Next Generation Water Science at the South Florida Water Management District

Two Examples of Science Innovation Leveraging AI/ML

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Showcasing AI/ML in Engineering, Water, and Climate Science

1

OPTIMIZATION, FORECASTING, MODELING (HYDROLOGY, OPS)

2

>10 YEARS OF ML APPLICATIONS AT SFWMD

3

EXAMPLES: PREDICTIVE MAINTENANCE, SIMULATION MODELS

Why Todays Talk

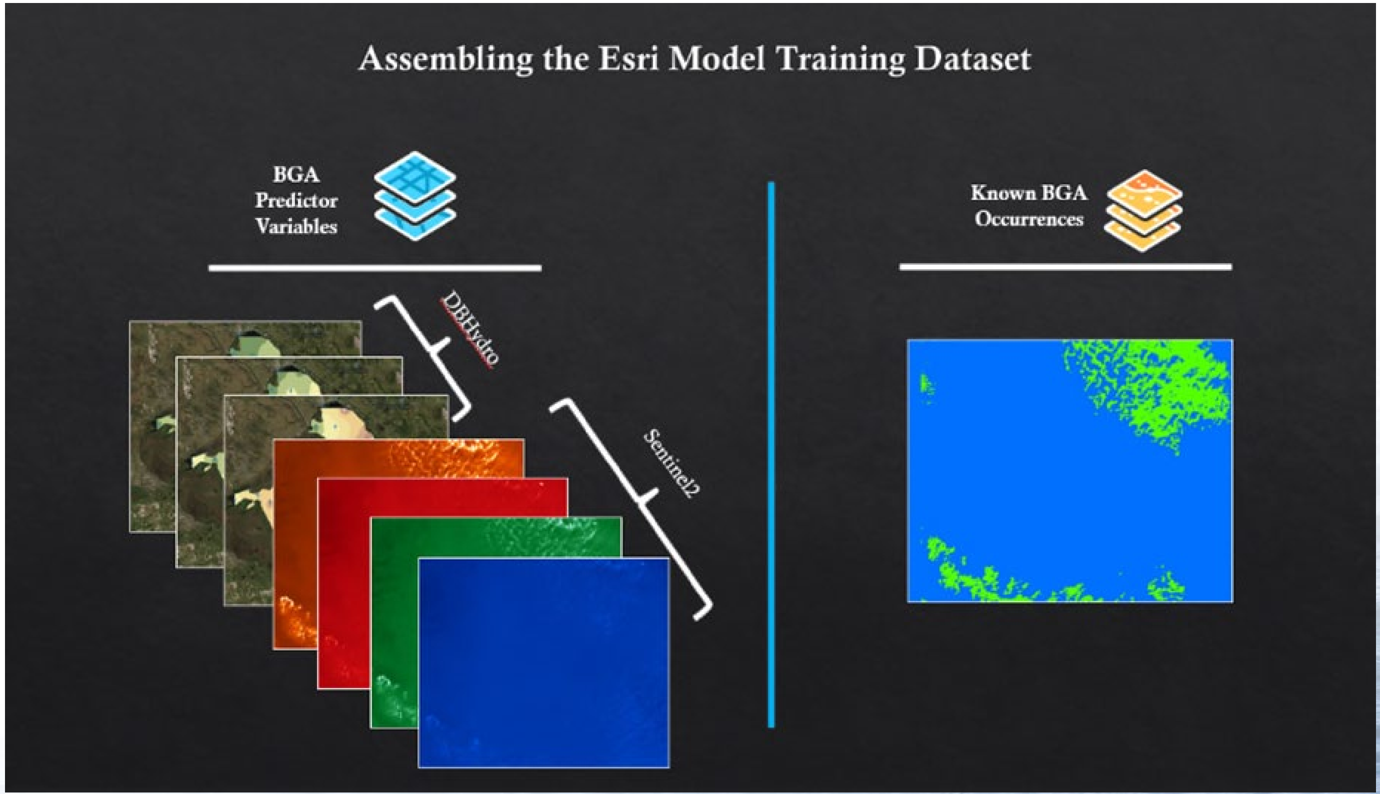
- AI is no longer futuristic
- Becoming part of every engineer's toolkit

Goal: is to share examples of two very different use cases at SFWMD

A Scientific Collaboration Around a Difficult Problem

The Challenge

- HABs remain difficult to predict.
- Many interacting environmental drivers.
- Traditional approaches struggle with highly multidimensional data.



….. Our objective wasn't simply to build a machine learning model. It was to build a scientific workflow that allows scientists to spend less time preparing data and more time making discoveries.

FDEP/SFWMD + Google Partnership

Collaboration with FDEP + Google Public Sector

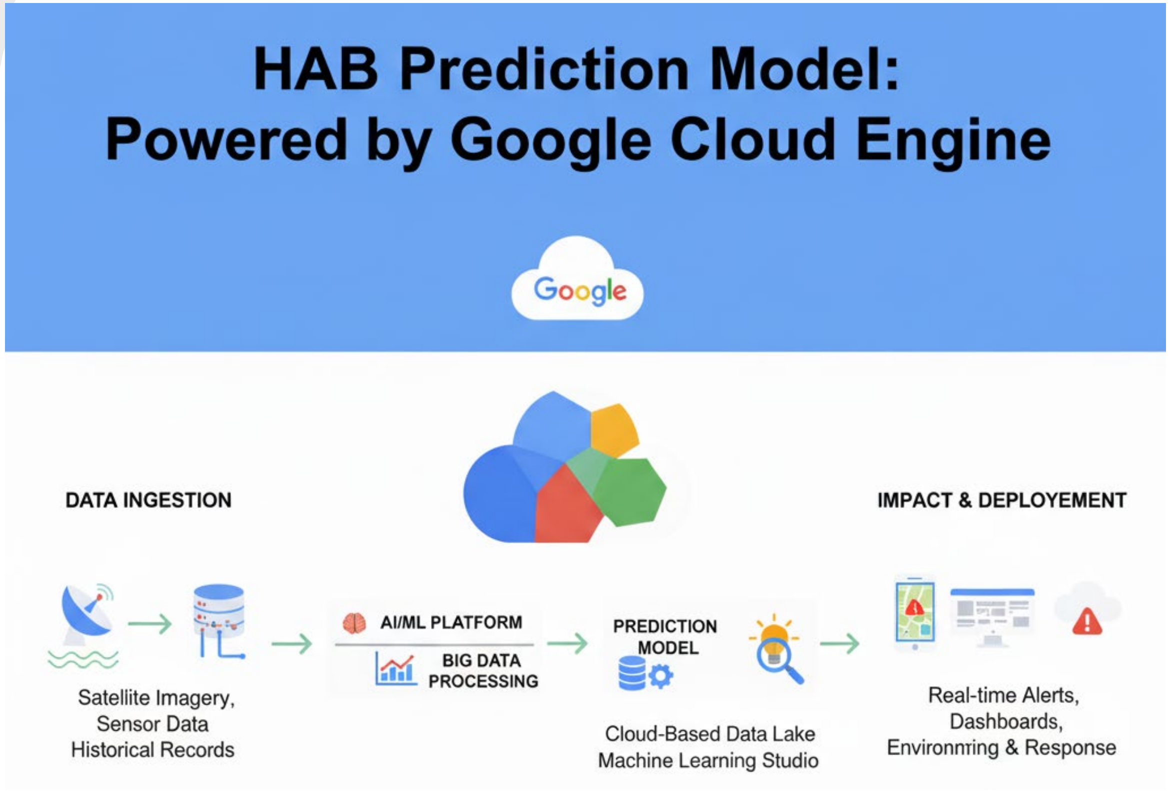
Objective: AI and Machine Learning Initiative with SFWMD Data and Science on Google Cloud Platform and Earth Engine

Use Case: Lake Okeechobee Hab Prediction Models

- Tools: Google Earth Engine, Google Cloud Platform (BigQuery, Vertex AI, Gemini, GC Kubernetes, …)
- Data sources: DBHydro, satellite data/imagery (Sentinel-2, -3)
- Prototype HAB prediction model

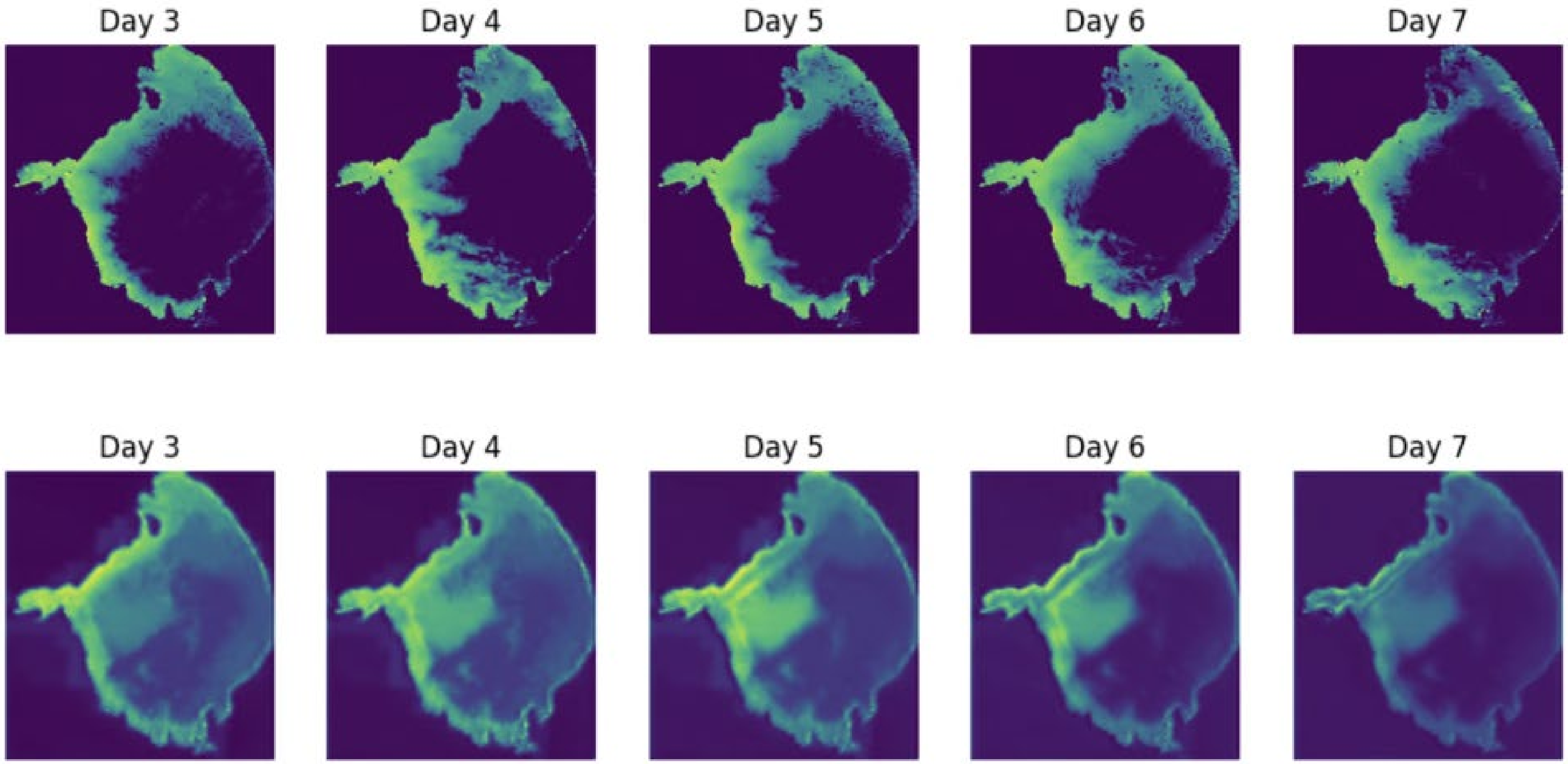
Follow on work – internal

- Hydroperiod tool
- CLOSE-HABS Model (University of South Florida with SFWMD and three other State universities as study partners to develop a decision support tool that will predict HABs in the Caloosahatchee River and Estuary, Lake Okeechobee, and the St. Lucie River and Estuary (CLOSE-HABs).



From Data to Prediction

- Prototype 1–3 day bloom forecasts
- Demonstrated an end-to-end scientific workflow
- Established a foundation for future applications



Example 2 - iModel

The ¿Model

AI-Powered Environmental Decision Intelligence

Developed in 2008, Years Before AI Became Mainstream

Alaa Ali, PhD, PE, PMP, F.ASCE., D.WRE

Chief Engineer

Modeling-SFWMD

The Challenge That Started Everything

- How can we operate one of the world's largest water management systems to simultaneously achieve:
  - Ecological restoration
  - Flood protection
  - Water supply reliability
- Traditional hydrologic models could simulate system consequences of operational decisions.
- However, they could not determine the operational decisions needed to achieve certain consequences.
- The iModel was developed to answer that question.

A Fundamental Shift in Thinking.

- Why the ¿Model was a breakthrough?
  - Reframed one of the most challenging problems in environmental engineering.
  - Unified physics-based modeling, artificial intelligence, and optimization
  - Shifted the focus from prediction to decision.
- The ¿Model demonstrated that artificial intelligence could be used not only to understand complex environmental systems, but also to determine how they should be operated.

Paradigm Shift: Changing the Question

Traditional Models	*i*Model
Operations	Desired Environmental Outcome
↓	↓
Hydrologic Response	Optimal Operations
Iterative Trial-and-Error	Objective AI-Guided Optimization

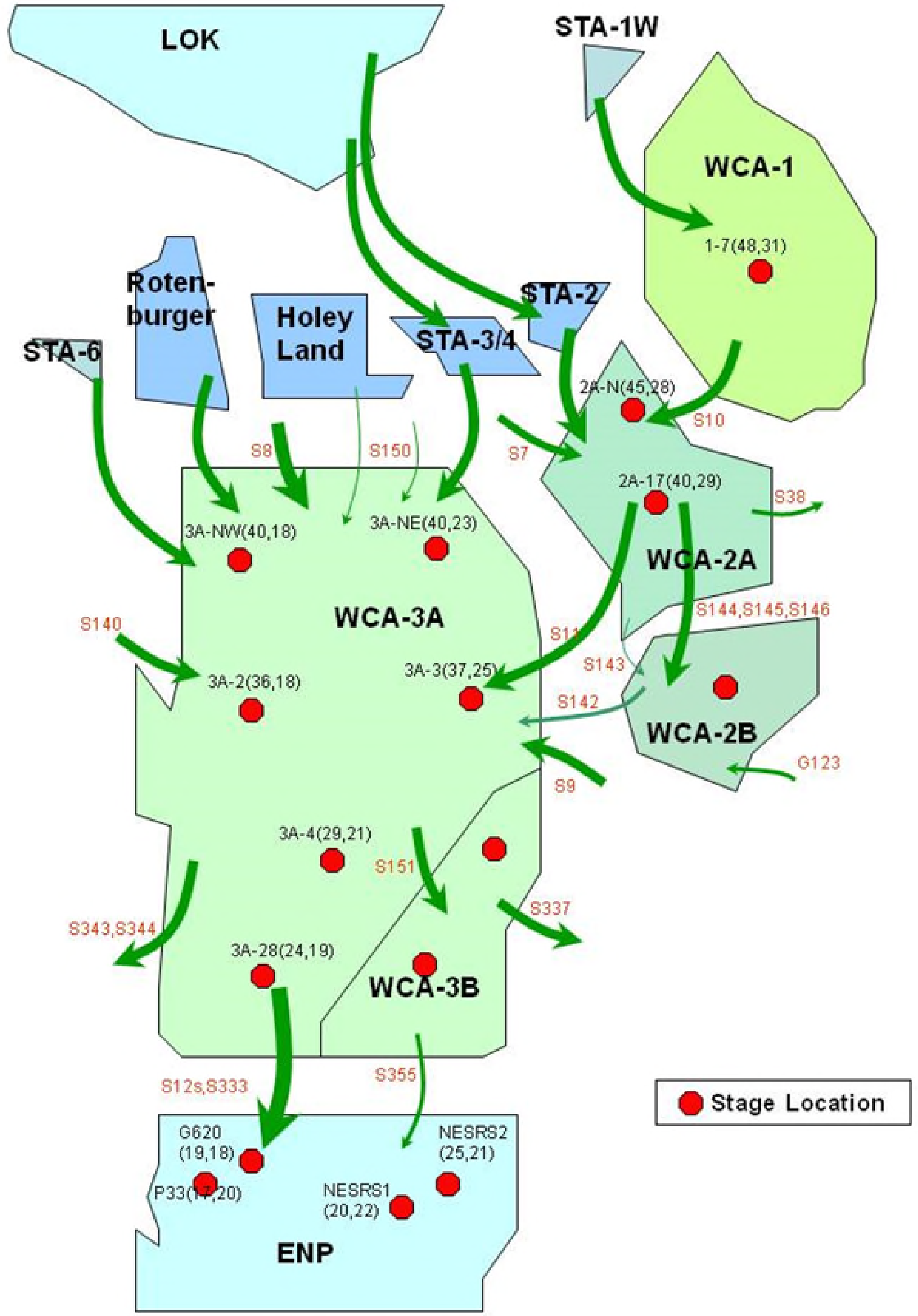
- The *i*Model transformed environmental modeling for predicting system behavior to computing operational decisions.

AI Before AI Became Mainstream

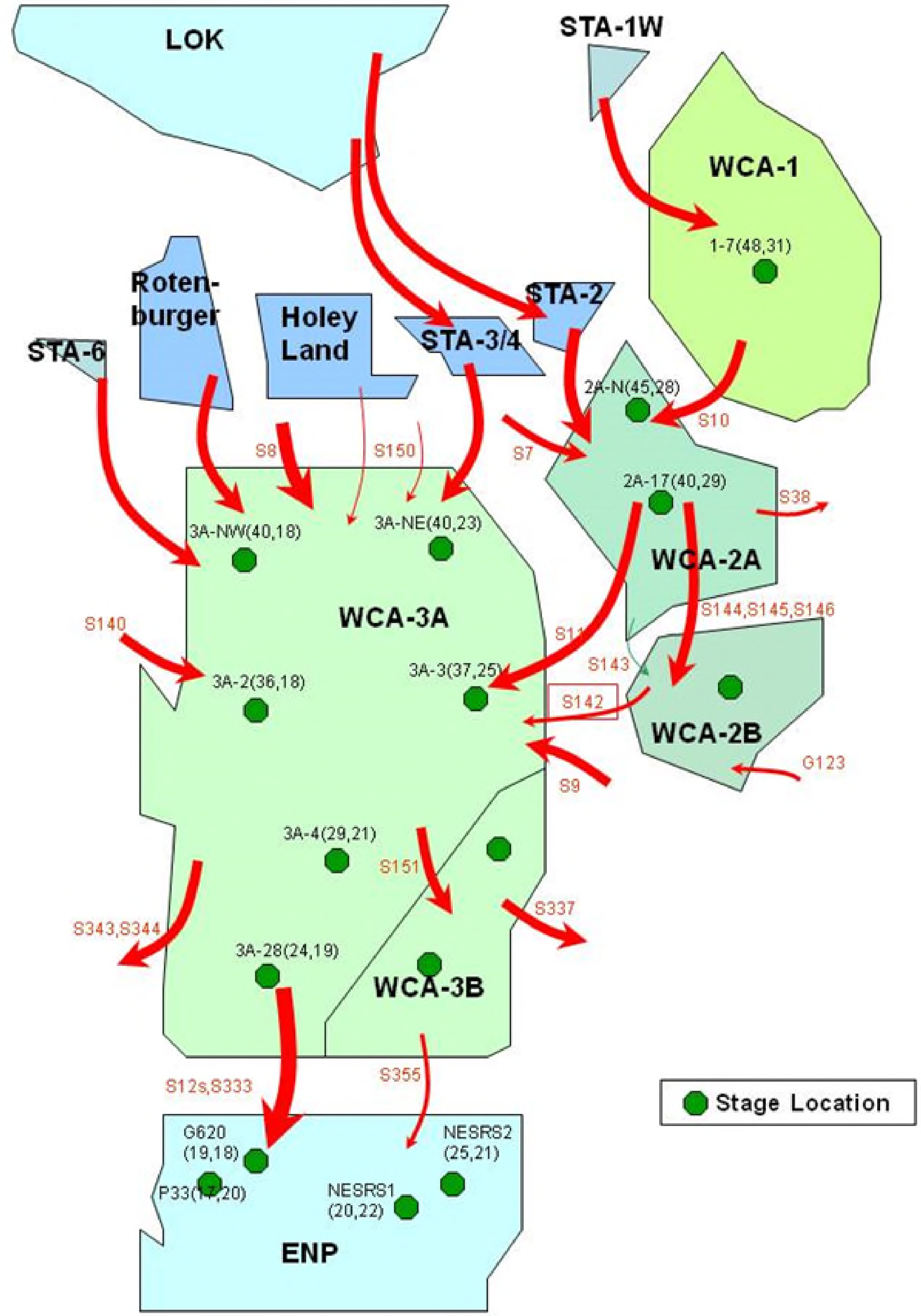
- Artificial Neural Networks
- Genetic Algorithms/Simulated Annealing/Pattern Search
- Hydrologic Emulators
- Decision Intelligence
- These technologies formed the foundation of the *i*Model in 2008.

S O U T H   F L O R I D A   W A T

DIRECT MODEL, → RSM

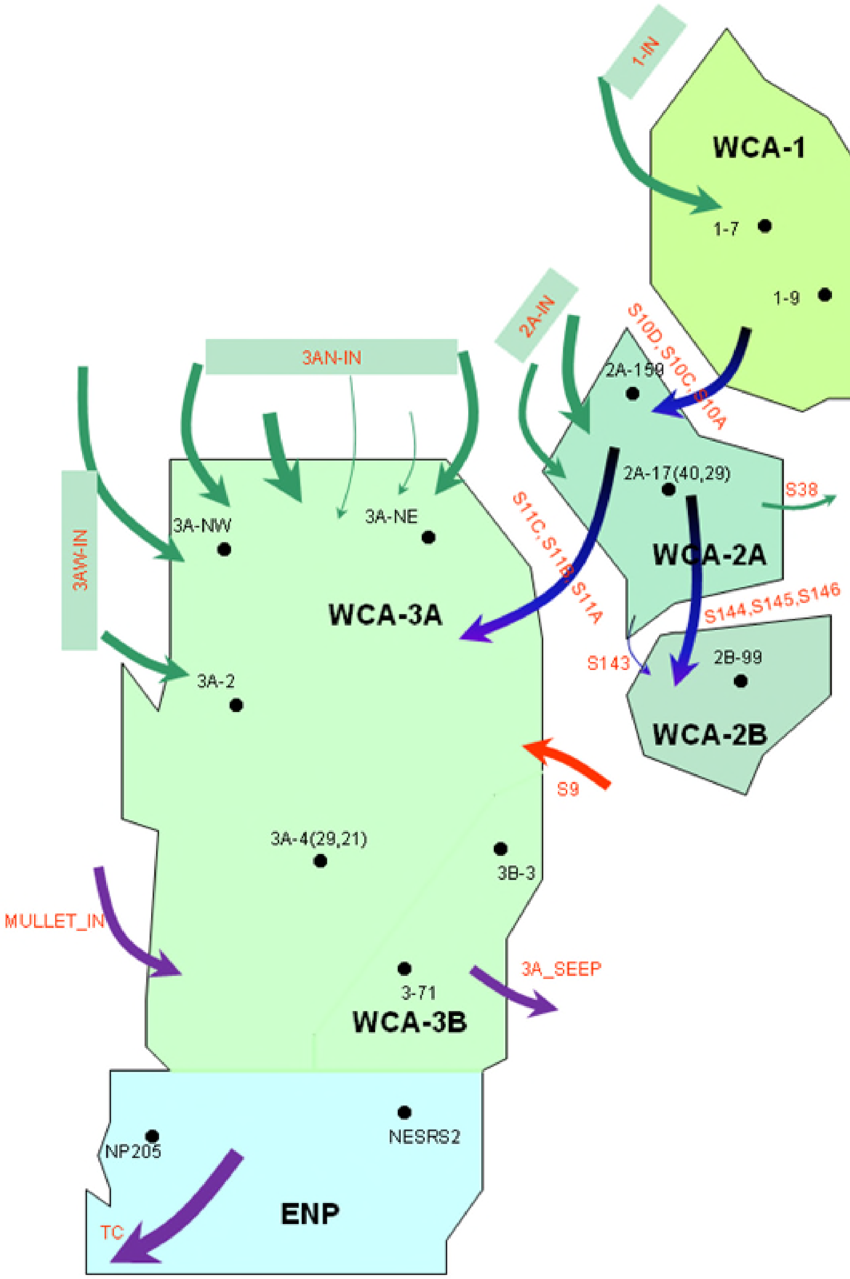


iNVERSE MODEL, → iModel



Real World iModel Projects

- River of Grass Restoration (ROG) – 2008
- Central Everglades Planning Project (CEPP) – 2011
- Restoration Strategies Operations - 2017
- Combined Operating Plan (COP) and Tamiami Trail Flow Formula – 2020
- CEPP South Validation – 2021
- Biscayne Bay & Southeastern Everglades Ecosystem Restoration (BBSEER) - 2024
- CEPP Operations 1.0 – 2026



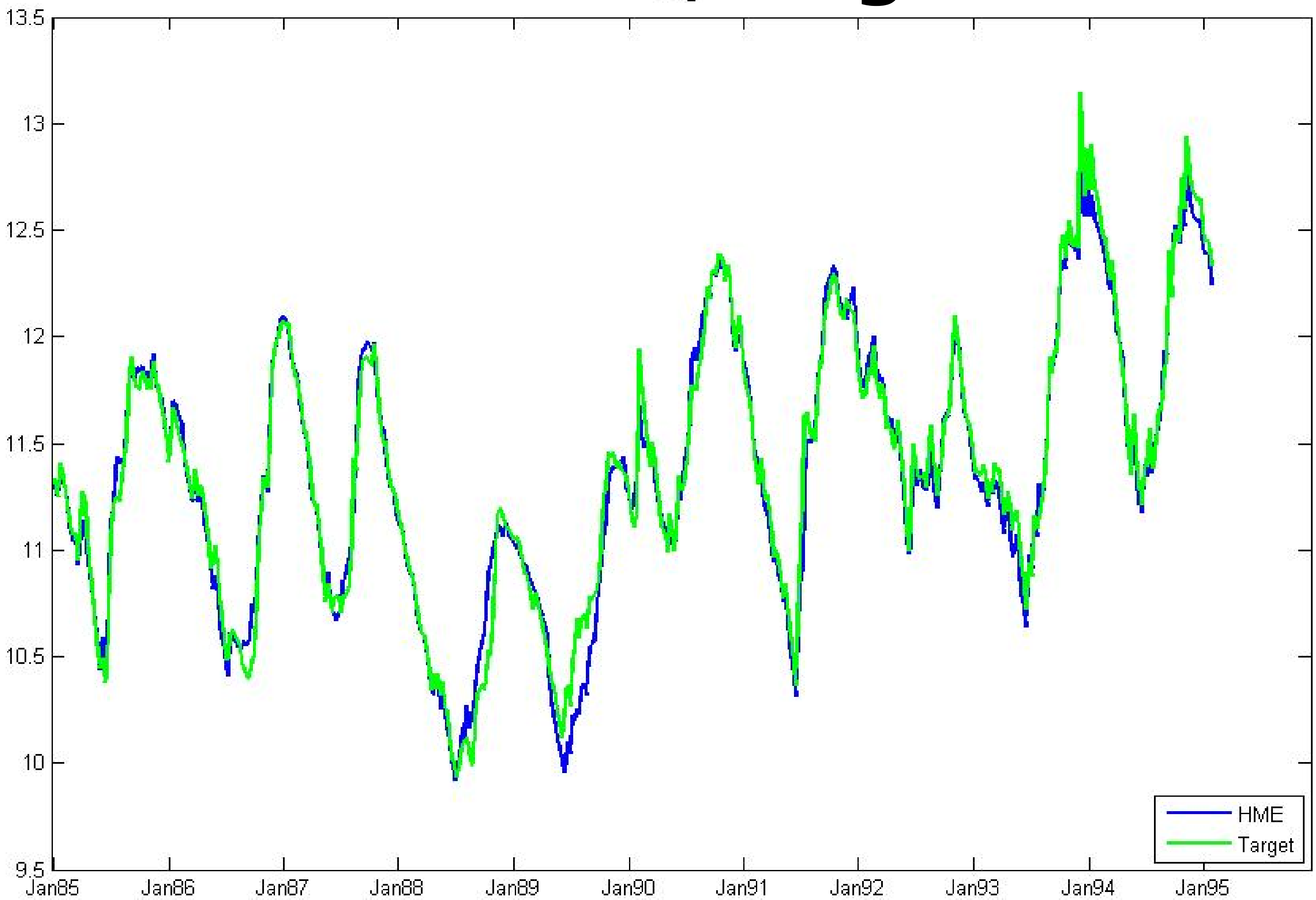
iModel Application to the River of Grass Restoration

Trust Through Verification

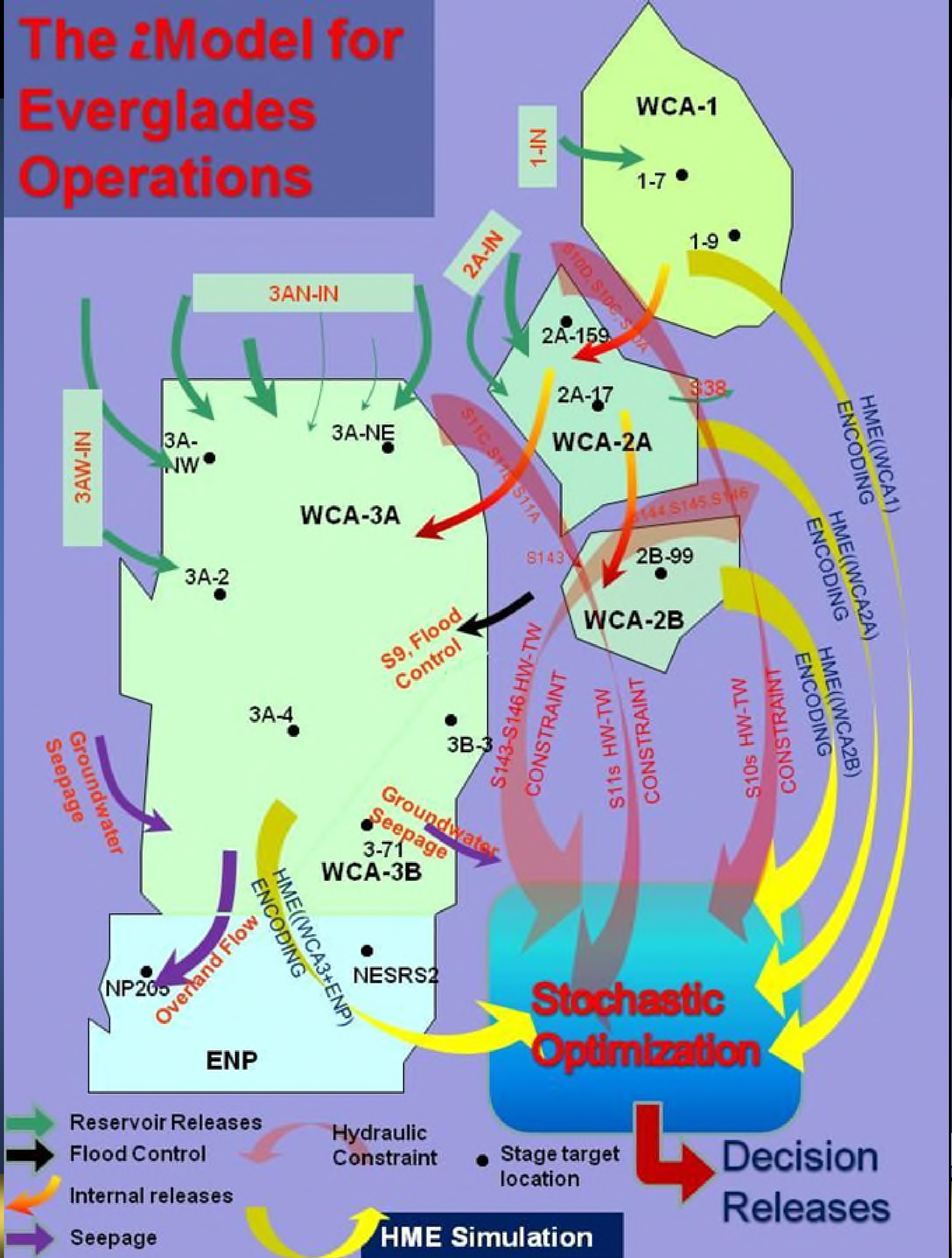
- AI identified optimal operational strategies.
- Every solution was verified using the full physics-based hydrologic model.

- **Physics remained the final authority.**

HME verification during 1985-1994



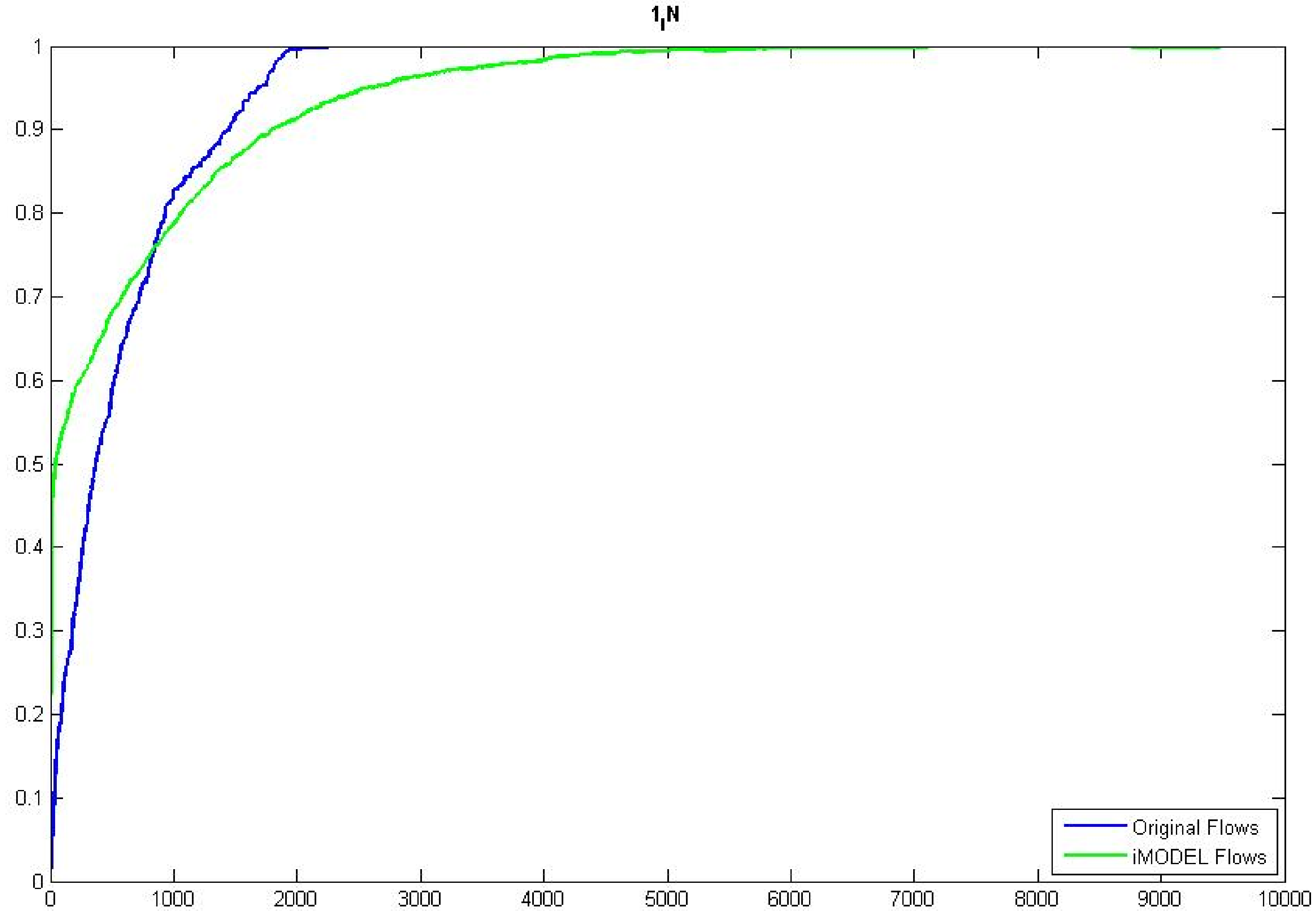
The iModel for Everglades Operations



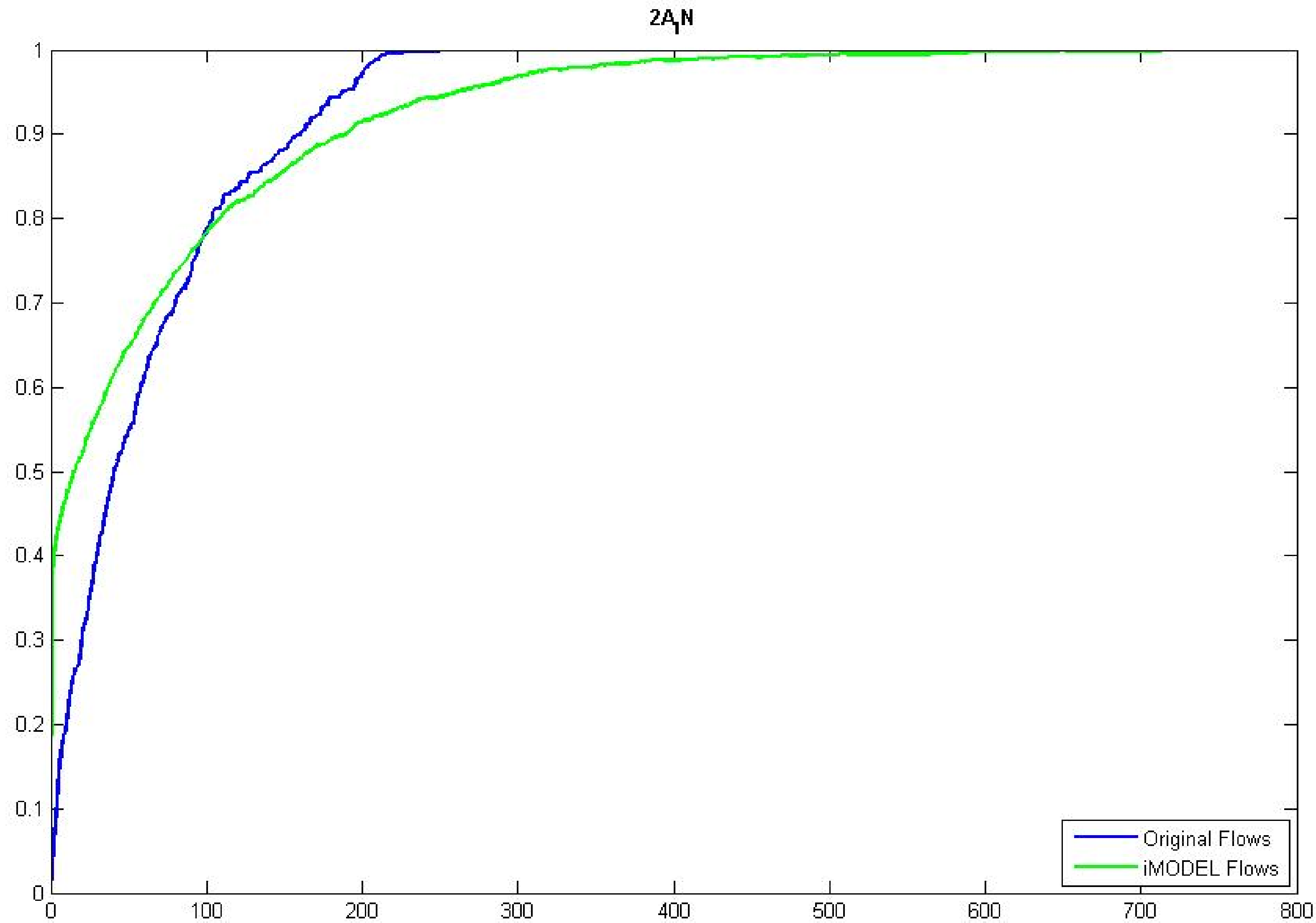
FLOW COMPARISONS

- Original flow from RSM
- iModel optimal flows

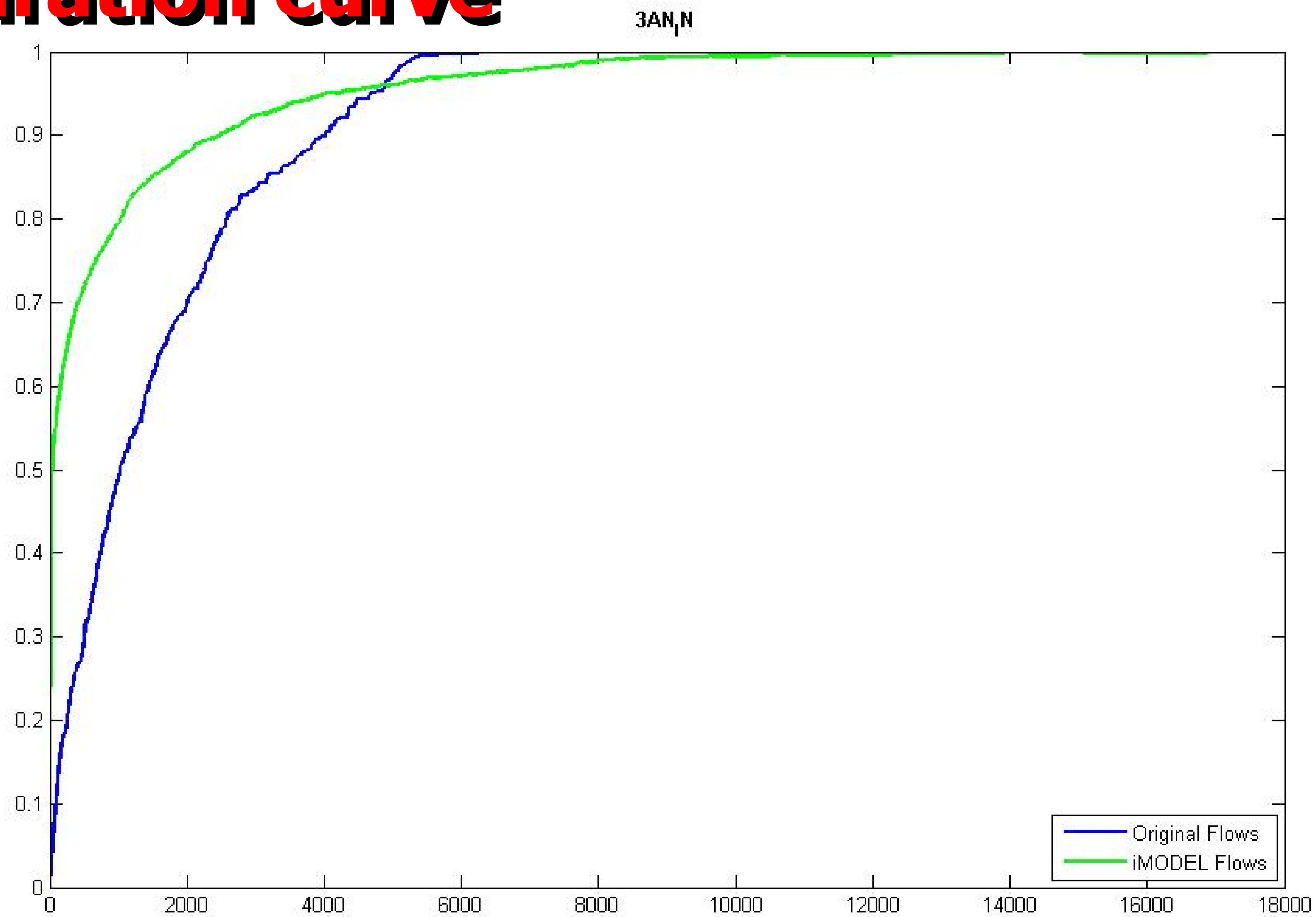
Original flow and iModel flow duration curve



Original flow and iModel flow duration curve



Original flow and iModel flow duration curve



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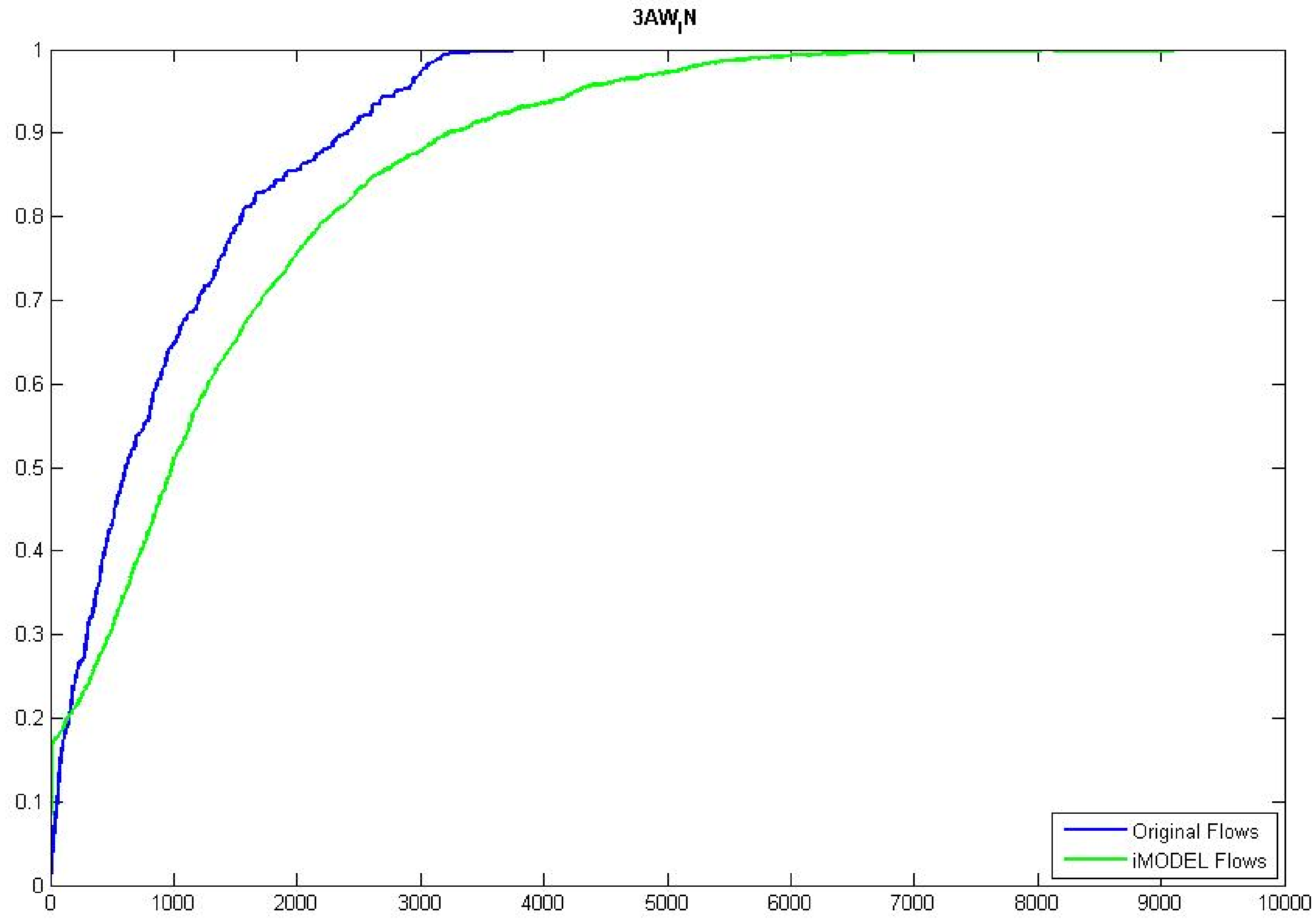

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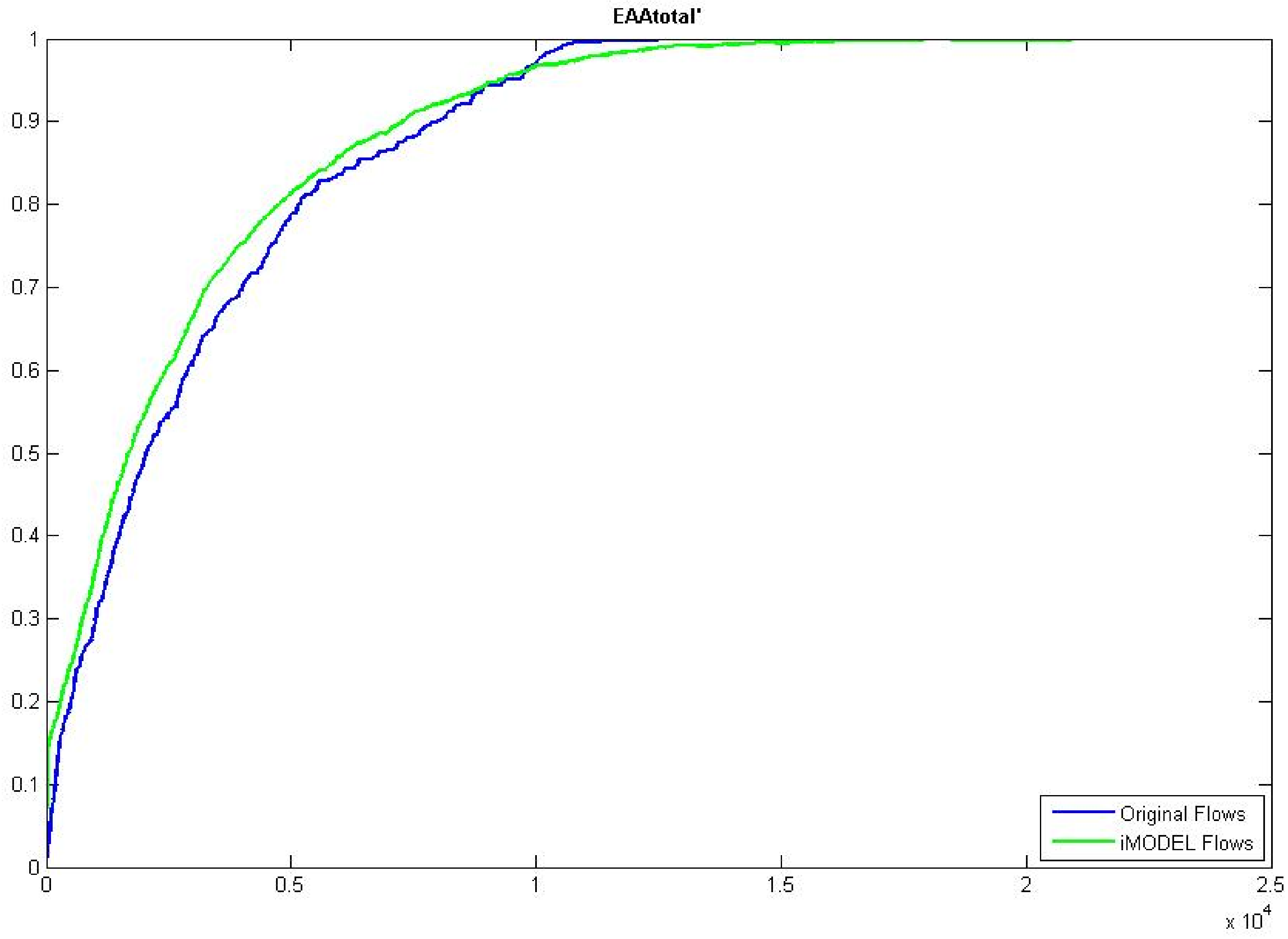

From Optimization to Decision Intelligence

- The iModel evolved beyond optimization.
- It became a decision-support framework.
- Decision makers could evaluate competing objectives and understand the trade-offs associated with each operational strategy.

Adversity Trade-Off Matrix, ATOM

Default	0.159	0.178	0.360	0.172	0.987	0.127	0.245	0.321	0.169	0.199	0.347	0.422	0.183	0.188	1.852E+06
	3A_NW'	3A_2'	3A_4'	3A_NE'	3_71'	3B_3'	NP_205'	NESRS2'	TC	2A_159'	2_17'	'2B_99'	1_9'	1_7'	MinQnorth
3A_NW'	-36.1%	4.7%	-0.4%	9.1%	1.6%	1.9%	-1.3%	2.6%	1.5%	2.5%	0.7%	0.5%	0.4%	0.7%	-2.9%
3A_2'	3.8%	-17.0%	-4.9%	-8.8%	1.8%	1.9%	1.3%	0.2%	0.0%	1.6%	1.9%	0.0%	1.1%	0.9%	3.3%
3A_4'	-2.5%	-3.0%	-47.5%	-3.4%	6.8%	12.1%	10.7%	15.4%	-0.6%	3.7%	5.1%	4.0%	3.2%	3.3%	3.1%
3A_NE'	12.1%	-5.3%	-4.2%	-22.5%	2.1%	0.0%	2.3%	-1.2%	-0.4%	1.5%	1.7%	-0.3%	1.3%	1.1%	4.8%
3_71'	27.4%	25.4%	52.1%	17.0%	-31.9%	35.1%	33.1%	111.4%	98.9%	4.0%	8.7%	-0.4%	4.5%	5.3%	-1.7%
3B_3'	0.0%	2.2%	2.4%	1.4%	0.5%	-52.9%	31.1%	0.8%	14.5%	2.0%	4.9%	-1.5%	2.0%	2.1%	1.1%
NP_205'	-5.4%	0.4%	-1.3%	2.8%	2.4%	21.4%	-46.4%	2.3%	3.2%	4.3%	1.4%	3.5%	1.1%	0.7%	-0.5%
NESRS2'	4.6%	3.8%	7.3%	1.3%	7.7%	0.2%	0.3%	-53.4%	-13.0%	2.8%	2.7%	0.2%	2.7%	2.9%	-0.1%
TC	0.1%	3.7%	-1.2%	3.7%	2.2%	17.5%	3.1%	-5.6%	-51.5%	2.1%	3.7%	0.3%	5.5%	5.4%	2.1%
2A_159'	3.6%	2.8%	0.8%	2.4%	0.7%	4.6%	4.8%	-0.1%	3.3%	-24.6%	11.2%	55.1%	18.0%	15.5%	0.9%
2_17'	-0.8%	0.2%	0.5%	0.7%	0.2%	2.3%	2.0%	1.7%	4.8%	10.1%	-29.7%	-9.1%	38.3%	32.6%	3.6%
'2B_99'	-0.3%	0.0%	0.0%	-0.4%	0.1%	-0.5%	1.5%	-0.1%	0.0%	3.4%	0.0%	-12.8%	0.9%	1.0%	1.2%
1_9'	0.1%	1.1%	0.7%	0.0%	0.2%	-0.8%	0.9%	0.8%	3.6%	6.0%	9.8%	0.3%	-34.4%	-18.0%	1.2%
1_7'	-0.4%	1.4%	0.6%	0.4%	0.3%	-0.5%	0.8%	0.8%	4.0%	7.3%	11.8%	-0.9%	-14.5%	-27.8%	0.8%
MinQnorth	-7.6%	3.4%	4.2%	6.9%	-0.5%	-1.1%	0.0%	-0.6%	4.4%	1.1%	5.5%	2.0%	20.4%	6.0%	-18.9%

Looking Back from 2026

2008	Today
Artificial Neural Networks	Deep Learning
Hydrologic Emulator	Digital Twin
Genetic Algorithms	Reinforcement Learning
Optimization	Decision Intelligence
Offline Analysis	Real-Time Operations
Historical Data	Live Telemetry
Hydrologic Forecasts	AI Forecasting

The terminology has evolved. The architectural vision remains remarkably relevant.

The Next Generation of the iModel

- Physics-informed AI
- Real-time Digital Twins
- Cloud optimization
- Uncertainty quantification
- Operational Recommendations for Decision Making

The Future

- Physics gave us understanding
- AI gives us intelligence
- Physics and AI together enable better environmental decisions.

- **THE FUTURE BELONGS TO PHYSICS + AI**