BAMS Article

Integrated Urban Environmental System of Systems for Weather Ready Cities in India

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ABSTRACT: Global urban population is projected to double by 2050. This rapid urbanization is the driver of economic growth but has environmental challenges. To that end, there is an urgent need to understand, simulate, and disseminate information about extreme events, routine city operations, and long-term planning decisions. This paper describes an effort underway in India involving an interdisciplinary community of meteorology, hydrology, air quality, and computer science from national and international institutes. The urban collaboratory is a system of systems for simulating weather, hydrology, air quality, health, energy, transport, and economy and its interactions. Study and prediction of urban events involve multiscale observations and cross-sector models, heterogeneous data management, and enormous computing power. The consortia program (NSM_Urban) is part of "weather ready cities," under the aegis of India's National Supercomputing Mission. The ecosystem "Urban Environment Science to Society" (UES2S) builds on the integrated cyberinfrastructure with a science gateway for community research and end-user service with modeling and interoperable data. The collaboratory has urban computing, stakeholder participation, and a coordinated means to scaffold projects and ideas into operational tools. It discusses the design and the utilization of high-performance computing (HPC) as a science cloud platform for bridging urban environment and data science, participatory stakeholder applications, and decision-making. The system currently integrates models for high-impact urban weather, flooding, air quality, and simulating street- and building-scale wind flow and dispersion. The program with the work underway is ripe for interfacing with regional and international partners, and this paper provides an avenue toward that end.

KEYWORDS: Coupled models; Communications/decision making; Decision support; Experimental design; Software; Urban meteorology

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Cities are cultural and economic drivers of communities. With rapid urbanization, the number of megacities has significantly grown in the last three decades and the trend is expected to continue. At the same time, cities are at risk of compound natural hazards (United Nations 2019a). Therefore, cities continue to be stressed for access to environmental services (managing land, air, water, noise reduction) and service infrastructure (such as roads, buildings, power, water supply, transport). With population and economic changes, cities also face issues related to gentrification, social equity, and ensuring support for vulnerable citizens. The increasing vulnerability to the urban sectors, especially due to climate change effects, adds another criticality. Urban global disease burden due to ambient air pollution is high and is exacerbated by pandemics such as COVID-19 (Liang et al. 2020). Urbanization imposes exaggerated effects on local hydrometeorology and air quality through exchanges between the urban and ambient atmosphere, further accentuating extreme events and damages (Bai et al. 2018; Liu and Niyogi 2020). Without an adaptation and mitigation strategy, these damages are projected to be multifold (Solecki et al. 2021).

Cities in emerging countries are experiencing unprecedented growth (Ritchie and Roser 2018). Urban areas are not only affected by the climate vagaries but are also contributing to the extremes. For example, Kishtawal et al. (2010) showed that increased monsoon heavy rains are a signature of urbanization across India, while Paul et al. (2018) identified increased spatial variability in the rainfall extremes due to urbanization. Kotharkar and Ghosh (2021) surveyed urban heat intensification within the south Asian context. Studies have also demonstrated declining air quality and large-scale health and mortality impacts in India and Asia (Ghude et al. 2016). Addressing these issues, municipalities and civic groups are seeking guidance from the science community to understand and manage the complex cascade of urban environmental processes (Limaye et al. 2018). For translating this guidance in a two-way service, an interdisciplinary coproduction approach is essential.

Within cities, environmental processes have notable spatiotemporal variation due to the heterogeneous urban terrain and often the numerical simulations of these variations require the accurate representation of microscale processes. The meteorological events affecting the city often have genesis and feedback beyond the urban domain and thus require a multiscale framework. The response of different forcings such as heating, roughness, thunderstorm, air quality varies from city to city. The urban impacts depend on the location, terrain, climate, socioeconomic conditions, and infrastructure, requiring research capabilities from cross-sector domains. Also, city-based research is often constrained due to siloed development and absence of cross-sector knowledge sharing platforms, the seamless coupling of cross-sector models, computing resources, and access to multiscale data. The cumulative advantage of “shared knowledge” of city researchers with contribution of multidisciplinary experts, community organizations, and citizens is critical for building impact-based forecasting methods scaling across cities for effective services.

Cities do not have to wait for a disaster to initiate environmental prediction systems (Grimmond et al. 2020). The way forward is proactive microscale cross-sector modeling, interoperable databases, city-level inventories, supercomputing resources, and value-added decision systems (McGovern et al. 2017). To that end, advances in supercomputers, satellite measurements, and urban-scale parameterization enable high-resolution modeling that can capture neighborhood-scale processes (Liang et al. 2018; Neumann et al. 2019). Furthermore, newer sources of observations and processing methods with high-performance computing (HPC) and fourth industrial revolution (4IR) technologies such as internet of things (IoT), mobile computing, big data, social computing, and artificial intelligence (AI) are augmenting urban science, creating an opportune moment for integrated urban services (IUS) (Gidhagen et al. 2020). Our IUS approach builds on the WMO (2019) definition: “provision of weather, climate, hydrology and air quality infrastructure (data, observations, predictions) to support and integrate traditional and new services, including extreme events such as thunderstorms, flooding and air quality, enabled by an advance digital ecosystem.” The smart-city mission is an opportune moment for transitioning to such IUS in Indian cities (Ministry of Urban Development 2015). In this context, a cross-sector science and technology platform for research and operational services is warranted.

The effort summarized in this paper builds off a large collaborative project underway related to the model of models framework encompassing weather, hydrology, air quality, health, energy, and socioeconomic processes across scientific and governance boundaries with different complexities and cascading influences. The project is being implemented in India under the aegis of the National Supercomputing Mission (NSM) of the Government of India (nsm.gov.in) with 70 supercomputers deployment across the country. Extending the “weather ready nation” (Campbell et al. 2018) framework to a “weather ready cities” concept, the consortia program (NSM_Urban) is titled “Urban Modeling: Development of Multi-Sectorial Simulation Laboratory and Science Based Decision Support Framework to Address Urban Environment Issues.” It focuses on modeling urban forecasting configurations for making actionable decisions and science-based risk mitigation. It has relevance beyond local levels [Central Pollution Control Board (CPCB); CPCB 2019; Pune Resilience 2020; United Nations 2019b]. The project’s objective is to extend IUS to urban environment cyberinfrastructure as a “collaborative, science and governance driven urban system” enabled by democratic access of technologies to make cities “sustainable” and “livable.” From this framework, the urban environment cyberinfrastructure (CI) emerged: “Urban Environment Science to Society” (UES2S) a multidisciplinary, multimodel, and HPC-enabled ecosystem translating research into services. It has a national and international collaboratory of cross-sector researchers, key stakeholders, and end users. The fully developed UES2S will be part of national services and adaptable to cities from other countries.

Science, technology, and service gaps and challenges

Understanding user needs and translating scientific data into “fit-for-purpose” information with advanced communication is critical in operational IUS. The building blocks involve data access, modeling, generating products to disseminate, and user integration and feedback (WMO 2019). The setup also needs to include prototypical scientific experiments, software development, and service deployment. Before the technological and modeling setup is developed, it is important to develop scientific understanding using case studies, the involvement of receptive, operational forecasting meteorological expertise and leadership, and the development of institutional partnerships through scalable pilot projects. These activities were aggressively set in motion 3–5 years before the actual kickoff through community workshops and pilot projects.

Science framework. Effective IUS are science questions and data driven. Traditionally, urban processes have been studied with sector or domain specific analysis—urban heat or energy management or flooding. However, considering the cross-section cascading impacts, the interaction between natural and anthropogenic processes, such as exposure from vehicular emissions, and floods due to paved roads or walls needs to be interactively considered. The study of feedback of infrastructure, localized meteorology, and resulting impacts on pollution and flooding as a continuum is essential for designing city solutions. This presents the first challenge for this collaboratory's end goal: the ability to simulate and study interfaces between urban events.

Despite the NWP models' improvements, accurately simulating small-scale variations due to microscale heterogeneities is still challenging. For this, regional- to building-scale seamless linkages are desired (Chen et al. 2011). For model integration, urban-scale representations also need high-fidelity regional initial and boundary conditions. The flooding patterns depend on infrastructure aspects such as infiltration, runoff pattern, and drainage structural information, and on the dynamical factors such as rainfall timing, intensity, duration, and spatial patterns. Understanding these spatiotemporal variabilities requires a number of customization and experimentation for assessing the influence of different parameterization, initial conditions, and urban representation of a model (Teixeira et al. 2019).

Urban model performance is highly dependent on the access and availability of different datasets. For example, weather and air quality model accuracy improves with the assimilation of urban surface data, land use–land cover beyond the urban area, gridded emission inventory, and satellite data (Baklanov and Zhang 2020; Kim et al. 2020). Thus, an integrated system needs an interface and access to different types of observations. Urban regions have relatively limited legacy data, and the inclusion of newer sources of measurements such as IoT, mobile phones, and crowdsourcing provides an opportunity for better spatiotemporal data. However, its inclusion in prediction models is still challenging. Also, the model verifications and validation need observational datasets. Often, these are in heterogeneous formats and not readily available, hindering urban environment research.

The coupling of covariate models is essential in understanding the atmospheric–chemical exchanges, hydrometeorological processes and interdisciplinary cause–effect analysis (e.g., Givati et al. 2016). Thus, instead of treating meteorology inputs as offline conditions, researchers are increasingly using the online, two-way coupling of air quality and meteorology (Grell and Baklanov 2011; Sharma et al. 2016). Therefore, creating a computing framework for such interactive models becomes a challenge. Additionally, linking multiscale models is also critical. For example, cities need information about neighborhood-scale pollution and emission sources. For better insights regarding street-level pollutant level, computational fluid dynamics (CFD) models configuring microscale mesh geometry that can simulate 3D turbulence, coupled with urban canopy models for surface energetics, pollutant transport within urban canopy layer need to be simulated. These models run with different numeric and physical options, such as a combination of finite difference (e.g., WRF) and finite volume (OpenFoam) for microscale simulations (Triscone et al. 2016). And these models require city morphological data: building height, type, open spaces, and anthropogenic activity data, such as traffic flow (Ching et al. 2018). Simultaneously, local processes are influenced by neighboring periurban or rural features such as upstream heavy rainfall or agricultural burning. Configuring models at different scales using two-way feedback gives a better representation of these events. This again highlights the need for coupling multiscale models to simulate regional conditions in surrounding regions, thereby improving the urban processes and predictions (Che et al. 2020).

Although, urban-scale environmental modeling has shown progress with finer resolution (grid spacing), with its ensemble of multi-initial conditions, multimodel runs improving the forecast skills (Karlický et al. 2020; Roebber et al. 2004), the access to computational resources is the bottleneck (Brasseur et al. 2019). Therefore, an important component of the collaboratory has to be an enabling computational ecosystem through access to HPC resources, and data management (Bassett et al. 2020; Carmen et al. 2017).

Integrated urban services. The perspective provided by the urban stakeholders for the collaboratory was primarily the last-mile approach. The stakeholder requirements related to short- to long-term urban planning and strategic decisions, such as identifying emission sources, implementing pollution control measures, building infrastructure, green spaces, business hub locations, and transport, are currently not coupled to the environmental and climatic impacts. This disconnect between urban planning and urban climate is well known (Friend et al. 2014). Pilot projects have shown the value of environmental and urban weather/hydromet modeling for event-driven actions such as short-term road closure, increased congestion charges, extreme event alert, and vulnerable population advisory (Baghestani et al. 2020). Also, city decision-makers highlight that the prediction information is often available for the entire city and not at the neighborhood scale. The impact being at microscale, the coarse information does not serve the purpose of communicating routine and strategic information and preparedness decisions to those affected or to those managing the risks (Baklanov et al. 2018). Thus, the requirement is for timely, granular communication transferring scientific knowledge to governance to have effective services for their clients (González et al. 2021). Besides this, the cross-sector services often operate in silos with independent objectives and usage patterns, without exchanging information or data; e.g., energy demand–supply management and urban heat island information are not available to the concerned city departments. For such applications near-real-time dissemination of risks and adaptive strategies is necessary as a part of the IUS.

Technology. IUS requires access to multiscale, heterogeneous data for effectively addressing the science, and the governance needs. Its unavailability is a major impediment in cross-sector modeling and impact research (Wang and Moriarty 2018). The extraction of meaningful data from numerous datasets and its processing is another technological challenge. Newer processing models such as machine and deep learning are offering value aid. Both from the perspective of speeding the predictions, and for improving the accuracy and timeliness of process-scale models, AI/machine learning (ML) approaches often augment NWP with pattern recognition, data fusion, newer data relations, data calibration, satellite data mining, better parameterization, and value-added forecast (Cho et al. 2020; Sun and Scanlon 2019). Domain and computer scientists together need to coaddress these challenges in coupling the physical models with ML, predictability, and data security (Reichstein et al. 2019).

Access and availability of computing power are critical for effective real-time simulations and the background research required. Even when the end user for the urban models is within the scientific community, it is known that urban canopy and CFD models consume considerable computing resources and time. Parallelization and optimization with efficient memory cache utilization, fast I/O, architecture specific optimization (e.g., GPU), load balancing, and scalability analysis influence the throughput time of model simulations (Liu et al. 2016; Michalakes 2020). Numerical models are complex in execution involving preprocessing, extensive simulations, postprocessing, libraries, memory management, parallel job submissions, and debugging (Simm et al. 2020). In operational executions, faster throughput time is critical. Researchers spend considerable time on these tasks and discovering, curating, and preparing data for research (American Geophysical Union 2019). Often, it is found to be cumbersome for scientists from cross-sector disciplines or with limited computational skills. Moreover, it distracts the primary goal of science discovery and limits collaborative experimentations. Another challenge is to manage the interoperability due to heterogeneous formats with variation in spatial (ward and neighborhood, subdivision, city, district), temporal (subhourly, daily, or longer term), or storage format (XML, ASICC, netCDF, HDF5, text) characteristics (Creutzig et al. 2019). For IUS to be scalable and valuable, efficient, standardized modeling and data protocols and methods to access newer data sources from crowdsourcing and social media are needed [Telecom Regulatory Authority of India (TRAI); TRAI 2020]. Archiving model output with appropriate cataloguing of type, frequency, schemes, location, parameters extracted for cross-sector model runs, comparisons, and AI training requires large storage and efficient compression techniques. This technological backbone is essential for the IUS to be effective.

Abstracting these computational ecosystem tasks, bringing science to platforms where data reside, and architecture specific model code optimization through cloud computing provides more "science productive" mechanisms for collaborative research (Duran-Limon et al. 2016; Moreno et al. 2019). Variants of cloud services, such as infrastructure as a service (IaaS), data as a service (DaaS), system as a service (SaaS) and modeling as a service (MaaS), offer researchers effective options for modeling and analysis. In the context of reducing carbon footprint, reusability of models, data, and tools through shared knowledge and cloud CI (Aronson 2015) are also advocated.

Harmonizing cross-sector research, aggregation of data, computational, and human resources, provides a value proposition across cities, especially in emerging economies. Democratizing the access to computing and making accessible to many small research groups, universities, and local stakeholders is a guiding pathway for the IUS setup.

To address the above gaps and challenges (Fig. 1), an easily accessible and centralized modeling and decision framework with city-tailored IUS services is outlined. In addition to the data, models, and decision systems, human capacity development is an integrated component of the collaboratory. This feature is often underdeveloped, and without the right educational and training program, the efforts in interdisciplinary urban sciences are not sustainable. Addressing this, opportunities for vertical integration of students, city staff, stakeholders, and researchers through knowledge sharing, formal postgraduation education, training programs, workshops, and summer schools are embedded within this collaboratory.

NSM_Urban program overview

Building on the framework outlined above, the NSM_Urban Collaboratory is formed to investigate urban weather, air quality, and hydrology events and develop impact-based solutions. The collaboratory was developed with national and international partnerships from the Indian Institute of Science (IISc), Indian Institute of Technology (IIT) Bhubaneshwar, IIT Madras, Indian Institute of Tropical Meteorology (IITM), Indian Space Research Organization (ISRO), Karnataka State Disaster Management Agency (KSNDMC), India Meteorology Department (IMD), Purdue University, and the University of Texas at Austin.

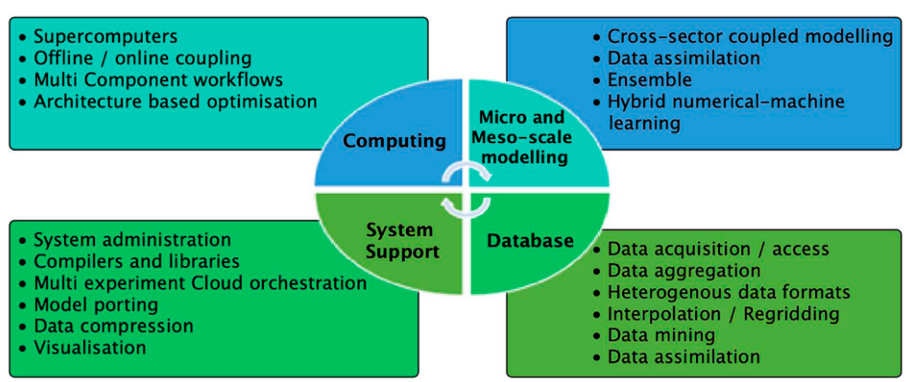

Fig. 1. Urban environment modeling and service challenges.

The program goals are to facilitate urban researchers with modeling and technology platforms for tailored end-user services. This is being achieved in two phases: phase I—"meteorology and hydrology, CFD, and air quality" modeling platform and decision support system (DSS); phase II—includes impact sectors, viz., health, economy, transport, and energy (Fig. 2). This paper deals with phase I, which has been operational since 2019.

The project objectives include the following:

1) Improve the understanding of urban-/neighborhood-scale atmospheric processes, extreme events, risks, and vulnerabilities and provide urban-scale forecasts through multiscale, multisector modeling research.
2) Promote cross-sector partnership translating research into end-user solutions.
3) Promote open science and open data by democratizing HPC resources and "bringing science to the data."
4) Strengthen the value chain from research to local governance to citizens with an end–end cyberinfrastructure "UES2S."
5) Build capacity through training and mentoring.

As stated, technological integration through CI is one of the important aspects of the UES2S. The infrastructure components underway include (i) knowledge repository of data (model initial conditions, observations, satellite data, model output, historical datasets); (ii) model portals (weather, hydrology, air quality, CFD); (iii) model scenarios and case studies (pollution mitigation, flood mapping, extreme events); (iv) design of interactive DSS with big data, 3D visualization, GIS, and end-user data dissemination and web and mobile app services; (v) scientific cloud services for urban environment IaaS, DaaS, MaaS, and SaaS with workflows; and (vi) capacity building (training and outreach).

The development mechanism of UES2S has an agile research approach, building on existing knowledge, data, and methods in a participative manner involving experts from weather, air quality, hydrology, computational science, and representatives of regulatory agencies (Jena et al. 2021; Mujumdar et al. 2021; Niyogi et al. 2020; Yalavarthi and Kaginalkar 2014). The work underway is structured with science groups for improving urban-scale environment model forecasts and technology groups for developing data and application services (Fig. 3).

Engaging stakeholders as knowledge coproducers is emerging as a powerful opportunity for enhanced urban climate studies and services (Commodore et al. 2017; Fragomeni et al. 2020; Meyer et al. 2018). NSM_Urban has two types of stakeholders: 1) within-project science stakeholders and in particular the cross-sector modelers and 2) decision-makers or application users from the governmental and private sector. The stakeholder engagement is integrated within the project activities, including the codevelopment of project ideas and scope. These examples include community of practice meetings with local municipality

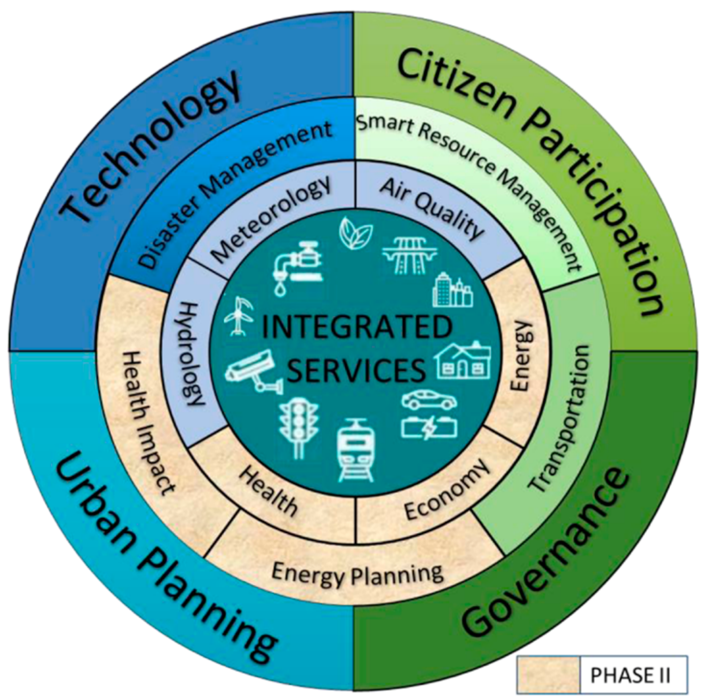

Fig. 2. UES2S integrated modeling and service scope. Phase I: Meteorology, air quality, hydrology. Phase II: Health, economy, energy models.

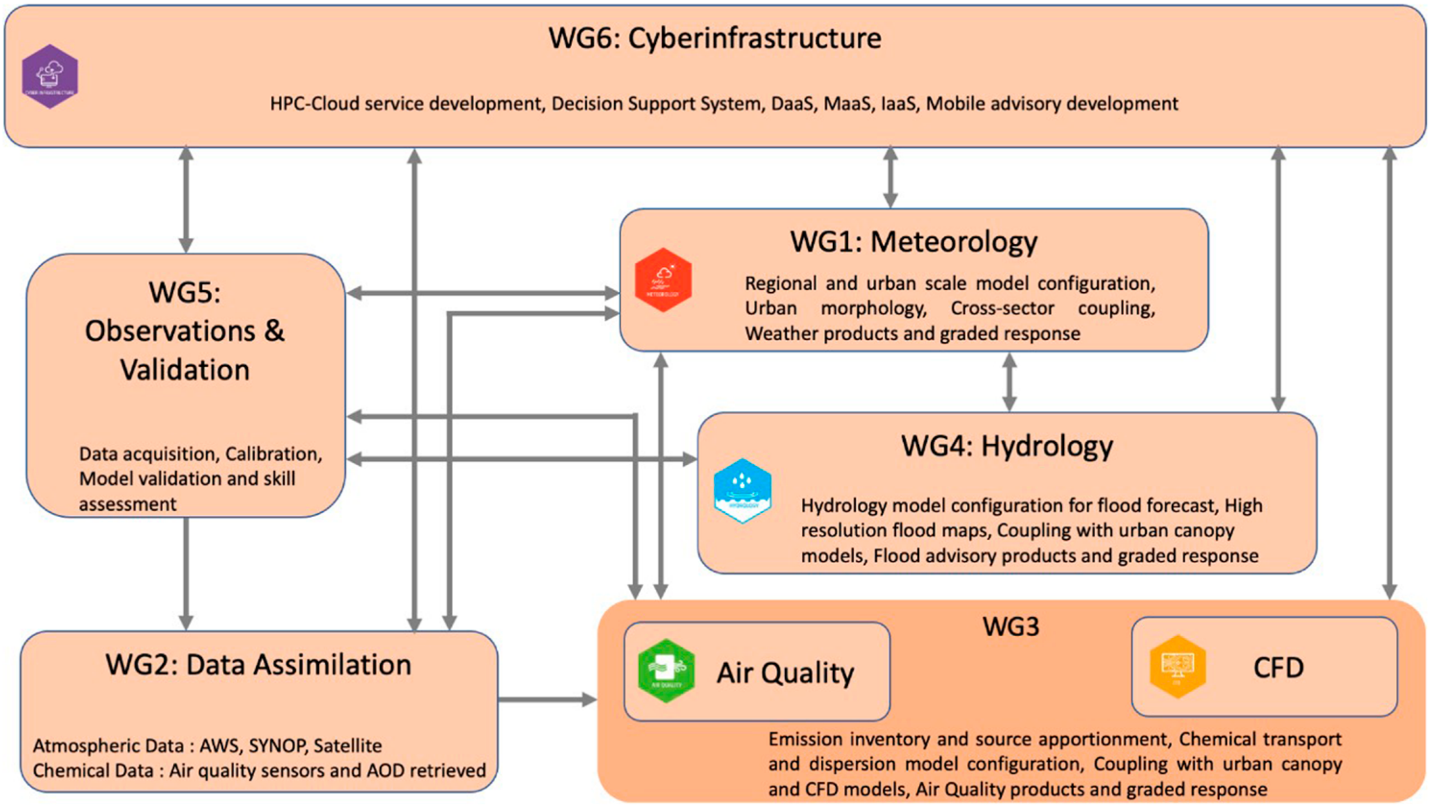

Fig. 3. NSM_Urban Collaboratory with science and technology working groups and component linkages.

environmental departments (in five cities: Ahmadabad, Bangalore, Bhubaneshwar, Delhi, and Pune), city and state disaster management agencies (Karnataka, Orrisa, Pune), smart-city managers, and municipal commissioners, as well as with researchers, educators, CPCB, and IMD.

These engagements sharpened the project objectives to proactively anticipate, and respond to the urban challenges. These activities had four major themes: 1) environmental challenges and risks faced by city operators; 2) requirements and expectations from the scientific community; 3) cross-sector data interoperability between science–science, science–governance, and governance–science systems; and 4) services creating values to the end users. This evolved into a triangulation development approach: requirement analysis, case study prototype designs, and peer review test bed of sector-specific knowledge transfer practices. The participative prototype development serves the joint "product idealization" leading to "realization" of the expected outcome. This is reflected in adopting the mixed system development life cycle method: spiral and iterative incremental (Ruparelia 2010).

A notable example is the cocreation of the system requirement specification (SRS) document that has helped build ownership among stakeholders in all aspects of the project. It enabled eliciting the functional and usability requirements, for example, 1) Pune city disaster management department needed information of not only flood vulnerable areas but also flood condition along all the routes from these areas to different hospitals for ambulance route planning, whereas modelers received information on flood hotspots, frequency, and stormwater drain network information from city administrators; 2) CPCB sought to provide advisory for mitigation measures, such as curtailing construction work in a ward with excessive pollution; and 3) development of the flood advisory in local language for citizens. The coproduction enabled the design of a "knowledge and usability" driven decision-making framework by mapping cross-sector user profiles (Fig. 4). Citizen participation is also integrated with the DSS and mobile app.

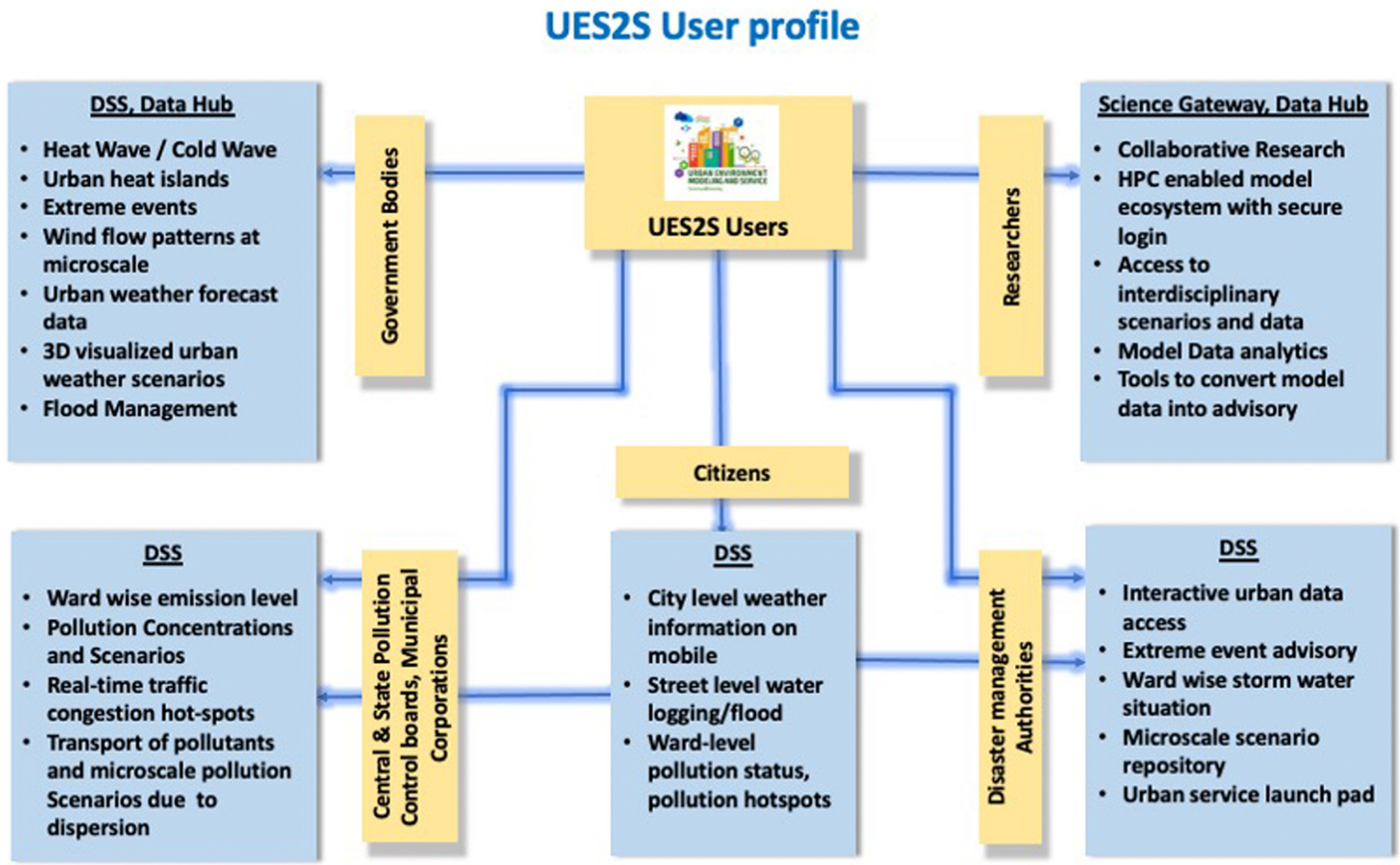

Fig. 4. UES2S user profile: Researchers, disaster management authorities, regulatory agencies, national environment services, and citizens.

UES2S cyberinfrastructure

The modeling and service cyberinfrastructure, UES2S concept is aligned with the emerging concept of "living laboratory" and "digital twin" approaches (Barlow et al. 2017), creating a value proposition for different stakeholders. UES2S CI has four modules: data infrastructure (data hub), modeling ecosystem [science gateway (SG)], DSS, and value-added analytics (urban intelligence) (Fig. 5).

The data hub has a DaaS facility (Allam and Dhunny 2019) for data and metadata access with tools such as urban morphology and urban local climate zone (LCZ) following the World Urban Data Analysis and Portal Tool (WUDAPT) (Ching et al. 2018). The data architecture has a readily available data catalog of (i) observations: in situ, smart-city IoT sensors, satellite, and radar; (ii) city data: urban morphology, demography, CCTV images, DEM, congestion information, and vulnerable areas; (iii) model data and metadata: global model initial conditions, assimilation datasets, and regional/urban model output; and (iv) social computing: social media, tweets, and crowdsourcing (available in phase II). Data are visualized using standard tools such as GRADS, NCL, VAPOR with 2D, 3D visualization, and GIS layers.

The SG follows the virtual laboratory concept (Blair et al. 2019; Zhuang et al. 2020). This involves abstracting underlying hardware, middleware, libraries, interfaces, and data processing, enabling modelers to choose "fit for purpose" selection. SG provides MaaS with built-in and plug-and-play model workflows with WRF, WRF Model coupled with Chemistry (WRF-Chem), AERMOD, OpenFoam, Storm Water Management Model (SWMM), Hydrologic Engineering Center River Analysis System (HEC-RAS), and HEC Hydrologic Modeling System (HEC-HMS) model configurations, facilitating ensemble simulations and generation of prebuilt model scenarios.

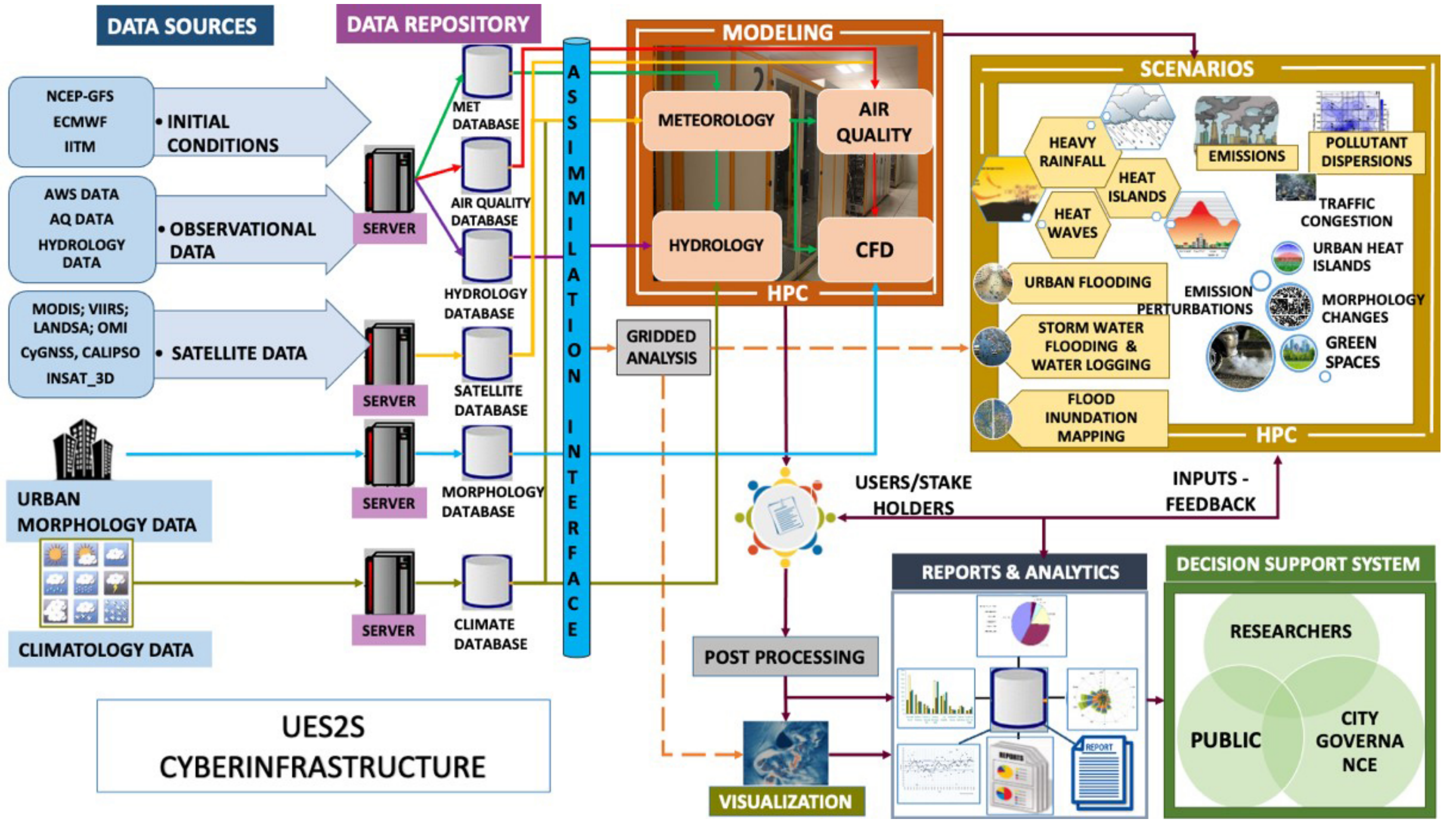

Fig. 5. UES2S system with data hub (blue), science gateway with modeling (red), urban intelligence with scenarios (brown), and DSS with visualization, analytics, and feedback data (mobile, crowd-sourcing) components (green and blue).

DSS setup is the integrator and interfaces for the research and the stakeholder community. The research supported output becomes valuable if automated and timely access to impact information accelerates the end-user decision-making. DSS supports, user query-driven interactive access to information derived through model output using the web and mobile platforms. It enables data dissemination and interactive interfaces for city environment data, scenario metadata, and infographics for tailored SaaS. For example, in mitigation planning, city regulators can interactively estimate the impact of emission control before recommending different measures (Fig. 6) using a GIS-based emission inventory module. The projected reductions are calculated considering applicability with a combination of actions such as restrictions on old vehicles, closure of brick kilns, and stopping heavy vehicles on a road sector.

For real-time decisions in extreme event situations, the timeliness of model forecast and appropriate decision-making is critical. This is supported, by building an expert system of presimulated "what-if" multimodel neighborhood scenarios of rainfall extremes, UHI, and pollution control enhanced with ML methods. In addition, user will be able to access model output and observation datasets for executing AI experiments through the "urban intelligence" module using big data analytics.

Understanding, predicting, and disseminating urban events

One of the highlights from the cross-disciplinary team exercise is the need to test the modeling configurations for similar, select cases. For example, the meteorological modeling team simulates the heavy rain case for domains used by the hydrological flooding team, and this domain is also of interest to the stakeholders. As a result, cross validation and evaluation of modeling platform and prototype case studies were undertaken as the team's first critical milestone. Several experiments pertaining to extreme rainfall, pollution prediction services, and flood management using a cross-sector modeling environment (Fig. 7) were undertaken to understand microscale

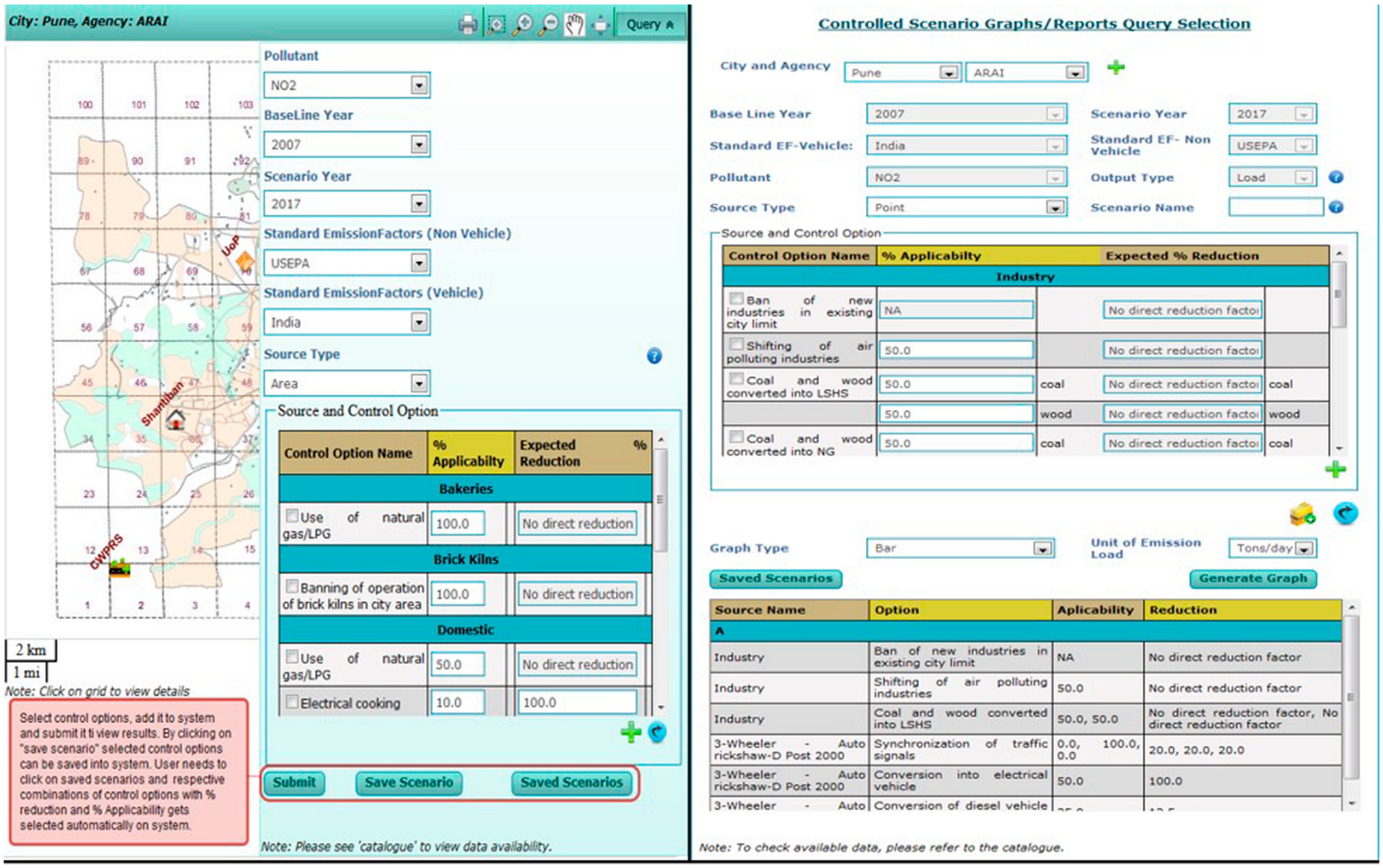

Fig. 6. DSS with interactive sector-specific pollution control options and applicability assessment with GIS and statistical analysis queries.

features and assess the forecast accuracy of urban environmental systems. In addition, experiments with extreme rainfall spatiotemporal analysis, the impact of urbanization, evaluation of modeling parameterizations for different urban case studies, impact on PBL, chemical, satellite, radar data assimilation for improving forecasts, sensitivity analysis, land use–land cover (LULC) and UHI effects, microscale weather–hydrology model coupling, emission source characterization, and the influence of nonlocal emission sources were carried out (Jena et al. 2020; Kedia et al. 2021, 2018; Kulkarni et al. 2020). These individual case studies discussed in this section serve two purposes: (i) eliciting digital ecosystem requirements (Jensen and Campbell 2019), as outlined in the previous section, and (ii) providing the design guidelines for upscaling the end-to-end application processes for other cities. Examples include automated workflows for model output conversion to DSS products and defining standard operating procedures (SOP) for different cities to undertake similar environmental services.

The UES2S allows research groups to conduct numerical experiments and simulations that are interoperable and reproducible by different teams. The end outcome is the ability to develop ensembles, and retain the model results and model configuration on a common computational workbench. This functionality allowed offline or fully coupled model integration. For instance, the WRF Model physics setup was based on considerable initial work undertaken for different cities. An example is given for Bhubaneshwar ("Case 1" section). The transferability of the configuration was cross validated by testing over other cities such as Pune and Bangalore with the same computing platform ("Case 2" section). The meteorological fields from WRF runs were ingested into the hydrological models as illustrated for the Bangalore case ("Urban flood management" section). Multiscale model simulations are demonstrated for Delhi ("Urban air quality modeling and early warning system" section). The project follows

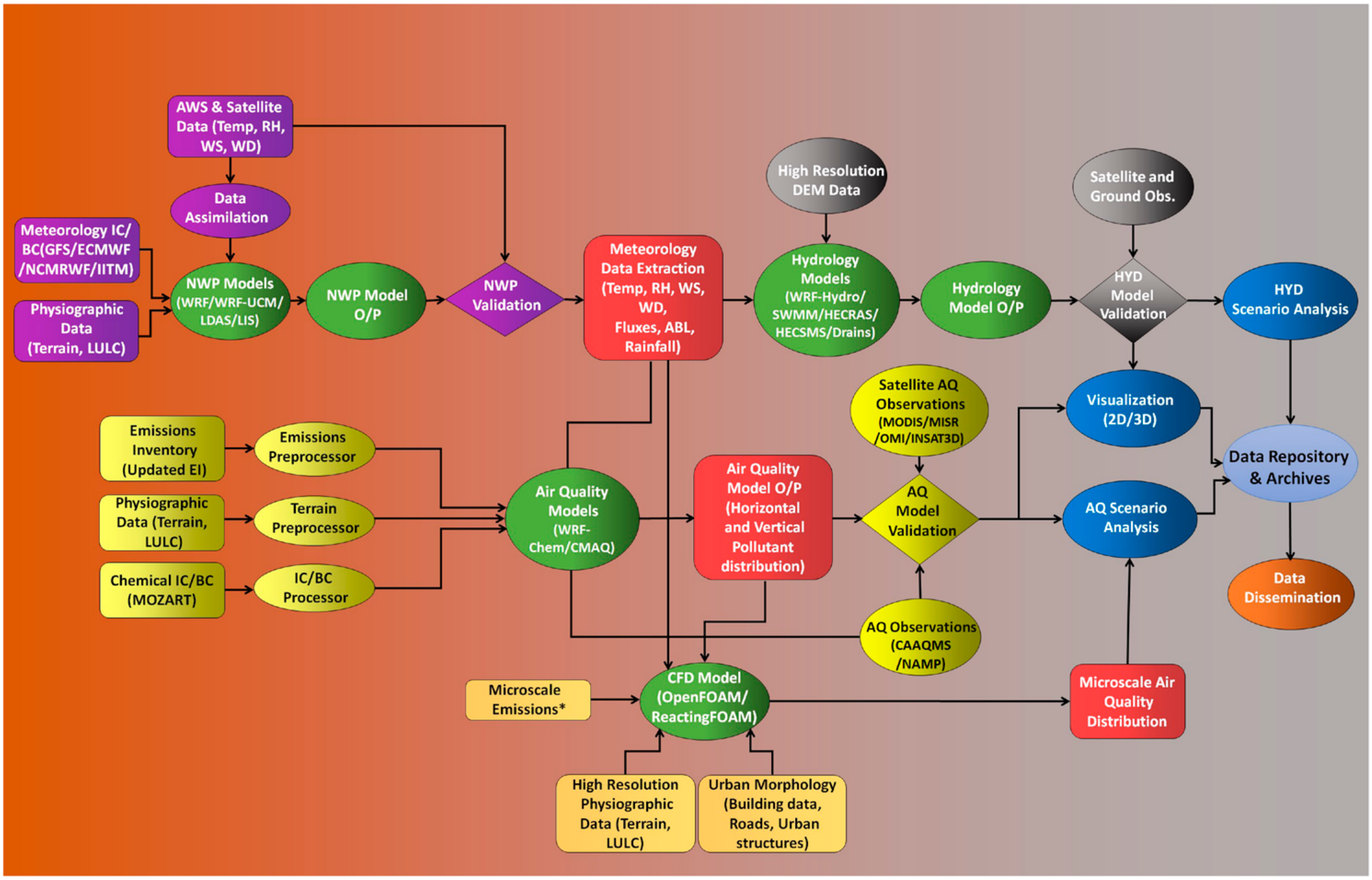

Fig. 7. Multimodel workflow in science gateway with plug-and-play component selection.

agile development with few case studies that are better developed due to the availability of city data as well as the proactive interest of city operators.

Urbanization impact and extreme rainfall episodes.

Case 1. A series of land-use experiments were performed to quantify the impact of urbanization in predicting the heavy rainfall events over Bhubaneswar, one of the first designated "smart cities" in India. Bhubaneswar is off the east coast about 50 km from the Bay of Bengal. This city has been impacted by cyclones, rains, and heatwaves and has a high vulnerability. How urbanization is interacting with these hazards and what can be done by the local agencies to help improve the livability have been the drivers for the study undertaken.

For this case, heavy rains resulting from a low pressure area over northwest Bay of Bengal (BoB) on 19 July 2018 were studied. The low intensified into a depression over northwest BoB on 21 July. The BoB cyclones have a relatively short life due to the small basin size. This system had a life period of 48 h and a relatively straight track. It produced widespread rainfall over triplet cities of Cuttack, Bhubaneswar, and Puri, leading to a heavy flood situation in parts of Bhubaneshwar (www.rsmcnewdelhi.imd.gov.in).

Different land-use experiments using WRF-ARW (Skamarock et al. 2008), consisting of three domains with a coarse domain of 4.5-km grid spacing (d01), an intermediate domain of 1.5-km grid spacing (d02), and a convection-permitting domain with 0.5-km grid spacing (d03) were performed. Experiments focused on the urban land-cover changes within the innermost domains to assess the rainfall changes due to urbanization. The model physics followed prior configurations that have been used over the Indian city for heavy rain simulations (Patel et al. 2020). Land-use maps for Bhubaneswar–Cuttack City were derived for

1980, 2000, and 2019 from different satellite datasets available at the U.S. Geological Survey (USGS). A supervised classified LULC map was used to assess the urbanization and LULC change from 1980 to 2019 (Figs. 8a–c).

Model urban physics experiments with the combination of urban canopy model (UCM), namely, without UCM (NoUCM) and single-layer UCM (SUCM) along with the different land use (CNTL; i.e., with default land use; 1980, 2000, and 2019) were performed. Daily and subhourly rainfall from IMD at 4-km grid spacing IMERG–Global Precipitation Measurement (GPM) was used for verifications. The time–longitude cross section of 3-h rain (mm h^{-1}) obtained from all the model experiments and the corresponding GPM rainfall is shown in (Figs. 8d–l). The NoUCM experiments showed higher rain irrespective of the LU changes over the urban region (Figs. 8e–g).

The results showed notable variations in the simulated rain for the four experiments. A peak rainfall of above 70 mm h^{-1} is simulated from all the NoUCM experiments. Except for the 2019 land-use experiment, the remaining three experiments of SUCM exhibited higher

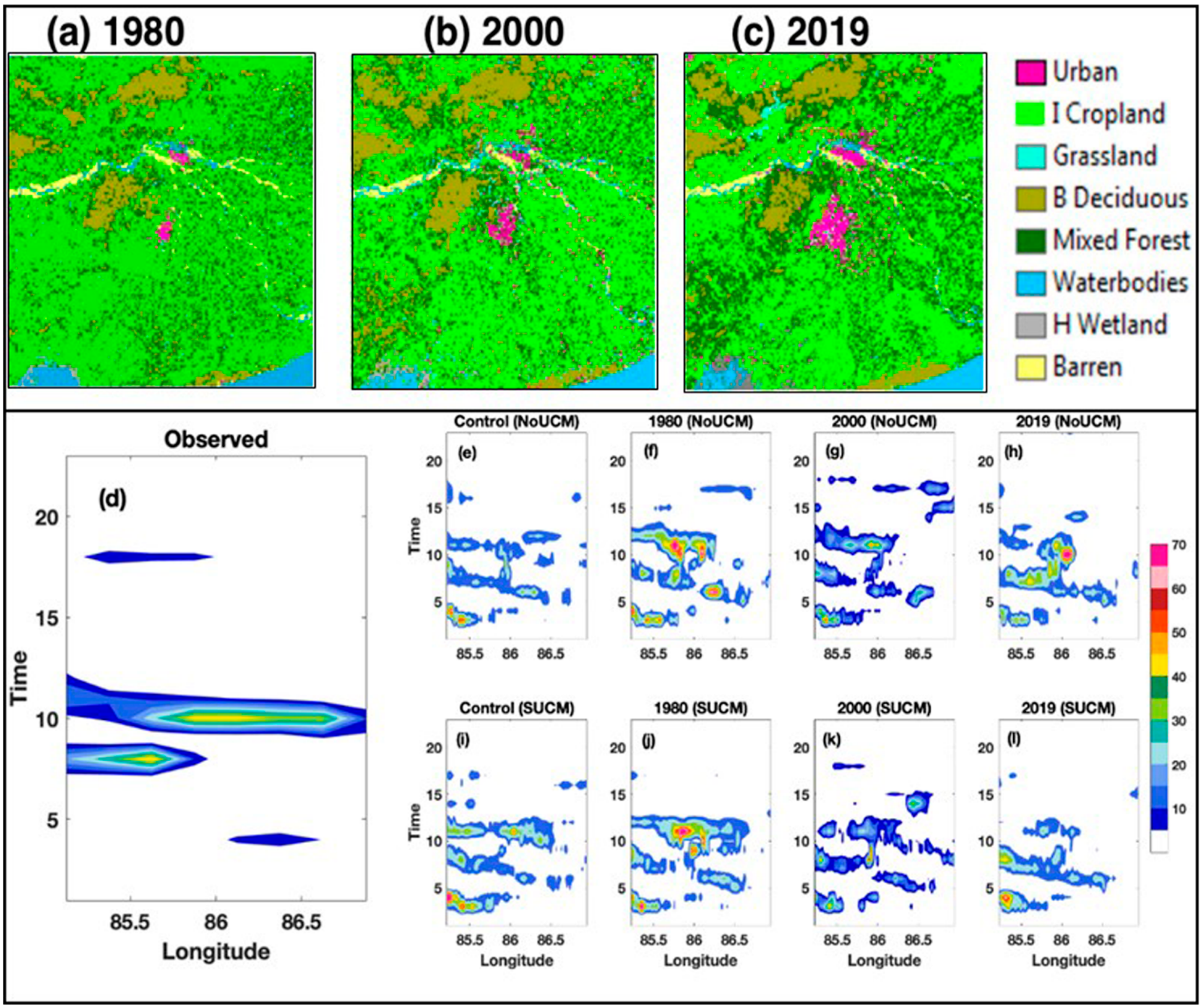

Fig. 8. Classified LULC map for the Bhubaneswar and Cuttack region for (a) 1980, (b) 2000, and (c) 2019. The time–longitude cross section of 3-hourly rain (mm h^{-1}) obtained from (d) GPM, (e) CNTL (NoUCM), (f) 1980 (NoUCM), (g) 2000 (NoUCM), and (h) 2019 (NoUCM) land-use experiments are presented. (i)–(l) As in (e)–(h), but with single-layer urban canopy model (SUCM).

rainfall (Figs. 8i–l). The prediction bias was reduced when the model was updated with the 2019 land use, and when the urban physics was explicitly incorporated in the experiments (Mohanty et al. 2019). This can be attributed to urbanization enhancing the heating of the built-up area and the changes in the rainfall (Niyogi et al. 2020). In addition, the presence of localized urban heating, and surface heat flux gradients around urban–periurban regimes aided the circulation around the city. This localized feedback potentially shifted the rainfall away from the city (Schmid and Niyogi 2013). The results are in tandem with prior reports that reported urban rainfall reduction over the city and enhanced mesoscale convection and rainfall dissipation due to heat islands (Liu and Niyogi 2020).

The results provide an example of the rainfall changes that are expected due to the urbanization changes, and the need for considering different model physics and urban configurations in developing the analysis and workflow design. As this region is prone to heavy monsoon rains which cause urban flood risk, the meso- and microscale model products are shared with IMD and Orissa State Disaster Management Agency (OSDMA).

Case 2. The previous case focused more on the process-scale assessments and was a research-centric endeavor. This case is slanted toward the computational setup and the research to operation transition requirements. For this, the WRF ensemble modeling setup with consideration of optimal configuration was the primary goal. In that, 46 experiments simulating multiple extreme rainfall events over Pune (Fig. 9e), about 200 km inland and in the Western Ghats rain shadow region, and 27 experiments for Bangalore in south-central India were carried out (Fig. 9a).

This discussion pertains to two specific rainfall cases. First, a heavy rainfall event over Pune during 24–25 September 2019, with accumulated rainfall of 123 mm. Pune, unlike the nearby coastal city of Mumbai, receives relatively fewer heavy rain events. Therefore, the 24 September event, with over 100 mm in a single day, was regarded as a catastrophe by the local media as it claimed human lives and large economic losses (Hindustan Times 2019) (Fig. 9g). The second case is a 24-hr extreme rainfall event over Bangalore from 0830 LT 8 to 0830 LT 9 September. This is in accordance with the daily rainfall readings obtained from the automatic rain gauges. (Fig. 9c). The objective for simulating these events was to evaluate WRF capability with sets of experiments using different initial conditions, domain size and resolution (Fig. 9d), LULC data, assimilation, and sensitivity analysis for six different microphysics schemes [e.g., Lin (Fig. 9h), Thompson (Fig. 9h), Ferrier, Goddard, Morrison, WSM5] and two PBL schemes (YSU, MYJ) (not shown in the figure) and as input to flood models ("Urban flood management" section). The model was configured with the outermost domain covering the Indian subcontinent (9 km), domain 2 covering India (3 km), and the innermost domain of 1 km over Pune and Bangalore. Simulations using NCEP GFS ($0.25° \times 0.25°$) and IITM GEFS ($0.125° \times 0.125°$) using initial conditions and a 6-h interval (Figs. 9c,g) were compared. Sensitivity analysis with old LULC (having a lower urban fraction; MODIS LULC-2005) and recent LULC [having a high urban fraction; Advanced Wide Field Sensor (AWiFS)-2018] data using AWiFS was conducted (Figs. 9b,f). Interestingly, for this ensemble studies, the land-cover and urban representation change had a relatively lower impact than other factors on the simulated rainfall. The results indicate that the model setup can capture some features of the heavy rainfall event. The impact of urbanization on extreme rainfall is nonuniform and highlights the need for continued robust analysis. The diversity in the results from the research to ensemble quasi-operational setup highlighted the need for interaction between the urban modeling team, customization of the urban schemes, and additional assessments, which will continue to be undertaken in the collaboratory.

Urban flood management.

An urban flood forecasting module addressing end-to-end requirements is developed for Bangalore urban region as one of the first prototypes. This was derived from an earlier project

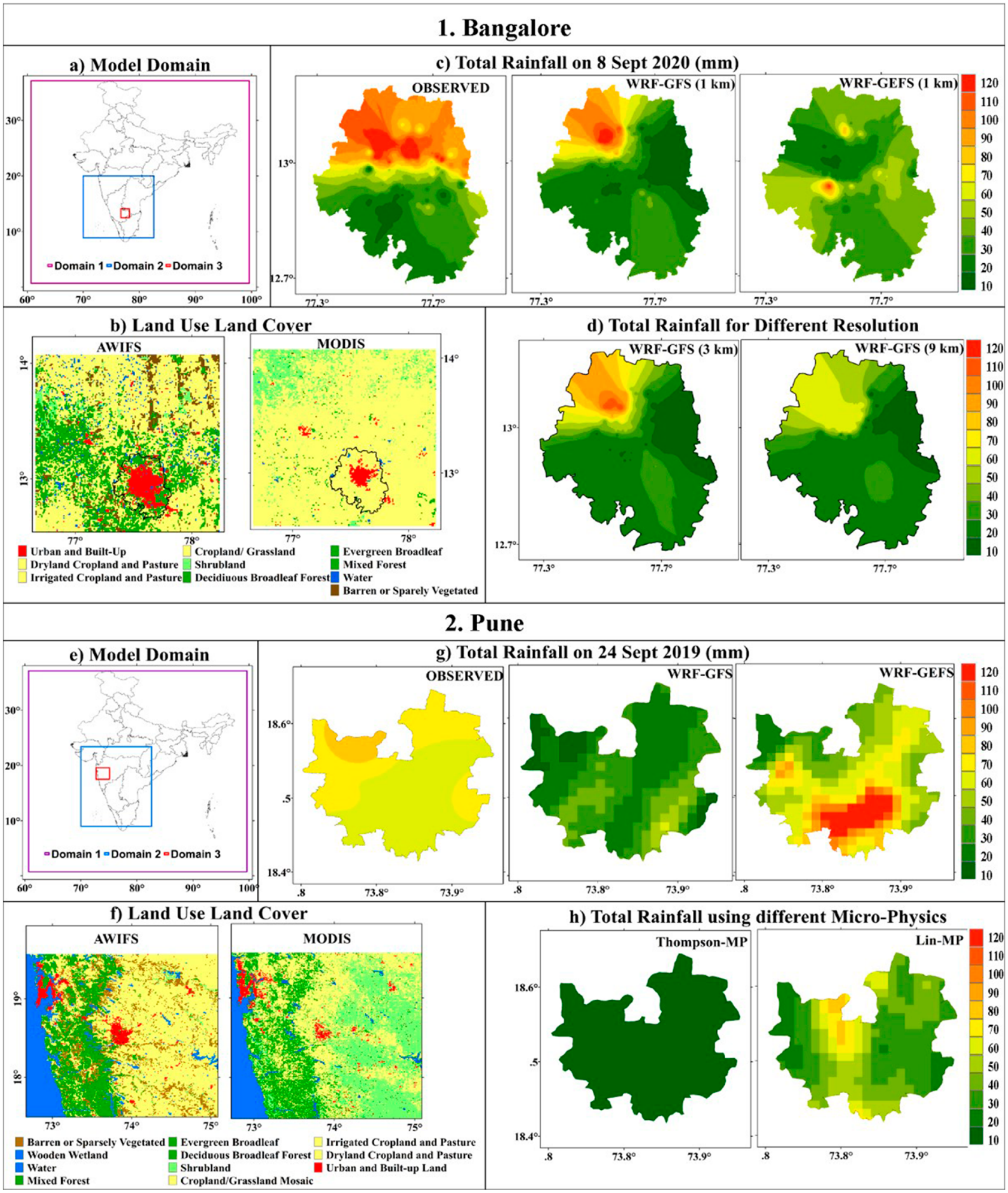

Fig. 9. Accumulated rainfall at Bangalore on 8 Sep 2020 and at Pune on 24–25 Sep 2019 simulated using WRF Model. (a) Bangalore and (e) Pune locations. (c),(g) Initial-condition comparison. (d) Resolution comparison. (b),(f) LULC sensitivity analysis. (h) The microphysics evaluation.

(https://sites.google.com/site/urbanfloodmodelbangalore/home). This case study focused on designing an SOP of SG to scale the prototype to other cities to help develop guidance for flood management. The urban flood system takes the WRF Model output as the input. This weather output is localized with the assimilation of location-specific weather data (Mujumdar et al. 2021), for a calibrated flood model. This setup is adaptive for various possible flood scenarios for assessment and for forecasting the flood vulnerable areas.

In this case study, the experimental setup has 1-km ("Urbanization impact and extreme rainfall episodes" section) and 3-km grid-spacing WRF configuration over Bangalore with a 15-min location specific forecast as input to the SWMM. The hydrological model setup over Hebbal valleyis shown, one of the three major valleys in Bangalore, the other two being Koramangala-Challaghatta (KC), Vrishabhavathi (Fig. 10a). The input data such as stormwater drainage network, channel dimensions, contours, and building shapefiles were obtained from a partnership with the local municipality. Water depth data at 15-min intervals from three water-level (WL) sensors were used for model calibration. The SWMM model was executed using the observed rain gauge data and rainfall predictions from WRF (both at 1 and 3 km). The flood model was found to perform well with modeled inundation depth found to be 1.77 m compared with the 1.54-m observed flood depth by the WL sensor for one of the events. The flow hydrographs from the flood model were used as an input to the HEC-RAS model developed over the same domain. The mesh in HEC-RAS 2D is at 10-m grid interval to generate flood-inundated area (Fig. 10b).

The model output, flood hydrographs, inundation and spread, and the observations from network of telemetry-based real-time monitoring system serves as an input to a citizen and government feedback system to help identify the vulnerable locations in the city. The workflow has multimodel components, and a mobile app—"Bengaluru Megha Sandesha" (BMS; translated as Bangalore Cloud Messenger)—provides location specific rainfall, flood forecasts, and inundation information across the city (Fig. 11). It also includes nowcast temperature, rainfall, relative humidity, and wind speed and direction. This application is run through KSNDMC interfacing with a number of governmental organizations, media, public safety, and citizenry (mobile app BMS).

The BMS application's recent success story is a case of seamless information dissemination and response for the flood event on 8–9 September 2020 ("Case 2" section). Bangalore City and its surrounding region are divided into eight zones. For this event, two zones received widespread heavy (>64.5 mm) to very heavy (>115.6 mm) rains, while two zones received moderate (>15.6 mm) to very heavy rains, and one other zone received moderate to heavy

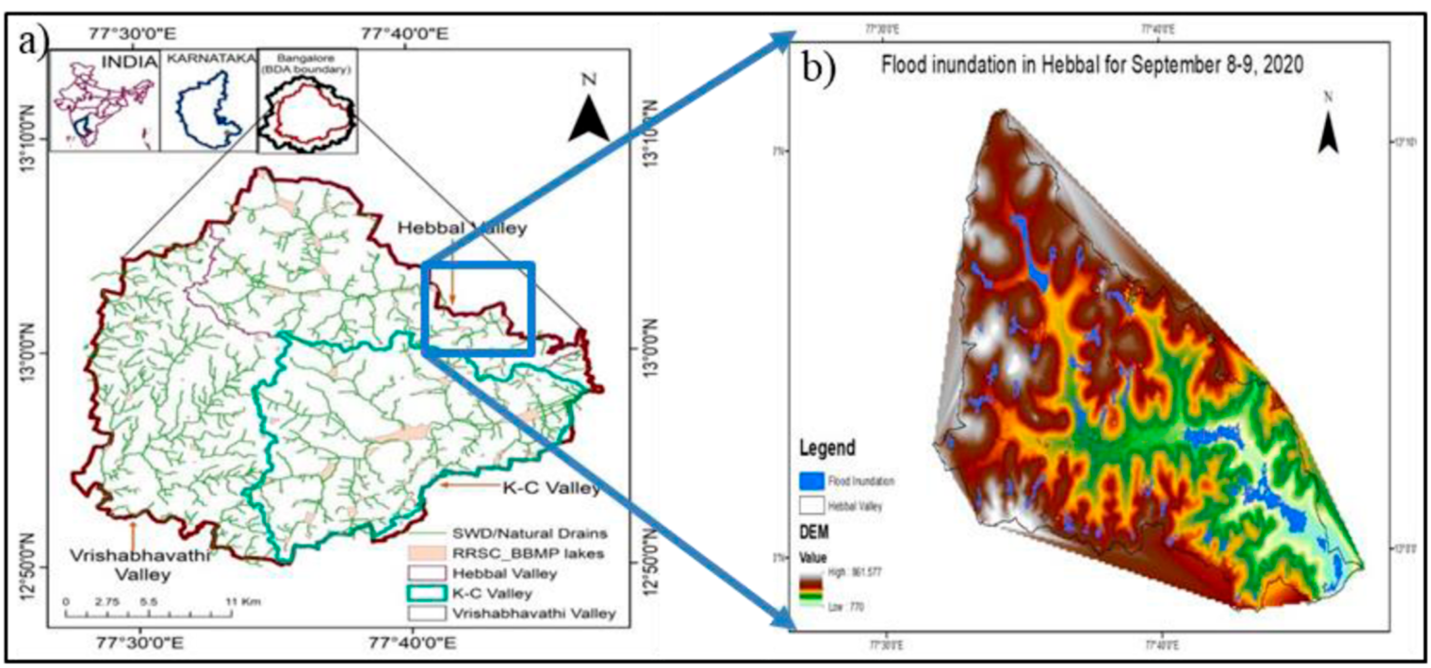

Fig. 10. (a) Boundaries of the three valleys within Bangalore City–Vrishabhavathi, Koramangala–Chellaghatta, and Hebbal (Mujumdar et al. 2021), (b) flood inundation for Hebbal valley generated using HecRAS for 8 and 9 Sep rainfall event is overlaid over the DEM developed from 1-m-interval contour provided by Bangalore Development Authority (BDA).

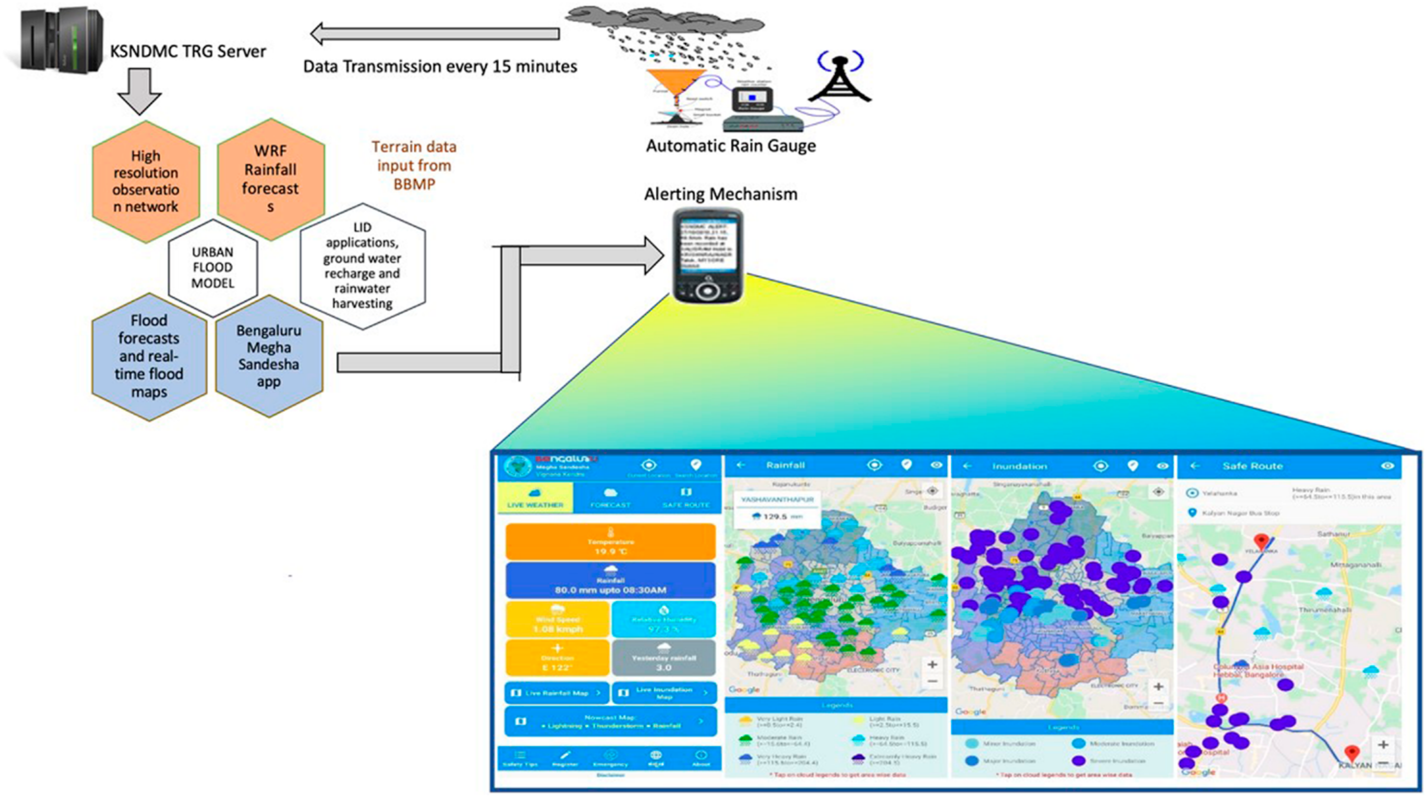

Fig. 11. The multimodel flood management workflow with BMS app displaying the nowcast weather parameters, inundation maps, and the safe alternate routes in Google Maps.

rains. This spatial variability was recorded and communicated using an in situ sensor network. This network measured a rainfall maximum rain rate of 102 mm h^{-1} for a brief period, a daily rainfall maximum of 139 mm and waterlogging 2 m above flood level in some vulnerable zones. The bulletin provided flood forecasts over vulnerable areas with a 3-day lead time. The stakeholders have effectively utilized the BMS app for alternate transit information, safe routes with rainfall/inundation overlaid on Google Maps as citizen advisory (Fig. 11), and citizen feedback. Its usability is evident from the feedbacks received on BMS, which has localization (Kannada language) advisory support.

Urban air quality modeling and early warning system. The urban air quality modeling group within the NSM_Urban has been working with Delhi as the test case. The pollution levels in Delhi and northern India have been alarmingly high, often exceeding national standards. Short-term (1–3 days) air quality forecasts provide information to the decision-makers to reduce public exposure. A fine-gridded (400 m) operational air quality prediction system has been developed to predict air pollution events in Delhi and issue warnings to take necessary steps as per the newly designed Graded Response Action Plan (GRAP) of the Government of India. This modeling effort involved chemical data assimilation, dynamic downscaling, and $PM_{2.5}$ forecasting at finer gridscale. An example of an extreme pollution event of winter 2020 is discussed.

The framework consisted of a fully coupled state-of-the-science WRF Model coupled with Chemistry (WRF-Chem) and three-dimensional variational (3DVAR) framework of the community Gridpoint Statistical Interpolation (GSI) system (Ghude et al. 2020). Model configuration has three domains set up with the outer domain (D1) covering the Indian subcontinent (10-km grid spacing), the middle domain covering the national capital region (NCR) of New Delhi and neighboring states (at 2-km grid spacing) (D2), and the innermost domain centered over Delhi (400-m spacing; Fig. 12). The D1 domain was provided with the 6-hourly chemical

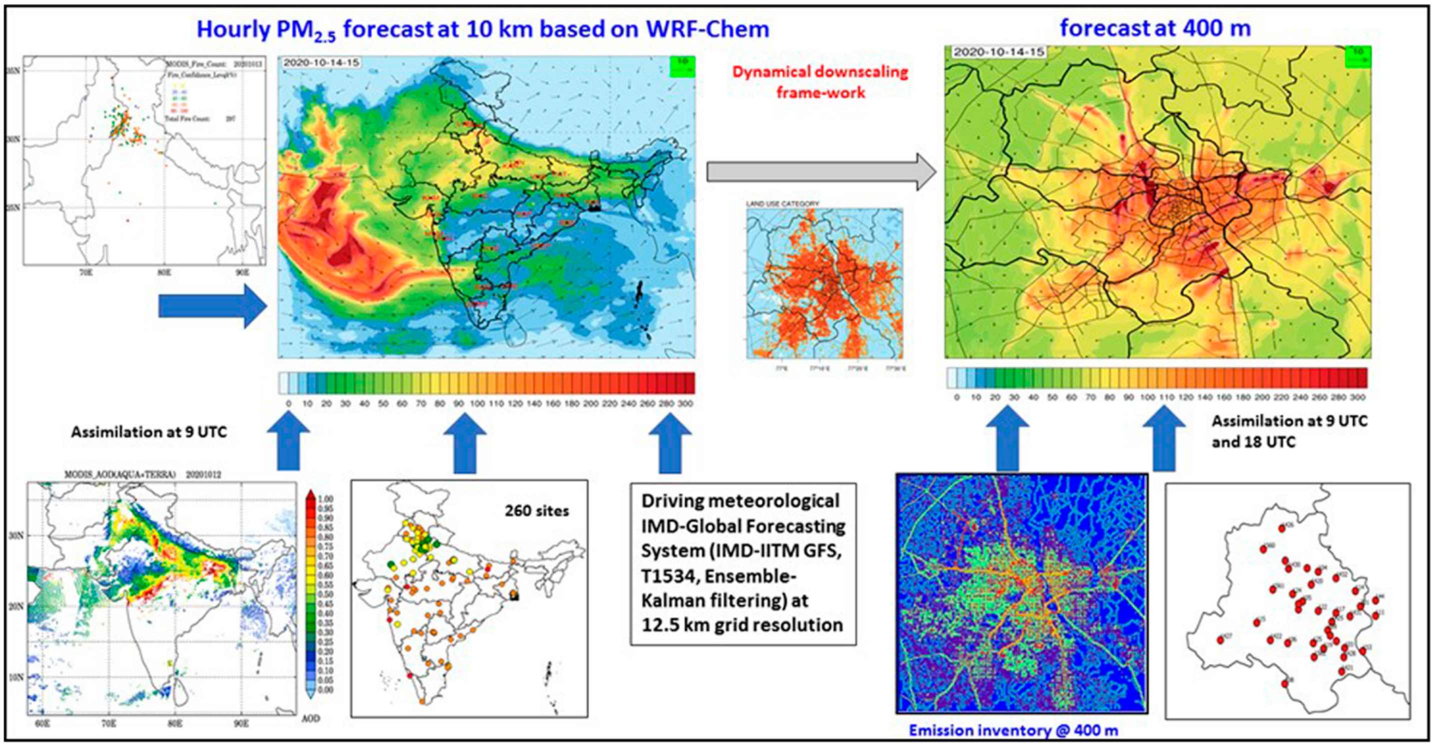

Fig. 12. (top) Quick overview of operational air quality forecasting setup with WRF-Chem three domains (10 km, 2 km, and 400 m) with (bottom) emission inventory (400 m) and chemical data assimilation

boundary conditions from the Model for Ozone and Related Chemical Tracers 4 (MOZART-4) 10-yr climatology. Chemistry output from D1 for every 3-h interval was dynamically scaled to establish a chemical boundary for the second domain (D2), whose output sets boundary conditions for the innermost domain. The meteorological initial and boundary conditions were based on the analysis and forecast product (ensemble Kalman filtering) produced by the IITM–Global Forecasting System (IITM-GFS; T1534) spectral model at 12.5-km grid resolution available every 3 h. The system assimilates satellite aerosol optical depth (AOD) retrievals at 10-km grid resolution from MODIS (both *Aqua* and *Terra*) in the outer domain and surface data from 43 air quality monitoring stations in Delhi in both the outer and innermost domains. For the urban air quality modeling system, one of the policy-relevant inputs we received was to have the ability to simulate emissions within Delhi and from nearby regions. For this, real-time fire data emissions on stubble burning were estimated from the VIIRS fire count in the outer domain. Two anthropogenic emission databases were included in the forecasting setup. Emissions Database for Global Atmospheric Research Hemispheric Transport of Air Pollution (EDGAR-HTAP) 2010 emissions at D1 and D2 and scaled to 2019 and for innermost domain, a 400-m gridded emission inventory for the year 2018 was used (Jena et al. 2021).

Figure 13 shows the comparison between the day 1 forecast at 400-m grid resolution and observations. The forecast captures the temporal variability in $PM_{2.5}$ observations quite well on most of the days. The observed $PM_{2.5}$ temporal variation over Delhi indicates frequent large-scale open biomass burning and wintertime synoptic-scale meteorological conditions combined with significant anthropogenic emissions. The mean bias on the first day of the hourly forecast was quite low ($-2.1\ \mu g\ m^{-3}$) and then was slightly more by about $-9\ \mu g\ m^{-3}$ on the third day of the forecast.

The model shows a promising capability to capture this variability, aiding IMD and CPCB in preparing GRAP for implementing control measures 72 h in advance, such as restriction on construction activities and regulating heavy vehicle inflow in Delhi (https://cpcb.nic.in/Task-Force-on-Graded-Response-Action-Plan-GRAP/). This has significantly

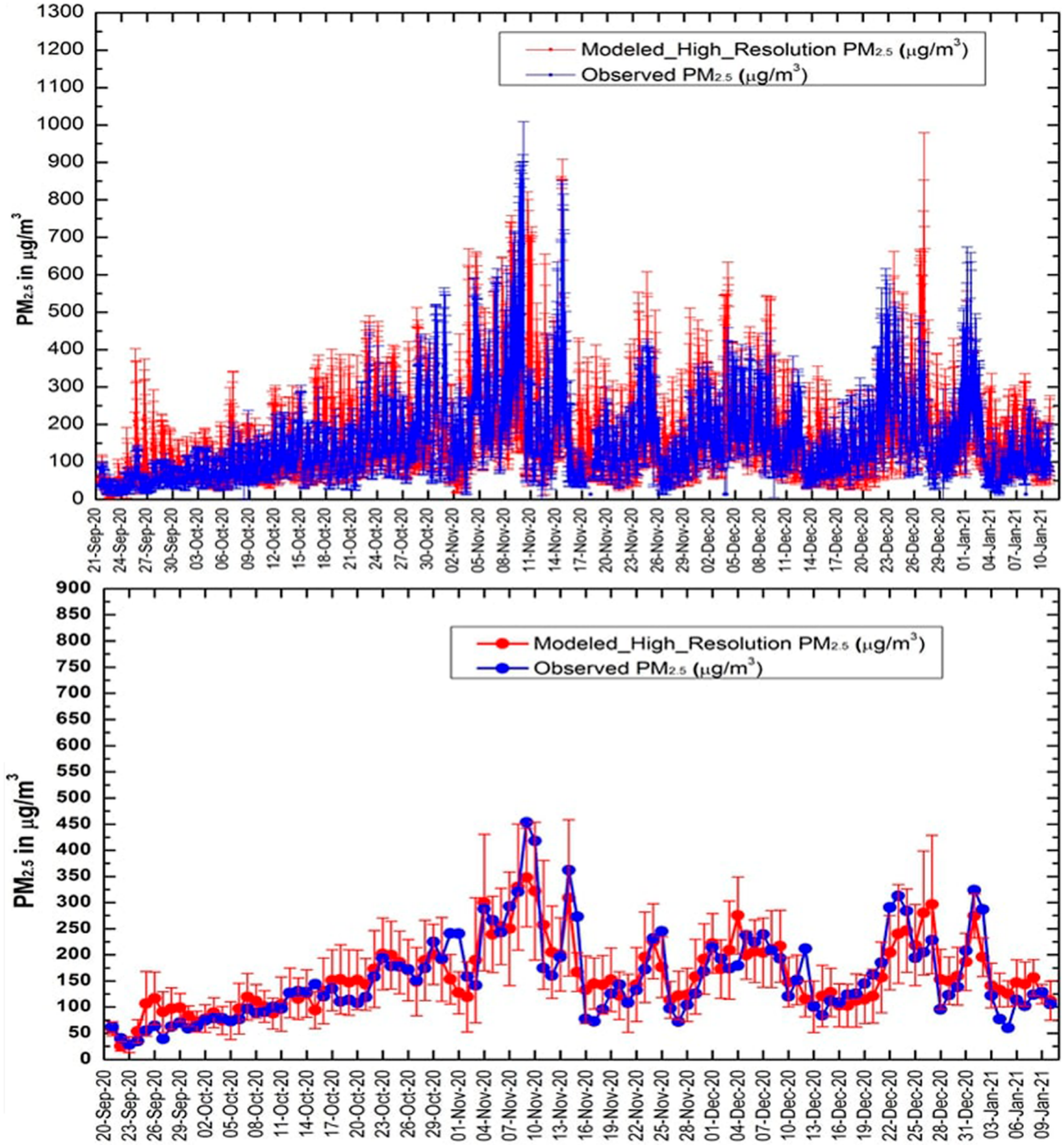

Fig. 13. (top) Hourly forecast verification (blue: mean $PM_{2.5}$ from 43 air quality monitoring stations; red: forecast at 400-m resolution with AOD and surface data assimilation). (bottom) Comparison between daily mean observed and forecasted $PM_{2.5}$ for the period from 21 Sep 2020 to 9 Jan 2021 for Delhi.

contributed to a buildup of the trust of the end users and policy-makers for taking science-based, well-informed decisions and actions as well as the confidence to scale the solution to other cities.

Summary

The framework developed under the UES2S will facilitate urban environmental research and accurate, timely, and tailored for the end-user needs through a science-driven service platform. It enables developing if–then vulnerability studies, and the cascade of risk that can be ascertained both directly, and via feedbacks as outlined in studies such as Hossain et al. (2017) and Pielke et al. (2012). Ultimately, the goal is to provide tools that help identify solutions beyond the disciplinary silo by integrating stakeholder, as well as environmental engineering feedbacks for vulnerability assessments and response.

The approaches undertaken for integrating models, developing case studies, partnerships with stakeholders, integration of offline or coupled forecasts for different applications from weather forecasting to air quality and hydrological modeling, and HPC-cloud deployments are transferable to other domains. Involving the stakeholders in a participatory manner right through the project conception and research design tasks was beneficial for the project components and is recommended as an effective practice in urban environmental studies. This is reflected in the modular use by the city-based as well as national stakeholders such as Bhubaneshwar, Pune, and Bangalore [Bruhat Bangalore Mahanagar Palike (BBMP)] municipality, CPCB, and OSDMA. The models and computational tools used in different applications are open and community-based. Using such a setup for research to operations to stakeholder decision-making, a robust assessment, beyond the case studies typically reported in the literature, would emerge. Further, the experiential knowledge from each city is being collated and presented as best-practice SOP for modeling and operationally integrated services for other regions. The usability and fit for purpose would be a metric to consider.

The UES2S showcases a successful interdisciplinary collaboration in developing a product useful to the decision-makers and citizens. Experts in urban meteorology, air quality, hydrology, data assimilation, computing, and governance work as a synergetic team in the project. In this exciting process, the research team from one domain has learned to understand the requirements of a team from another domain. It has continually coevolved to improve the utility of the product. In addition, the common supercomputing platform on which the teams build and test their domain models has also strengthened the cross-discipline synergy, with facilitation from system specialists.

Aligning with findable, accessible, interoperable, and reusable (FAIR) data principles (Stall 2019), UES2S champions open science. UES2S is a technology-agnostic platform offering scientific HPC cloud by simplifying scientific discovery process and reducing "time to go on the floor" for end-user solutions (Kaginalkar et al. 2021). Data sharing, access, interoperability, knowledge integration, institutional capacity building, and the model integration framework with a genuine participatory research and stakeholder integration in an end–end manner is the backbone of UES2S. The UES2S cloud service has other benefits: reducing "nonscientific" tasks of HPC, such as purchase, acquisition, and system administration, and reducing the carbon footprint.

UES2S is a step toward nonproprietary, open, public partnership for research and development in India's urban environment. The resulting products and cyber tools will be part of the citizen services of smart cities. With the realization of recommendations of expanding urban-environment science research as a mature field of study (WMO 2015) and SENDAI framework (United Nations 2015), we are hopeful that UES2S will be a catalyst for "weather ready cities." Though UES2S is created primarily for Indian cities, it can be extended to global cities, specifically from emerging economies in the future (Gonzalez and Niyogi 2021; Lee et al. 2022).

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