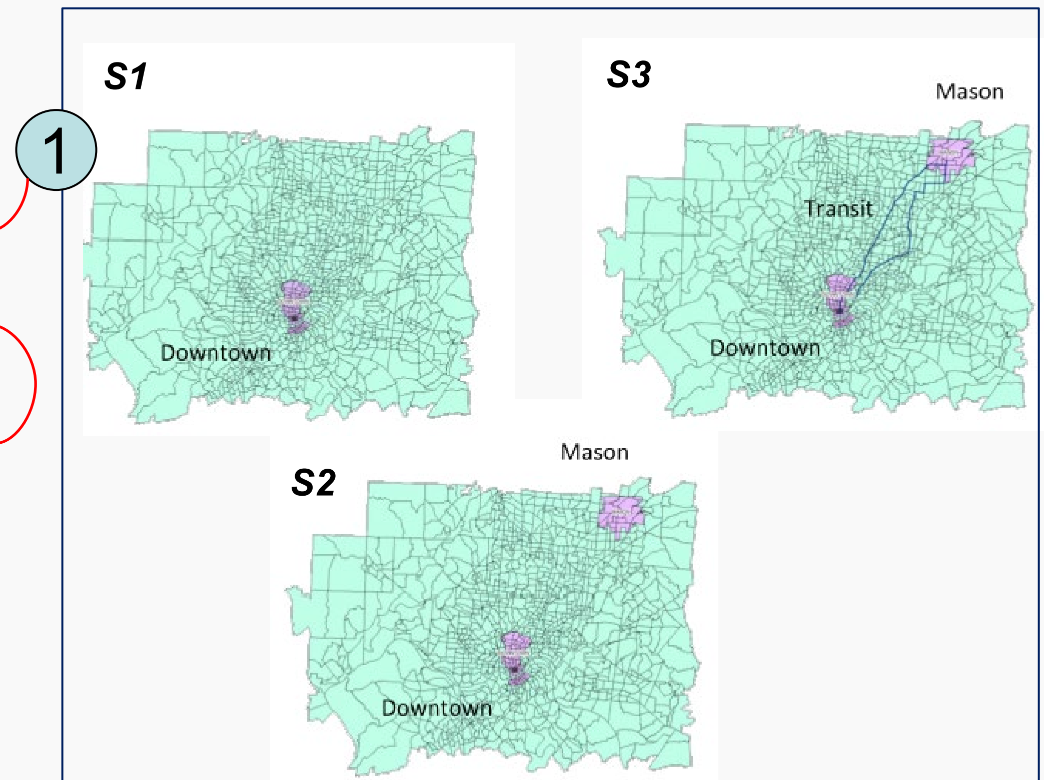
Two AI-application examples

- Regional level analysis for adaptation scenarios in Cincinnati metro area: Mobility and emissions
- Project level analysis for adaptation: Efficiency and emission

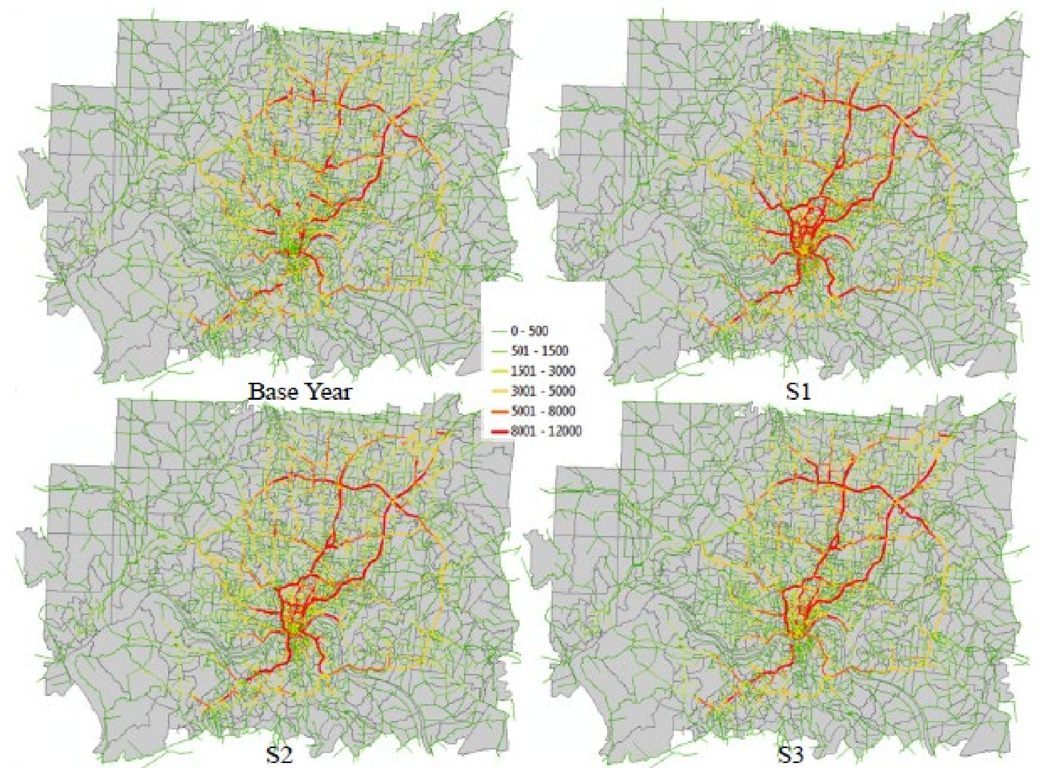
Example #1: Regional-Level Traffic Analysis

- Air-SUSTAIN offers a digital twin for analyzing development scenarios
- Population, employment, and economic conditions model-simulated for S1, S2 and S3
- Outputs in traffic volume, transportation efficiency (i.e., energy, delay, etc.), GHG and CP emissions



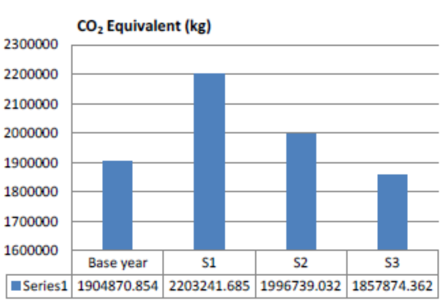


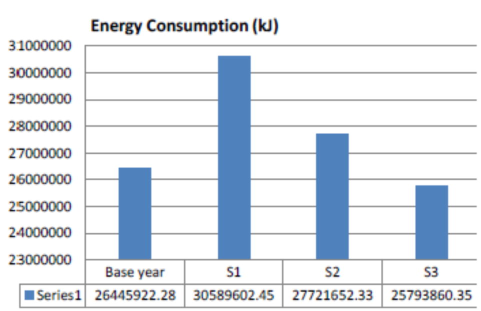
Regional-Level Analysis Results



Peak Hour (7-9am) Simulation

- Compared to base year (2010), traffic patterns for S1-S3 policies would differ by 2030
- Smart growth S3 (multi-center, mass transit) offers better transportation efficiency, energy consumption, and GHG avoidance by ~18%
- Now Cincinnati metro area developed into multi-centers, partially along S2 scenarios. And no consideration of vehicle electrification
- Further analysis on water infrastructure adaptation given the urban configuration
- Such digital twin model can be improved by reinforcement learning (RL) with updated data in model & parameterizations – future work





Scenario	Base Year	S1	S2	S3
Average queue length (vehicle per link)	9	12	12	12
Average wait time (minute per link)	2.03	2.87	2.56	2.08
Total Delay (vehicle·hour)	113,456.4	205,121.3	179,796.6	153,018.4
Average Delay (minute per vehicle)	10.8	16.1	14.1	12.0

AI Role as Objective-specific

Fuzzy logic, pattern recognition, etc.

Regenerative AI

Hybrid systems, physical-informed

ANN, GA, ML …

Digital twin

Decision support systems (DSS)

Robust statistics

Sensor, ambiguous data

Agent-based

1956 | 1990 | 2000 | 2010 | 2020

Process control …

Systems control …

Decision support …

Multi-objective optimization

Project-level adaptive management (CV in traffic flow)

Regional-level adaptive planning (efficiency, GHG, EJ)

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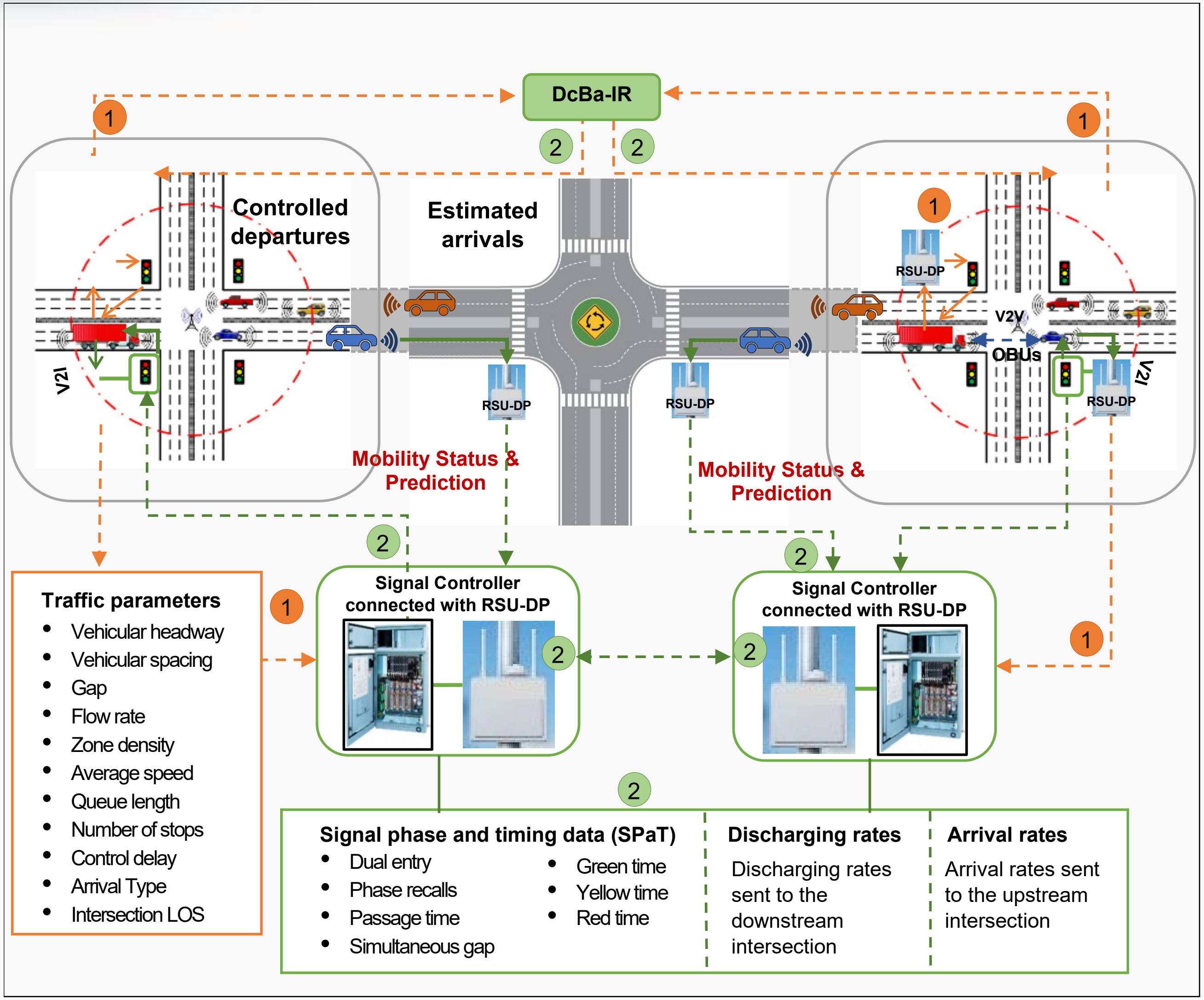
Example #2: Connected Vehicles in Traffic Management

- Real-time data become ubiquitous
- Vehicle-to-vehicle, vehicle-to-station data communication, and adaptive signal control, are essential
- Emerging are the science, hardware and infrastructure that come together for better traffic management



Intelligent Roundabout Systems Architecture

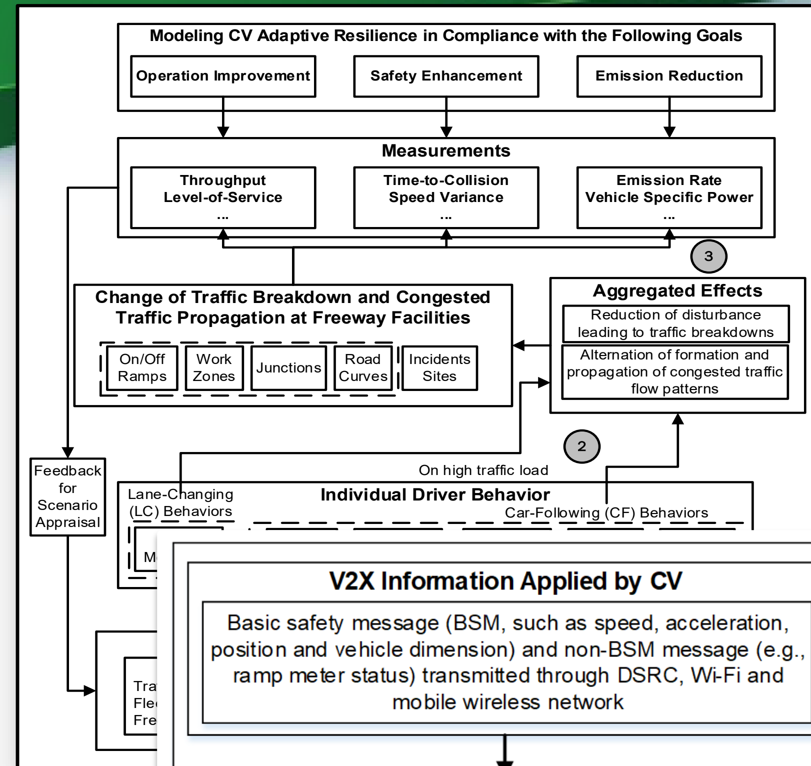
Lin (2024)

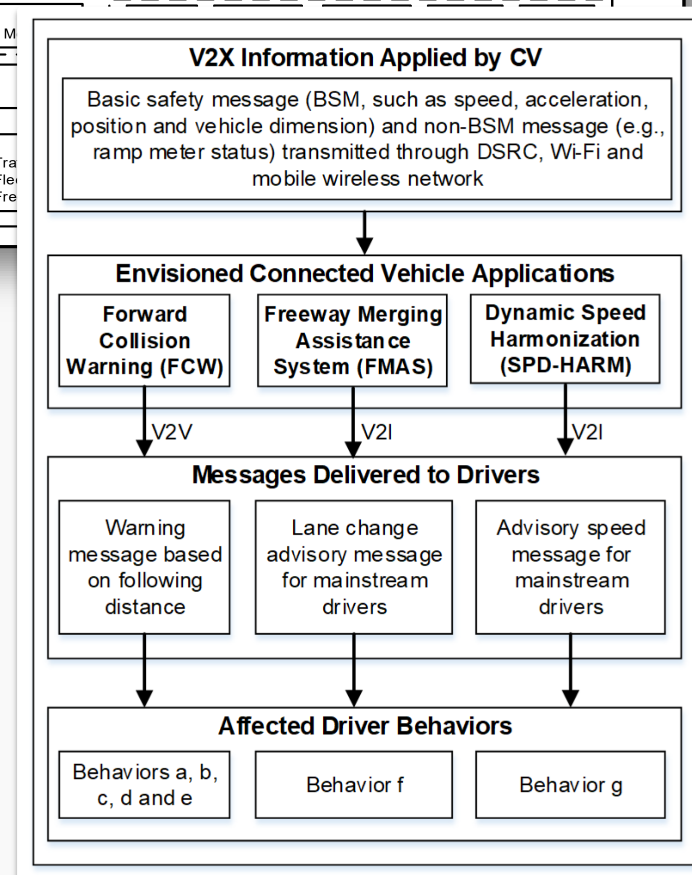
Connected Vehicles – Models and Principles

Overview for Connected Vehicles

ID	Name	Definition/Comments
a	**Reaction time**	Delay between the emergence a traffic stimulus and the execution a relevant action.
b	**Estimation errors**	The following distance and relative speed to the leader can only be estimated with limited accuracy.
c	**Temporal anticipation**	Drivers can predict traffic situation for the next few seconds.
d	**Spatial anticipation**	Drivers consider the immediate preceding and further vehicles ahead.
e	**Desired distance**	Desired following distance a driver tries to maintain in the car-following state.
f	**Lane-change desire**	Motivation for gaining speed advantage or continuing a route.
g	**Desired speed**	The maximum speed a driver attempts to reach if there is no constraints from other road users.

- CV generates regulatory, warning or advisory messages based on safety and operation information exchanged among vehicles.
- Drivers adjust behaviors once receiving the messages.
- Data-driven applications





Wei, Liu and Yang (2017)

Connected Vehicles – Models and Principles

Methodology: Modeling Traffic Flow under CV

Incorporating CV affected driver behaviors into car-following (CF) and lane-changing (LC) model.

- Reaction time, estimation errors, spatial anticipation, desired speed, and desired distance are incorporated in the Intelligent Driver Model (IDM) CF model developed by Kesting, A., Treiber, M., & Helbing, D. (2010).

IDM:

$$\underbrace{\dot{v}(t)}_{\text{Acceleration}} = \underbrace{a}_{\text{Maximum acceleration}}\Bigg[\underbrace{1-\overbrace{\left(\frac{v(t)}{v_0}\right)^4}^{\text{Speed term}}}_{\text{Free-flow component (FC)}} \underbrace{-\overbrace{\left(\frac{s^*(v,\Delta v)}{s(t)}\right)^2}^{\text{Spacing \& relative speed term}}}_{\text{Interaction component (IC)}}\Bigg]$$

FC: $a\left[1-\left(\frac{v(t)}{v_0}\right)^4\right]$ (Speed: $v(t)$; Desired speed: v_0)

IC: $-a\left(\frac{s^*(v,\Delta v)}{s(t)}\right)^2$ (Desired distance: $s^*(v,\Delta v)$; Spacing: $s(t)$)

After incorporating driver behaviors, IDM becomes:

$$\dot{v}_\alpha(\underbrace{t+T_r}_{\text{Reaction time}}) = FC(t) + IC(t)$$

FC: $a\left[1-\left(\frac{v_\alpha(t)}{v^*}\right)^4\right]$ — v^*: Desired speed under CV

IC: $-a\cdot c\underbrace{\sum_{\beta=\alpha-n}^{\alpha-1}}_{\text{Spatial anticipation}}\left[\frac{s^*(v_\alpha(t),\Delta v_{\alpha\beta}^{est}(t))}{s_{\alpha\beta}^{est}(t)}\right]^2$

Desired distance under CV: s^*

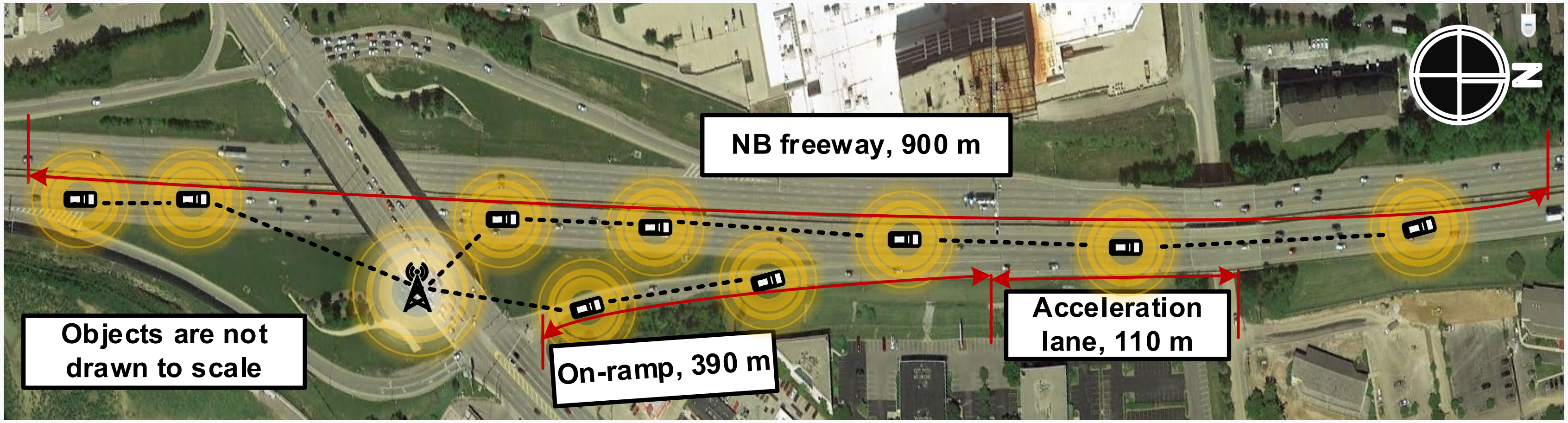
Estimation errors of relative speed: $\Delta v_{\alpha\beta}^{est}(t)$

Estimation errors of spacing: $s_{\alpha\beta}^{est}(t)$

Wei, Liu and Yang (2017)

Case Study on Connected Vehicles

Case Study: NB I-71 near Exit 12 at Kenwood, Cincinnati



Site description:
- NB I-71, near Exit 12 in greater Cincinnati area, Ohio.
- 3 freeway lanes, 1 on-ramp lane.
- Freeway peak hour volume 4400 veh/hr, 4.5% truck;
- Ramp peak hour volume 950 veh/hr, 1% truck.
- Recurrent congestions, isolated bottleneck.

Data collection:
- Traffic count from 6-22 to 26, 2015, 3:30-6:30pm.
- Travel time and speed collected 2013-2015, multiple weekdays, 7:00-9:00am and 4:00-6:00pm.
- Travel time and speed collected using GPS equipped probe cars.

Wei, Liu and Yang (2017)

Example: Connected Vehicles

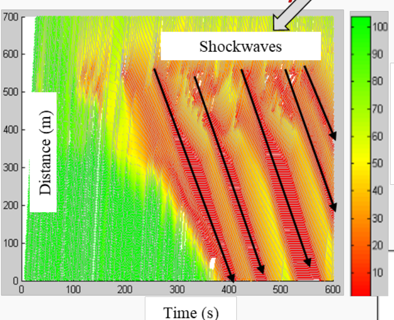
Case Study: Results on traffic management and emission controls

Liu et al. (2017), Wei et al (2017)
Wei, Liu and Yang (2017)

CV affected behaviors

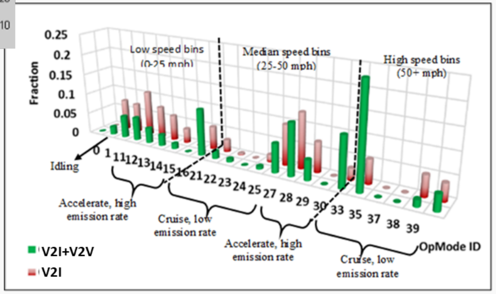
Traffic Disturbances
- Reduced frequency
- Altered temporospatial patterns
- Transformed intensity
- Interrupted propagation

- Triggering events that cause traffic breakdowns.
- Caused by LCs, overreactions and delay in responses.

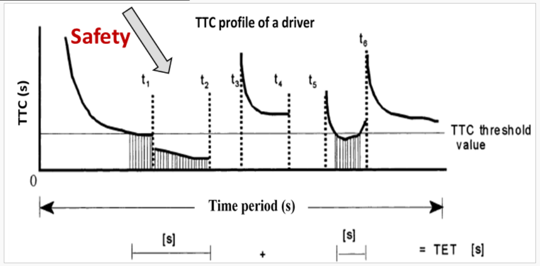


Throughput, density, delay, and speed, as well as congestion propagation pattern

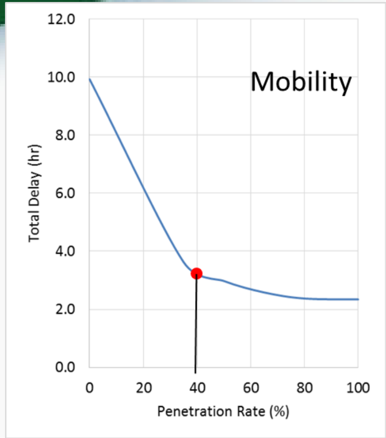
Emission

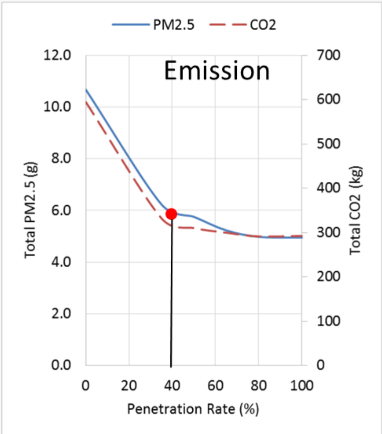


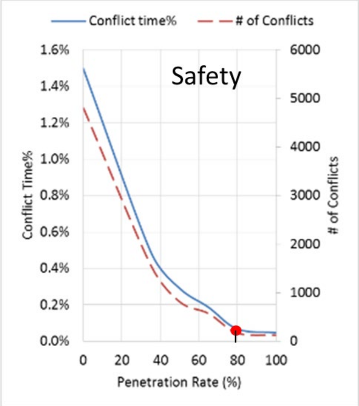
Emission rate



# of conflicts, conflict time%







Forward Collision Warning (FCW) Impacts

- FCW improves mobility, emission and safety.
- Improvement increases with larger penetration rate.
- 40% → turning point for mobility and emission curves.
- 80% → turning point for safety curves.

Summary

- AI applications in urban planning and engineering are beyond the traditional "weak" AI phase by providing advisory support to decision-making in the form of digital twin or physics-informed AI models
- EPA's Smart Urban Design (SUD) platform uses integrated model simulations of transportation and water systems under land use, climate and development scenarios. As a digital twin, its outcome helps decision-making in urban development and adaptation for resilient infrastructure.
- The Air-SUSTAIN model simulations allow regional-level analysis for urban adaptation. It also enables project-level analysis in applications such as CV-enabled traffic management to improve efficiency and GHG/CP emission reductions.
- Future AI developments focused on uncertainty management and multi-objective (e.g., traffic efficiency, climate and EJ) optimization.

Thank You!

Yang.jeff@epa.gov

weihg@ucmail.uc.edu

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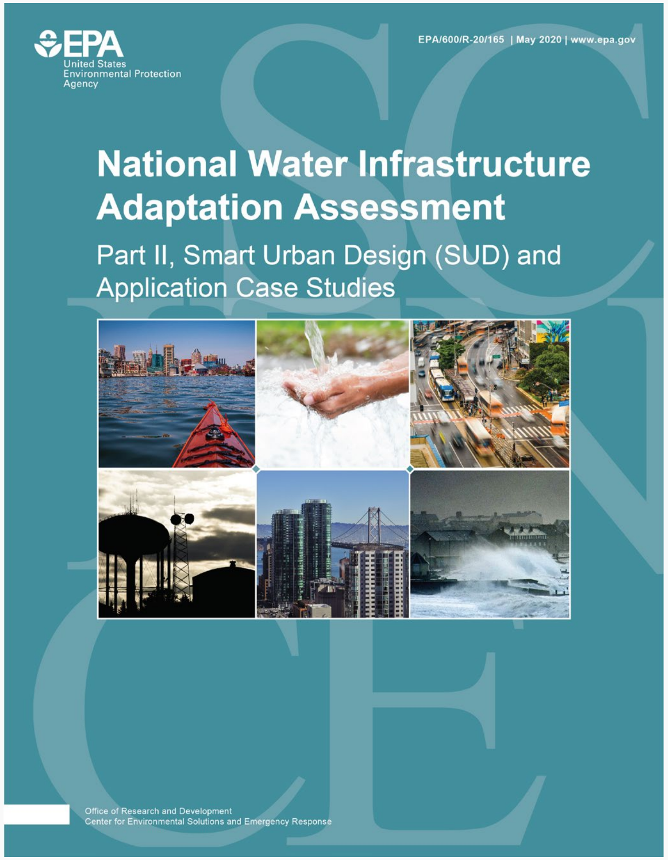

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