An AI-Assisted Approach to Represent Human Influence on Surface and Subsurface Hydrology

Ethan Coon (coonet@ornl.gov)[1], Sudershan Gangrade[1], Christa Brelsford[1], Dan Lu[1], Carly Hansen[1], Debjani Singh[1], Shih-Chieh Kao[1], and Scott Painter[1]

[1]*Oak Ridge National Laboratory, Oak Ridge, TN, USA*

Focal Area(s)

(2) Predictive modeling through the use of AI techniques and AI-derived model components: This white paper focuses on using artificial intelligence (AI) to discover connections across processes and scales and to represent those processes in predictive models of anthropogenic impacts on the water cycle.

Science Challenge

Perhaps the most important challenge for Earth system predictability is the interaction of humans with the water cycle. Humans rely on the water cycle to provide readily available freshwater, and human decisions are affected by changes to water availability and quality. Furthermore, humans alter the water cycle through reservoirs; diversions for irrigation, power generation, and stormwater management; land use change; and groundwater pumping to ensure these services [1]. This two-way interaction is inherently difficult to predict over decadal scales; anthropogenic alterations to the water cycle are a complex product of both endogenous behaviors that shape the magnitude of demand, such as individual decisions, laws, and economic and demographic change, and exogenous stresses that shape water availability, such as climate change and drought, floods, and other extreme events. As water is crucial to national security, this challenge must be addressed to improve water cycle predictability; this issue has been highlighted by the inclusion of the water cycle as a pillar of the BER EESSD Strategic Plan [2].

Rationale

The water cycle is significantly influenced by human actions, both directly via activities such as reservoir regulation, flow diversion, and groundwater withdrawals and indirectly by anthropogenic changes in the environment such as land use change. Drought and groundwater depletion are tightly linked through human activity, as drought results in reduced streamflow and increased need for irrigation, driving farmers to pump more groundwater. Urbanization and the resulting land use change are exacerbated by sea level rise and extreme weather events, resulting in increased risk of salinity intrusion and coastal flooding. These are two of many examples where human actions are tightly linked with the natural system, resulting in systematic changes to the water cycle. Tightly coupled natural and anthropogenic processes are increasingly seen as large and fundamental uncertainties, resulting in a corresponding increase in socio-hydrological research [3],[4].

Human action has altered natural hydrologic conditions to such a level that it no longer can be overlooked in Earth system models (ESMs) [5],[6]. Human action, and how it changes in response to climate and economic change, may be the largest uncertainty in the water cycle over seasonal-to-decadal time scales. However, while many physical processes have been included in ESMs to characterize natural surface and subsurface hydrology, a process-based representation of human influences on freshwater resources is lacking. With few exceptions, incorporating the effect of humans on the water cycle is currently limited to trends and macroeconomic models at global scales. *These cannot capture the fast, nonlinear, interconnected yet localized changes typical of*

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human actions and impact. However, process-based representations of human behaviors in ESMs faces two fundamental challenges: a lack of direct observations of the needed process and a lack of understanding of the processes governing feedbacks between the natural system and human action.

Narrative

Given the lack of process-based models to predict human decisions, deep learning and AI may be the best approaches to (1) discover hidden decision rules from a diverse set of observations, (2) represent human influence on the water cycle in models, and (3) predict how human influence may evolve in a changing environment.

Use of diverse but indirect data streams and AI to enable water process discovery.

Direct observations of anthropogenic influence on the water cycle are rarely available; when they are, such data are typically sensitive, restricted information. However, an increasingly broad collection of indirect observations is available; these must be used instead. For example, while direct observations of urban influences on surface water are difficult to acquire, urban population growth and land use change are directly quantifiable. Diverse data streams measure urbanization and land use change: (1) remotely sensed imagery measures the spatial and temporal evolution of imperviousness over multiple decades; (2) census microdata and synthetic population data measure demographic and socioeconomic context at fine spatial resolution on annual-to-decadal timescales; and (3) digital trace data measure population movement and behavior change in response to extreme events on relatively short time scales. Urbanization and land use change in both headwater and coastal catchments in turn govern runoff generation and therefore flood prediction. In cases such as this, diverse indirect observations across scales could be used to infer anthropogenic effects, informing predictions of surface water diversions and reducing uncertainty in the water cycle.

However, because the underlying processes are difficult to quantify, AI-based techniques are crucial for ***discovering*** characteristic relationships in these data and their resulting hydrologic consequences across spatial and temporal scales. Considering the diversity of data and the incomplete understanding of the physical system, we hypothesize that Bayesian networks (BNs) can best extract information from available data and knowledge. BNs can model the causal relationships among various aspects of human influence and are especially useful when varying levels of data describing those relationships are available. Different disruptive scenarios, including those consistent with shared socioeconomic pathway scenarios, can be simulated; and a sensitivity analysis of parameters can be performed for a robust analysis.

Use of AI to improve process representation in ESMs

Given relationships between observations and anthropogenic alterations to the water cycle, it remains a challenge to ***represent*** the processes that cause alterations and to predict how those processes will change in the future. In particular, incomplete understanding of the underlying processes and the spatial and temporal scales at which these processes interact makes incorporating human influences in ESMs difficult. For example, reservoir operators must optimize across many competing objectives, including meeting mandated release policies; ensuring flood control; and providing minimum environmental flows; as well as maximizing the value of power generated and providing water as a service to cities, to irrigators, and for recreational use. Complete representation of such decision-making in water systems may not be feasible through conventional modeling approaches, as models typically represent a generalized reservoir, rarely incorporate local information, and cannot include variation and uncertainty due to individual operator decisions. These generalized models, while useful at the coarsest scales, limit the certainty of how humans might be affecting these systems.

AI-based applications for representing hydrologic processes have demonstrated great promise in recent years. Many studies have used AI to infer historical patterns linking rainfall and runoff and then forecast future streamflow [7],[8]. We hypothesize that similar techniques, based on long short-term memory recurrent neural networks, can be used to infer correlations between environmental conditions and the diversions and fluxes that result from human decisions. To this end, we hypothesize that physics-informed recurrent neural network models can be used to represent direct anthropogenic alterations to the water cycle by considering different input scenarios and parameterizations, and then using explainable AI techniques such as layer-wise relevance propagation to identify the human influence. These techniques allow the inference of specific relationships between inputs and outputs, which in turn advance our model understanding and inform model development.

Characterizing changing human decisions under environmental stress and extreme events

Aggregate human decisions can rapidly shift under stress, causing large swings in the water cycle. For example, California's agricultural production is heavily dependent on groundwater consumption, a resource that is essentially nonrenewable and is under systematic stress. This dependency is even more profound in drought conditions; in wet years, groundwater makes up about 20% of California's statewide water supply, while at the height of a recent drought, groundwater made up 35% of the supply. When and where groundwater pumping is no longer economically viable as a hedge against drought, agricultural production and irrigation behavior will change profoundly. The timing of this shift will be spatially heterogenous, as the cost of groundwater pumping is heavily dependent on local subsurface hydrology and the economic returns from agriculture vary by crop, climate, and demand. Given the extent to which agricultural water use dominates Californian flow regimes, the consequences of this shift on the water cycle will be far reaching but are poorly understood.

High-resolution, localized models of surface water and groundwater coupled to models of farmer and institutional decision-making are necessary for accurate prediction, and ensembles of scenario-driven simulations are necessary to quantify the range of possibilities inherent in this nonlinear system. Such models will be computationally demanding; it will likely not be computationally feasible to run sufficient realizations to quantify scenario-driven uncertainty. Instead, AI-based surrogate models and hybrid process–and–AI models will be essential to provide the necessary model throughput. Surrogate models have seen a wide range of applications, including for precipitation patterns [9], and, in cases of hybrid models, for improving the performance of process-based models [10]. These techniques, along with flexible software platforms to enable hybrid models, will be crucial to ***predict*** the wide range of potential outcomes as human decision-making responds to environmental stress.

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