Hydrotwin: an AI-based physics and optimization framework for improved water resource resilience in systems experiencing adverse events

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Focal Area

Water for Energy **Hydrotwin** is an artificial intelligence (AI)-driven framework designed to revolutionize ***water for energy*** and improve water resource planning through rapid, reliable water flux simulation. This digital replica of the water cycle uses AI and machine learning-enabled data fusion and physics to identify adverse events and test optimizations for improved water resource management. The **capability leverages hydro-, data-, and AI-science information and knowledge to create an unbiased, holistic assessment tool for water-energy security-related threats and opportunities. Hydrotwin** would be adaptable to many different scenarios, including hydropower, marine energy, pumped storages, and grid technology, which are of interest to the U.S. Department of Energy's Water Power Technologies Office (WPTO).

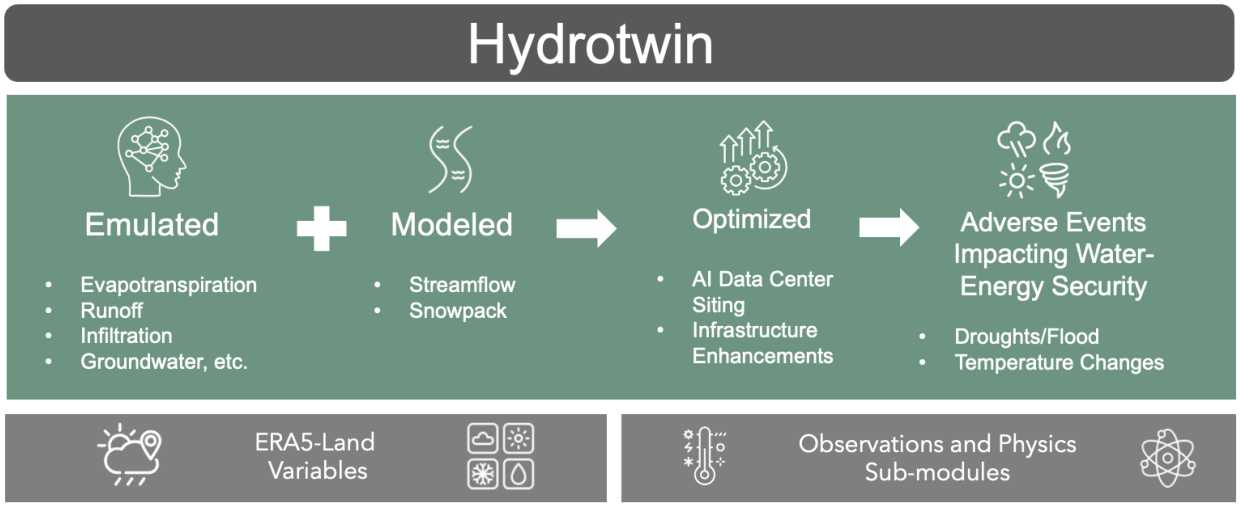


Figure 1. A Hydrotwin for improved water resource planning through rapid, reliable water flux simulation, including optimization and adverse events for water-energy security.

Existing Challenge

Water resources (e.g., surface water, groundwater) are critically threatened due to overallocation and earth system changes, creating a coupling of concurrent crises that threaten the stability of the United States's water and energy nexus[1]. Snow resources are dwindling, rain patterns are shifting, and surface/groundwater reservoirs are declining[2]. Agricultural intensification, changes in irrigation technology, and population growth all increase pressure on water systems[3–5]. As we move ahead into an uncertain future for water resource demand and supply, a massive challenge exists to optimize water systems to be resilient to a range of press/pulse extreme event states and

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conditions. Optimal decision-making needs include investments for siting of water and energy resources to achieve resource adequacy (the ability of an electricity system to meet demand for power under a wide range of conditions), such as reservoir operations that can prepare for potential future droughts or floods, and flow routing through or around fire-affected pipeline and electrical grid networks. These optimal sitings and routing would aim to improve water and energy resource and systems resiliency to adverse press/pulse events.

Research on the link between water resources, management and security has been impeded by a lack of holistic perspectives. Water resource management in the U.S. is scattered across agencies, with no national vision, and lacks dynamic, holistic, and equitable solutions to address contentious, worsening water crises[6]. The nation lacks a data-informed, responsive water management tool that can address these issues and their impacts on national security *as a whole*[7].

Existing water models such as the National Water Model[8] are designed as flood forecast tools with specific and narrow scopes. Physics-based models, on the other hand, are important for representing basin-scale hydrology but are computationally expensive, inflexible, and require extensive calibration[9–11]. Policy-focused decision support tools therefore, by necessity, often rely on simplifications of the natural system and require managers to 'put all the pieces together' on their own. Tools which are more user-friendly and decision relevant are badly needed.

Near-Term Opportunity

Advancements in AI enable **Hydrotwin** to balance high-fidelity representation of physical systems with the agility needed to explore multiple future scenarios of water management strategies through either experimentation or advanced optimization methods[12]. **Hydrotwin** operates on a graphical domain of links and nodes capturing fluxes between physical locations rather than traditional computational mesh. This innovative graph representation provides key advantages over conventional computational physics-based models by reducing computational degrees of freedom from millions to thousands.

*What is "**Hydrotwin**"? A digital replica of the water cycle with high fidelity to reality, achieved via AI- and machine learning (ML)-enabled data fusion and physics; designed for experimentation and optimization to identify threats and test technologies to improve water resource management for water-energy security under adverse events.*

In the near term, AI data centers are springing up all around the country and will require vast, sustainable, and stable volumes of water to cool the computing centers that are enabling the AI revolution[13]. **Hydrotwin** provides an automated tool for on-the-fly representation of the physical system of environmental water flows, water management infrastructure, and water demand from agriculture, industry, and cities. **Hydrotwin** can determine the holistic implications of how water systems can optimally route flows to supply water for energy system uses under critical shifts in water resources.

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Where **Hydrotwin** shines is in its ability to rapidly respond to adverse events that have become common in today's world (e.g., flooding, wildfires, cold and heat outbreaks[e.g., 14]). Once a system's physical water delivery system requires an update (e.g., routing of water towards a wildfire-affected region or away from flooding areas) then **Hydrotwin** will rapidly produce thousands optimal candidate strategies to address the adverse event that can be individually considered by decision makers. Workflow development for **Hydrotwin** would require three main capability-building objectives (see Figure 1):

- Creation of **Hydrotwin** using multi-modal data and physical system understanding using vast amounts of public data
    - Physical system of water delivery
    - The engineered system of pipes, pumps, and reservoirs to enable water delivery
    - Human made system of water to energy delivery
- Development of a test suite of water resource optimizations using the scenario of an existing AI data center threatened with a wildfire outbreak
- Analysis using multiple adverse or extreme event scenarios to stress test **Hydrotwin**

Previous investments can be leveraged to achieve this, including the VotE platform (AI-ready hydrology data[15,16]), DP FEHM package (differentiable models of subsurface flow[17]), and technologies for uncertainty quantification[18].

Success Measures

The core measures of success center around assessing the extent to which **Hydrotwin** can inform water-energy security-related threats and opportunities. Has **Hydrotwin** identified a previously unknown threat to water security? Can **Hydrotwin** demonstrate or identify more optimal management practices than the status quo? Can **Hydrotwin** demonstrate the hydrological consequences of new potential data centers?

The overarching goal of **Hydrotwin** would be to achieve complete revolution of water resource management by enabling fast, accurate water cycle flux simulations to answer fundamental science questions and offer solutions previously unattainable without coordinated partnerships spanning multiple sectors. Success of this goal will be measured specifically through:

- Development of **Hydrotwin** such that it can answer scientific questions, and that uncertainty, scaling, transferability, and adverse event analysis can be carried out
- Successful demonstration of **Hydrotwin**'s capability in a site experiencing an adverse event, such as wildfire threatening the power grid around an AI data center.
- Publication of five widely available journal articles that would be accessible to the public (e.g., Scientific American), along with media to communicate key innovations
- Workshops and webinars to communicate results to the water resource community
- Stakeholder engagement efforts targeted toward the water resource community and sponsors to engage and build trust, and to scope carry-on funding in the future

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