Treating water to appropriate standards for different uses at the WEF Nexus

Never Stand Still | Global Water Institute

Dr Andrew Dansie

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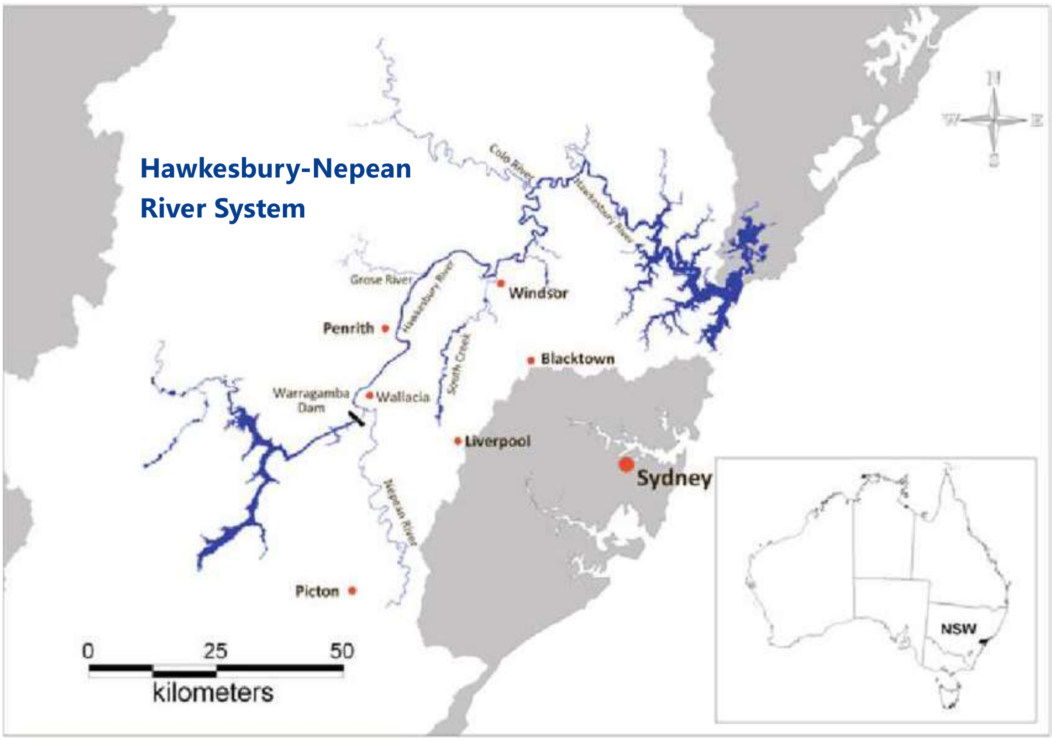

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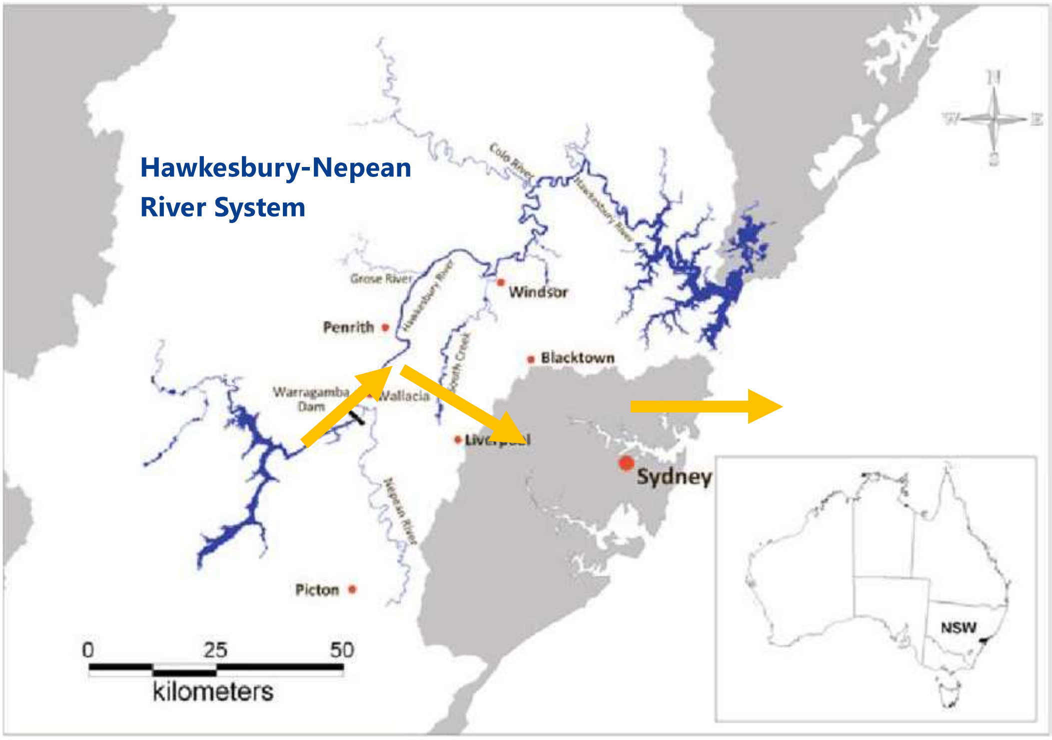

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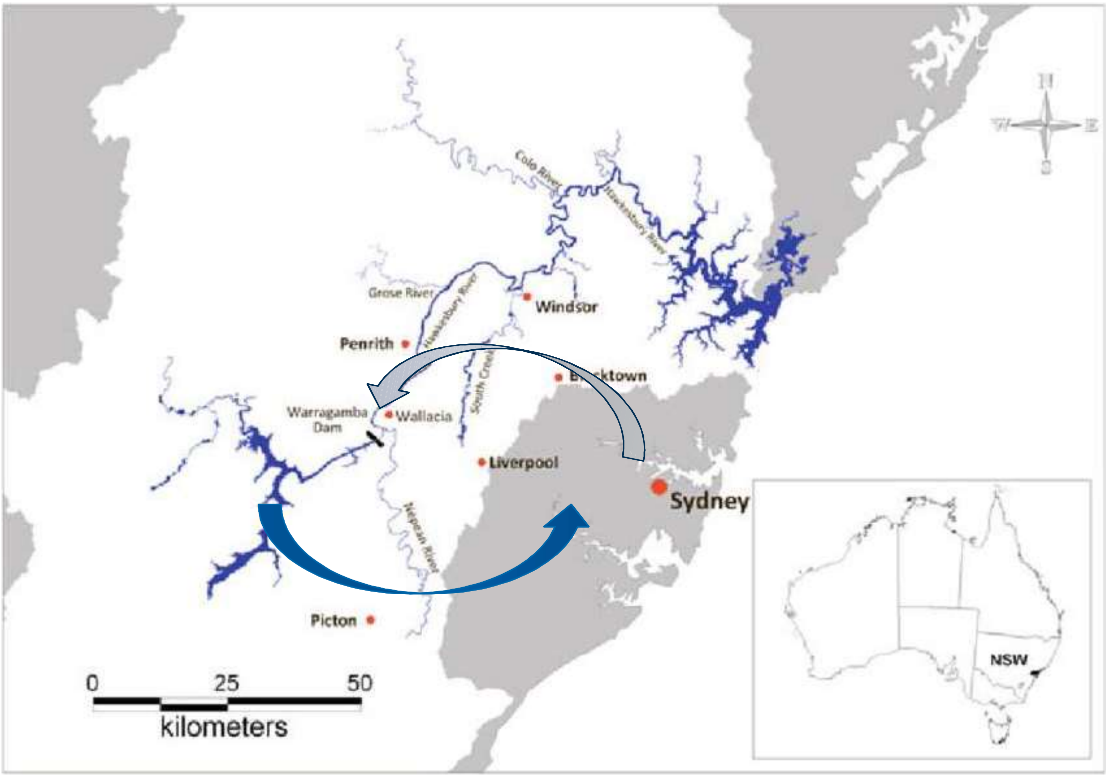

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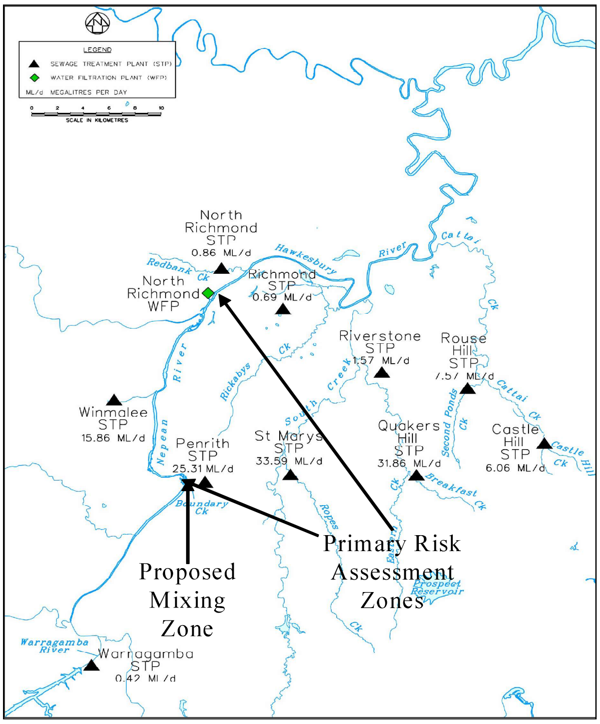

Provides up to 18 billion litres of highly treated water back to the river system below the Warragamba Dam

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Emerging digital technologies in water management and environment towards nexus (WEF) and SDGs (Big Data, IOT)

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Real-time cyanobacterial fluorescence monitoring

1) **Real time management of cyanobacteria remains a growing challenge** for water utilities and health authorities to maintain water supplies to a safe and aesthetically acceptable standard.

2) **Climate change and increased human activities** have prompted favourable conditions for the **proliferation of cyanobacterial blooms.**

3) **In situ fluorometers can be used** as a **real-time cyanobacteria detection tool** to maintain safe drinking and recreational water standards.

Choo, F., Zamyadi, A., Stuetz, R.M., Newcombe, G., Newton, K. and Henderson, R.K., 2019. Enhanced real-time cyanobacterial fluorescence monitoring through chlorophyll-a interference compensation corrections. *Water Research*, *148*, pp.86-96.

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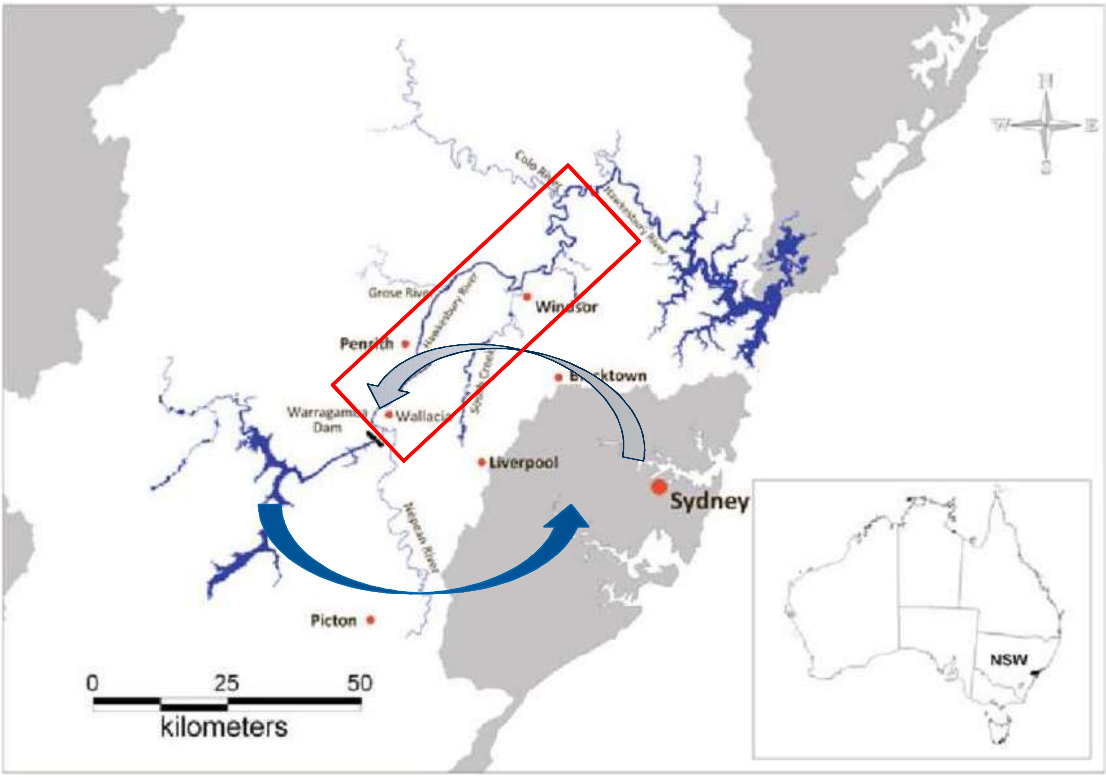

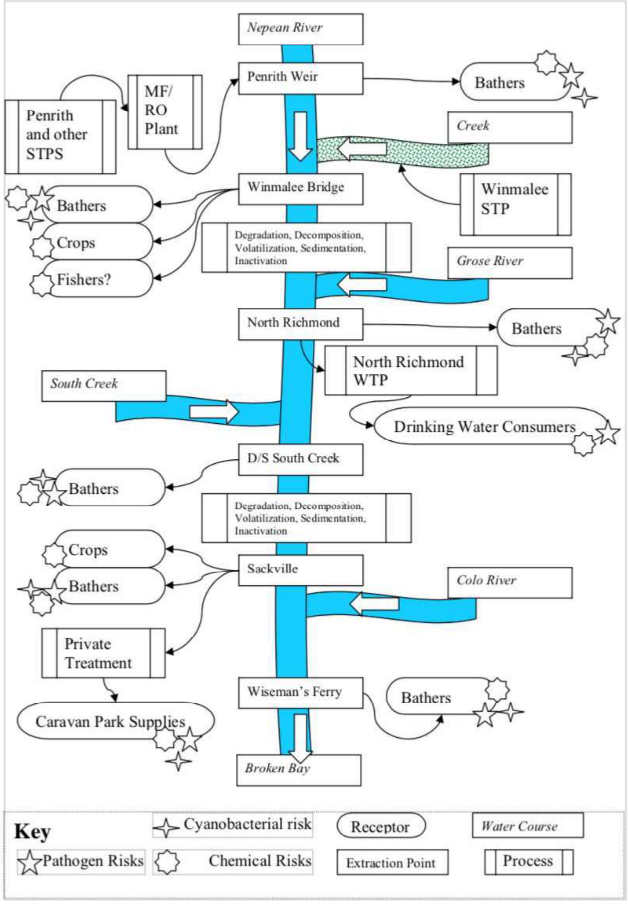

Figure 3-5. Conceptual Model of Likely HN Risk Exposure Pathways

ROSER, D., KHAN, S., DAVIES, C., SIGNOR, R., PETTERSON, S. & ASHBOLT, N. 2006. Screening Health Risk Assessment for the Use of Microfiltration-Reverse Osmosis Treated Tertiary Effluent for Replacement of Environmental Flows. Centre for Water and Waste Technology, University of New South Wales.

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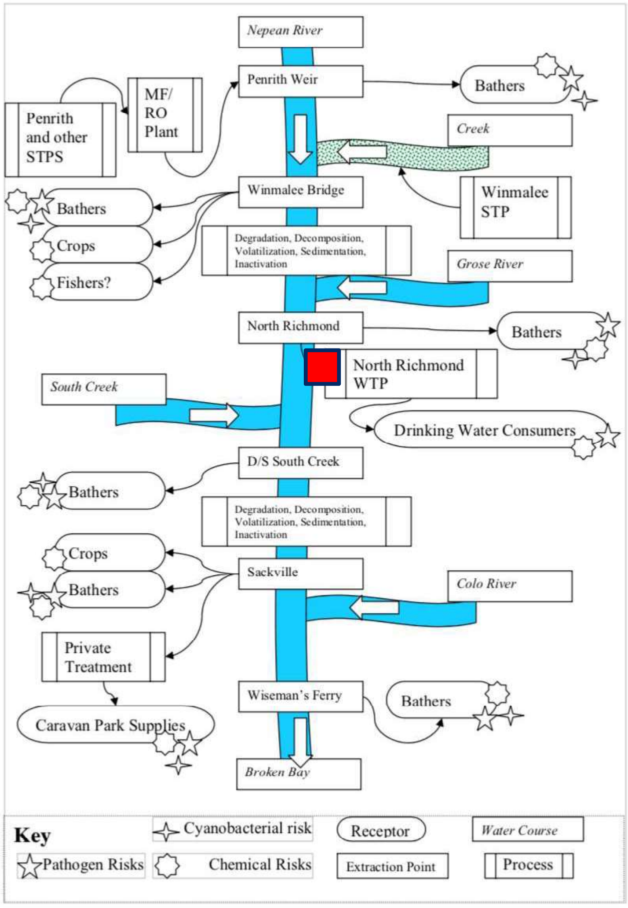

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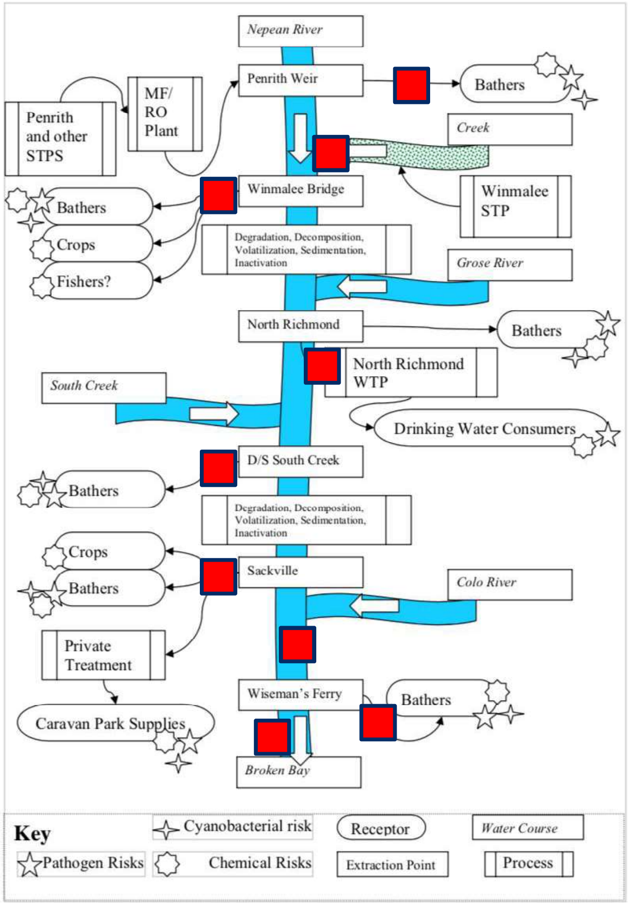

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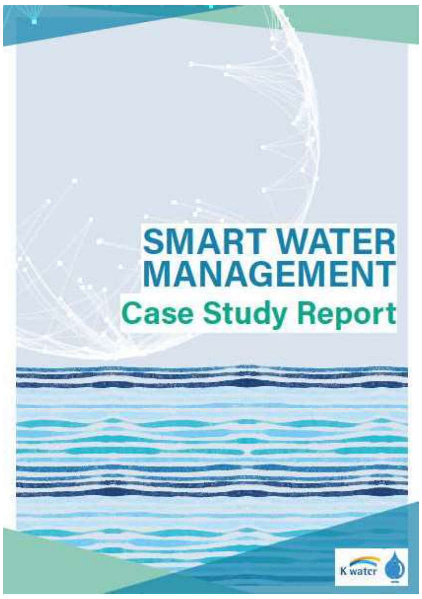
Bayesian Network for Big Data Management

- Belief Nets (BBNs), a type of artificial intelligence which capture human 'cause and effect' reasoning algebraically to facilitate 'reasoning under uncertainty'.

- BBNs use 'directed acyclic graphs' which visually look like flow charts. Unlike the latter though, nodes (e.g. a normal distribution function) and links (causal node relationships) are defined mathematically. BBNs proved remarkably adaptable and ideally suited to 'Smart' treatment performance analysis.



IWRA (2018) Smart Water Case Study Report, text box authors D. Roser, G. Carvajal, B. van den Akker, A. Keegan, R. Regel and S. Khan

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Bayesian Network for Big Data Management

1. BBNs can ‘learn’ from databases and relate online measurements (especially turbidity, sludge retention time and nitrate) to *Cryptosporidium* Log_{10} Reduction Values (LRVs), and how indicator (e.g. enterococci) behaviour reflects pathogen behaviour.
2. Combined with another AI approach (neural network Perceptrons) BBNs can also integrate disinfectant concentration, contact time, turbidity and pH measurements to estimate disinfection LRVs automatically.
3. Smart monitoring collects enormous amounts of treatment process data (i.e. big data) and supports real-time equipment management **BUT** one issue faced is that current data outputs provide a lot of data but can also provide a lot of unuseful information.
4. Through our research however we have shown that BBNs, Bayesian inference and statistical analysis can address this gap operationally and auditably by providing a framework for risk inference suited to regulators and water utilities.

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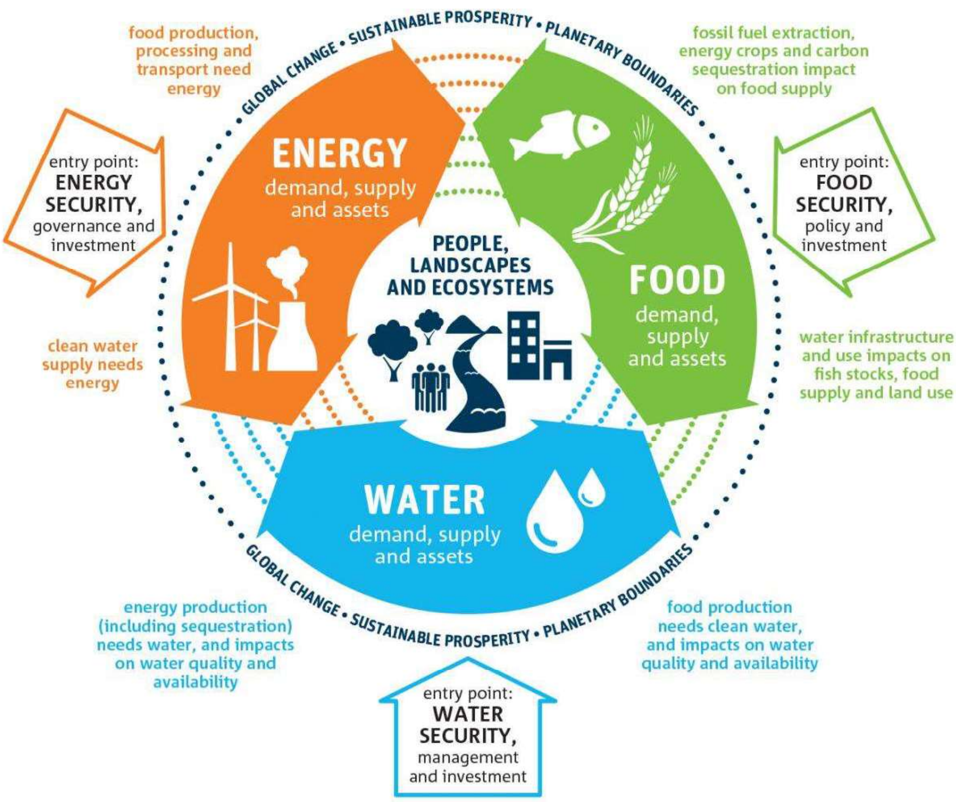

Image credit: http://www.iwa-network.org/learn/sustainable-development-the-water-energy-food-nexus/

In conclusion

- Automated, real-time water monitoring and appropriate big data management can allow for efficient and suitable allocation of water for different end-users.
- Competing water uses at the WEF nexus can be more efficiently managed by allocating water of varying qualities that is suitable for human, agricultural, industrial or environmental use.
- Real-time automated monitoring can assist this management as well as proactively account for monsoon and flood storage needs within catchment-wide management of WEF water resources.
- The lessons learned in the Hawkesbury-Nepean River Catchment are highly suited to Asia similarly highly-populated and climate change-impacted river basins.

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