I've always been fascinated by the ability of agronomists to quantify the effects of fertilization or pesticide treatments, with relative ease, from randomized research plots. Agronomists commonly report treatment effects of less than 5% with surprisingly narrow confidence intervals. What are they doing right, and what are we hydrologists missing?

I suspect that the difference is in the nature of the indicators used. For agronomists, the difference in yield between the treatment plots and control plots is often the indicator of choice. Mathematically, the mass yield of corn grain corresponds to the integration over time of the instantaneous productivity of a corn plant or a small plot during the growing season. The instantaneous productivity varies between night and day, as well as between sunny and cloudy skies, between warm and cold days, and there is also a treatment effect because of the applied treatment. If agronomists were able to measure the instantaneous productivity and compare it from one plot to the next, they would likely have a hard time distinguishing the treatment effect from all the other day-to-day effects.

Instantaneous productivity is much less indicative of the treatment effect because of its inherent variability, which is associated with highly variable driving factors. In contrast, overall production is a cumulative indicator, and instantaneous productivity is it mathematical derivative. The overall production, i.e., the mathematical integral of instantaneous productivity over time, is a more robust indicator of the treatment effect.

In other words, the different indicators are fundamentally different. Agronomists have demonstrated that cumulative indicators, such as crop yield, are robust. In contrast, derivative indicators, such as instantaneous productivity, are not robust because they are noisier and more sensitive to inherently variable drivers.

By analogy, I suggest that the individual concentration values measured by hydrologists, or even the indicators derived from individual event hydrographs and chemographs, correspond to the instantaneous productivities of crops and are very noisy derivative indicators. If that is the case, then overall indicators, such as cumulative flow volume or cumulative concentration load, ought to be more robust and more pertinent for detecting and quantifying the effects of management on water quality.

Do we have any evidence for that? Actually yes, and some of the evidence has been in existence for quite a while. Double-mass curves have long been used to detect drift and malfunction in flow monitoring instruments. The effect of treatment can also be detected in the break of the slope of a double-mass curve.

At North Carolina State University, we have been using these cumulative indicators for a while, and we have been able to quantify the effects of stream restoration on water quality, the impact of afforestation on water yield, and other effects. While agronomists only have access to end-of-season production data, hydrologists have access to time series data of cumulative loads and flow volumes. This creates an opportunity to detect breakpoints in the cumulative curves, as well as seasonal trends and patterns.

New tools, including statistical tools, are needed to analyze these cumulative indicators. In addition, the full time series of flow and concentration must be measured to calculate them. This means that robust methods to fill in missing data must be developed and agreed on. There is still much work to do in this area. However, we are convinced that cumulative indicators hold great value in hydrology, and we encourage researchers to use them.

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Digital Water and Its Impact on Sustainability

Khaleel Muhammed and Aavudai Anandhi

Digital water is an emerging research direction that involves using technology to manage water use. The digital water ecosystem is described by the International Water Association (IWA) as being composed of many stakeholders, including the public sector, peer groups, investors, industry associations, and academic institutions. In this brief article, we first describe the relationships among the aspects of digital water and then explain how digital water can be used to make water use more sustainable.

Aspects of digital water

The accompanying diagram adapts the digital water ecosystem described by the IWA into an illustration of the three aspects of digital water. The three aspects are industry, innovation, and information technology (IT). Each aspect can be further broken down into more specific components. Industry includes components such as water and wastewater treatment utilities, agriculture, manufacturing, as well as human components like finance and training. Innovation involves developing new methods, ideas, and products. IT is the use of computers, communication devices, and infrastructure to process, store, and exchange data.

The desire to move toward a more sustainable society drives resource-intensive industries such as agriculture, water utilities, and steelmaking to change their practices. This creates the need for innovation. Innovation is led by teams within industries and by cross-sector collaboration.

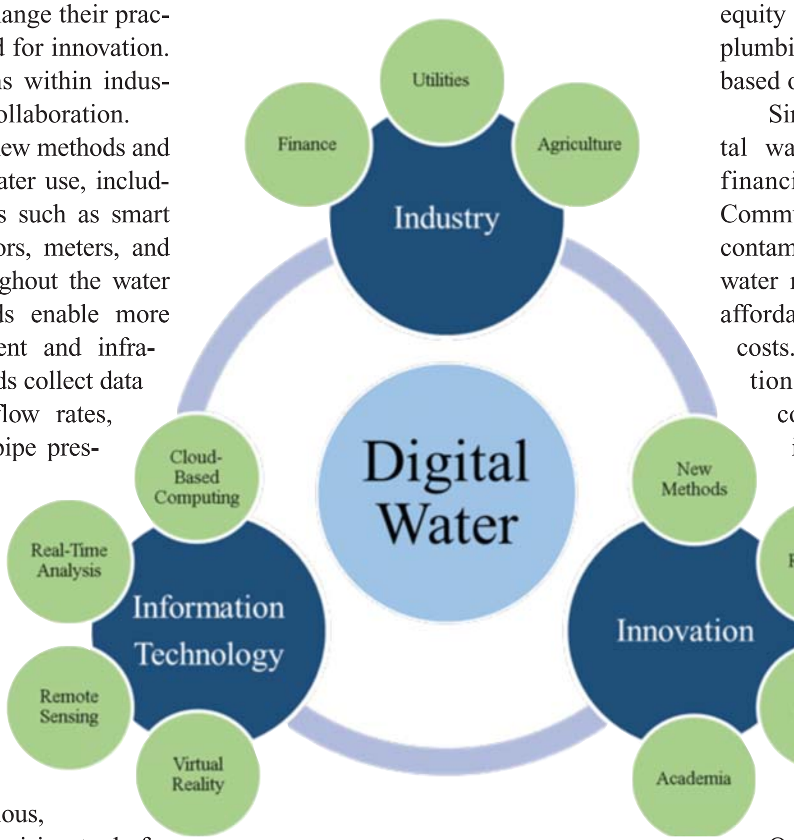
Innovation has led to new methods and technologies to monitor water use, including cyber-physical systems such as smart water grids that use sensors, meters, and actuators distributed throughout the water infrastructure. Smart grids enable more efficient water management and infrastructure planning. The grids collect data on water consumption, flow rates, peak demand times, and pipe pressures in real-time, which can then be transferred and analyzed. The transfer of data is automated using radio transmissions like the Global System for Mobile communications (GSM) and General Packet Radio Services (GPRS). Interpreting large amounts of data can be tedious, so robotics and IT are promising tools for automating repetitive tasks.

Alongside real-time data analysis, other IT applications for digital water include cloud-based computing for the delivery of databases, analytics, and intelligence over the internet; remote sensing, such as using satellite imaging to detect and monitor the physical components of an area; and virtual or augmented reality, which provides a cost-effective way of simulating real-world situations to test alternative scenarios. Digital twins (DT) also fall into the category of virtual reality. DTs are digital replicas of a physical system that mimic the system's behavior. DTs are a safe way to simulate the impact of abnormal events.

These information technologies can be used in combination to gather, distribute, and analyze data from both natural and artificial water networks. New methods and technologies bring new uncertainties, so the impact of new digital water solutions must be assessed before adoption.

Impact on Sustainability

Managing water resources is important for meeting the increasing water demands for agriculture, industry, and personal use. Irrigated agriculture uses 70% of freshwater globally. The three agricultural production categories that use the most water are cereals (27%), meat (22%), and dairy products (7%). These water use values may change, as the global consumption of milk is expected to increase by 19% by the year 2050. Using technology to perform analyses is an efficient way to optimize water use as well as predict changes in water use due to climate change, population growth, and economic development.



The three aspects of digital water.

A recent literature review asserted that digital water offers 77 benefits to sustainability. These benefits are grouped into three categories: environmental, economic, and social equity benefits. Environmental benefits include energy benefits associated with improved management, planning benefits due to increased knowledge and development of new algorithms, and water benefits from better monitoring. Economic benefits include reduced health and safety incident costs, reduced labor costs, and improved revenue forecasting. Social equity benefits are derived from reduced plumbing costs and customized products based on water use.

Similarly, the IWA suggests that digital water has community, operational, financial, and resiliency benefits. Community benefits are reduced water contamination, increased conservation of water resources, and increased long-term affordability through reduced operating costs. The operational benefit is automation. Along with reduced operating costs, another financial benefit is increased revenue. The resiliency benefits are derived from the adaptive nature of digital water systems. For example, high-resolution remote sensing promotes efficient irrigation of urban and agricultural landscapes by determining location-specific irrigation amounts for optimum plant health.

Optimizing global water use is important for sustainable development. The move toward digital water is the next logical step for optimizing global water use, considering the increased demand for water, global population growth, land use changes such as urbanization, and the reality of climate change.

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