Planning for a secure energy transition in Aotearoa

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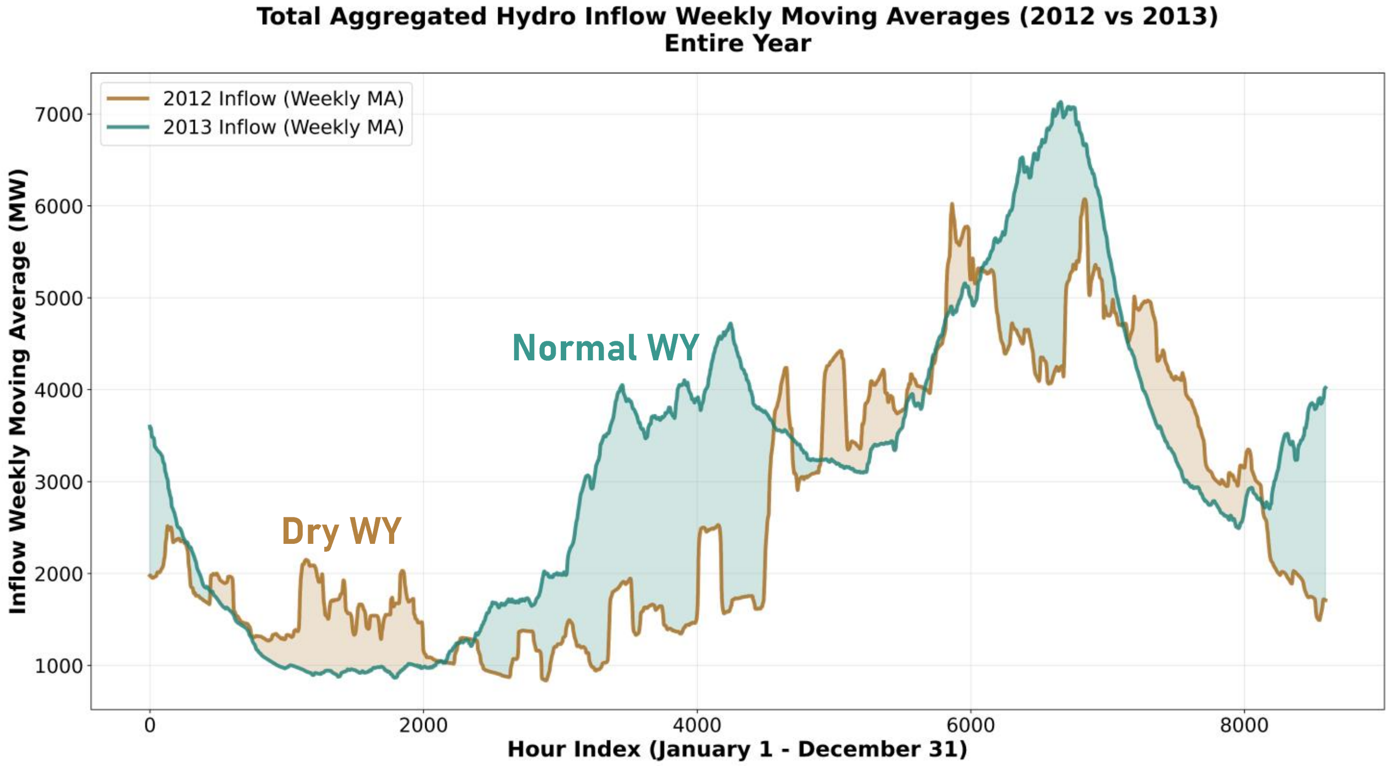
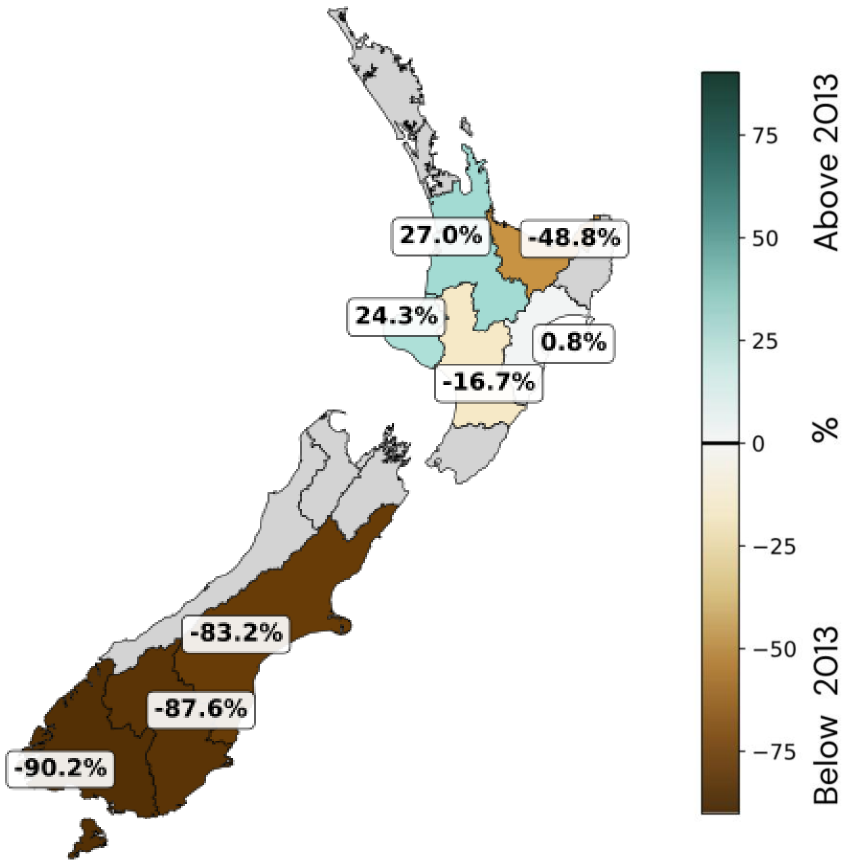
Familiar story: Dry winters in New Zealand

Low inflows impact hydro operation; historically backed up with fossil





In-Confidence

Source: Electricity Authority, ERA5

But what happens in a future system?

Changing demands, greater renewable penetration, new flexibility resources

NZ's electricity adequacy challenge historically strongly linked to hydrological variability and dry-year conditions

However, the future electricity system will be fundamentally different:

- Higher electrification of transport, industry, and heat
- Greater penetration of wind and solar generation
- Emergence of new flexibility resources (batteries, demand response, etc.)

As system inputs become more diverse, the relationship between hydrology and reliability may change…

How do reliability risks evolve in future net-zero electricity system?

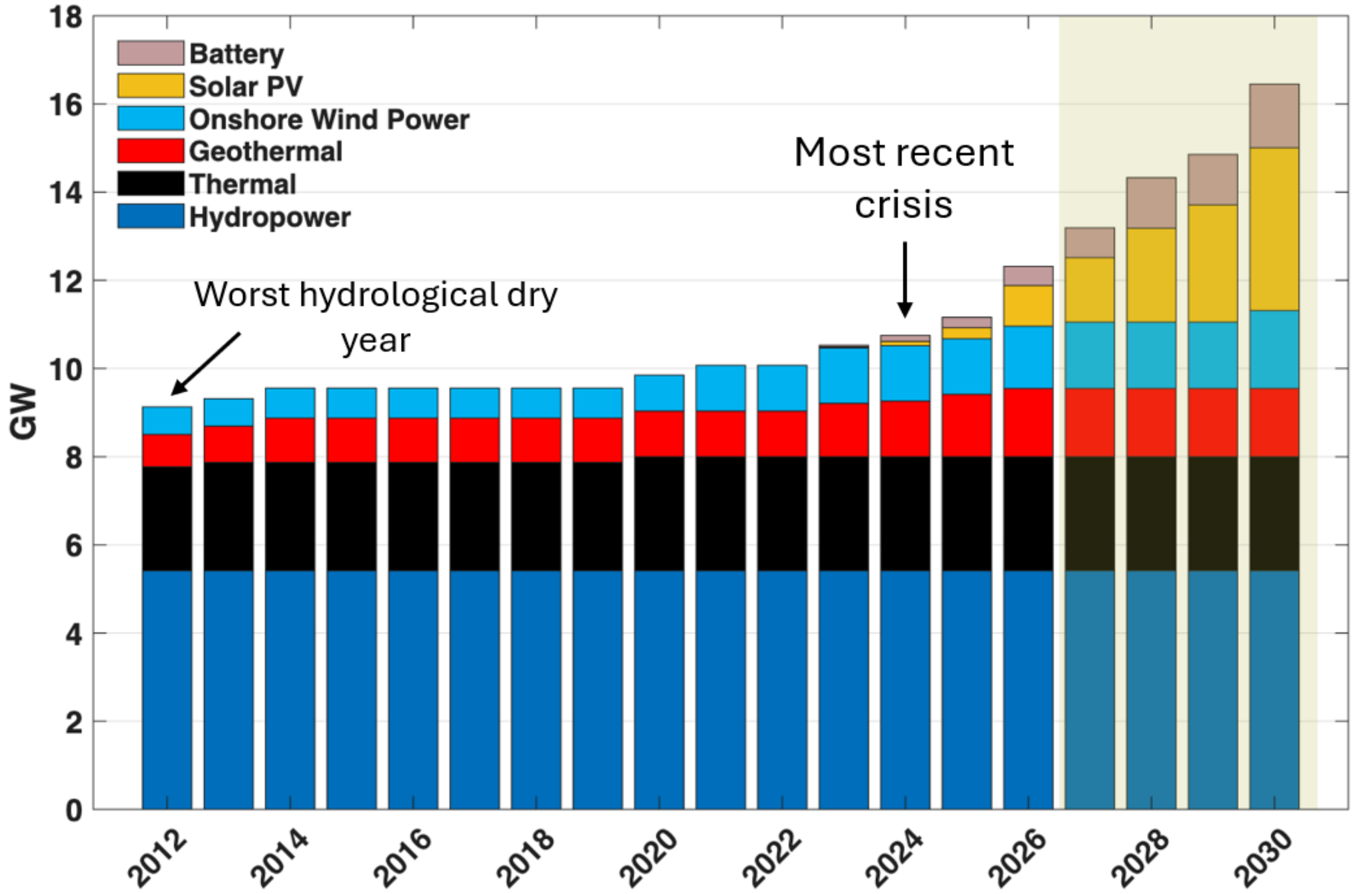
What can we understand from the pipeline?

Looking up to 2030, investment pipeline for solar, wind, and geothermal

>700 MW of renewable generation was **commissioned** during 2024–2025

From the investment pipeline:

- Using only advanced-stage projects (delivery stage or > 50% investigation stage)
- 3,200 MW of utility-scale solar and 350 MW of wind are **scheduled** for delivery between 2026-2030



Historical installed electricity generation capacity with expected capacity in the development pipeline by 2030. Shaded region showing planned new projects based on estimated delivery dates. (*Zegeer et al., 2026*)

Zegeer M.L., Satymov R., Vatankhah Ghadim, H., Titus K., Haas J., Peer R. (2026) Planned Renewable Development Can Mitigate Near-Term Dry-Year Electricity Risk in Aotearoa New Zealand. Royal Society of New Zealand. (In Review)

We tested optimal 2030 system under dry conditions

Using PyPSA-NZ, a least-cost optimisation model for Aotearoa New Zealand

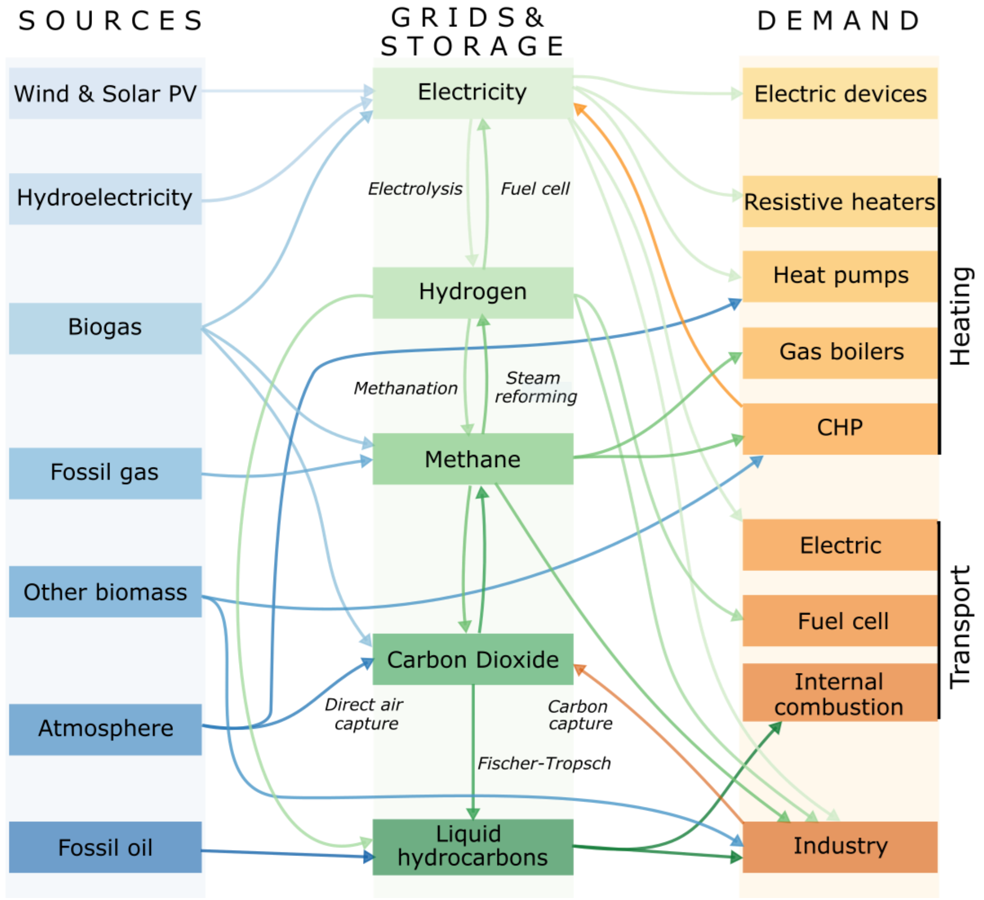
PyPSA-NZ uses a bottom-up framework that optimises **system cost**, manages **congestion**, and applies **CO_2 emission caps**.

Inputs:

- 2012 weather year
- 2012 demand pattern, projected to 2030 demand
- Existing generation capacity

Added constraints:

- New capacities capped at pipeline capacity



https://pypsa-eur.readthedocs.io/en/latest/supply_demand.html

PyPSA-NZ applies the PyPSA-Earth framework

Objective function, decision variables, and technical constraints

$$\min \sum_{y \in Y} \left(CAPEX_y \cdot x_y + \sum_{t \in T, z \in Z} OPEX_{y,t,z} \cdot g_{y,t,z} \right)$$

- **CAPEX:** Capital Expenditure
- **OPEX:** Operational Expenditure
- **y:** Technologies (generation, storage, transmission expansion, etc.)
- **t:** Time periods (e.g., hourly steps)
- **z:** Spatial zones/nodes

Decision variables:

- **$g_{y,t,z}$:** Dispatch (generation or storage output) of technology **y** at time **t** and zone/node **z**
- **x_y:** Investment decision – capacity added (e.g., MW) for technology **y**

PyPSA-Earth solves LOPF

Nodal balance (In=Out)

Kirchhoff's Current Law (KCL) at every bus:

$$\sum_{y \in Y_z} g_{y,t,z} - d_{t,z} = \sum_{l \in out(z)} f_{l,t} - \sum_{l \in in(z)} f_{l,t}$$

- **$d_{t,z}$:** Demand at time **t** and zone/node **z**
- **Decision variable $f_{l,t}$:** Real power flowing through transmission line **l** at time **t**

Kirchhoff's Voltage Law (KVL):

Flows linked to θ differences

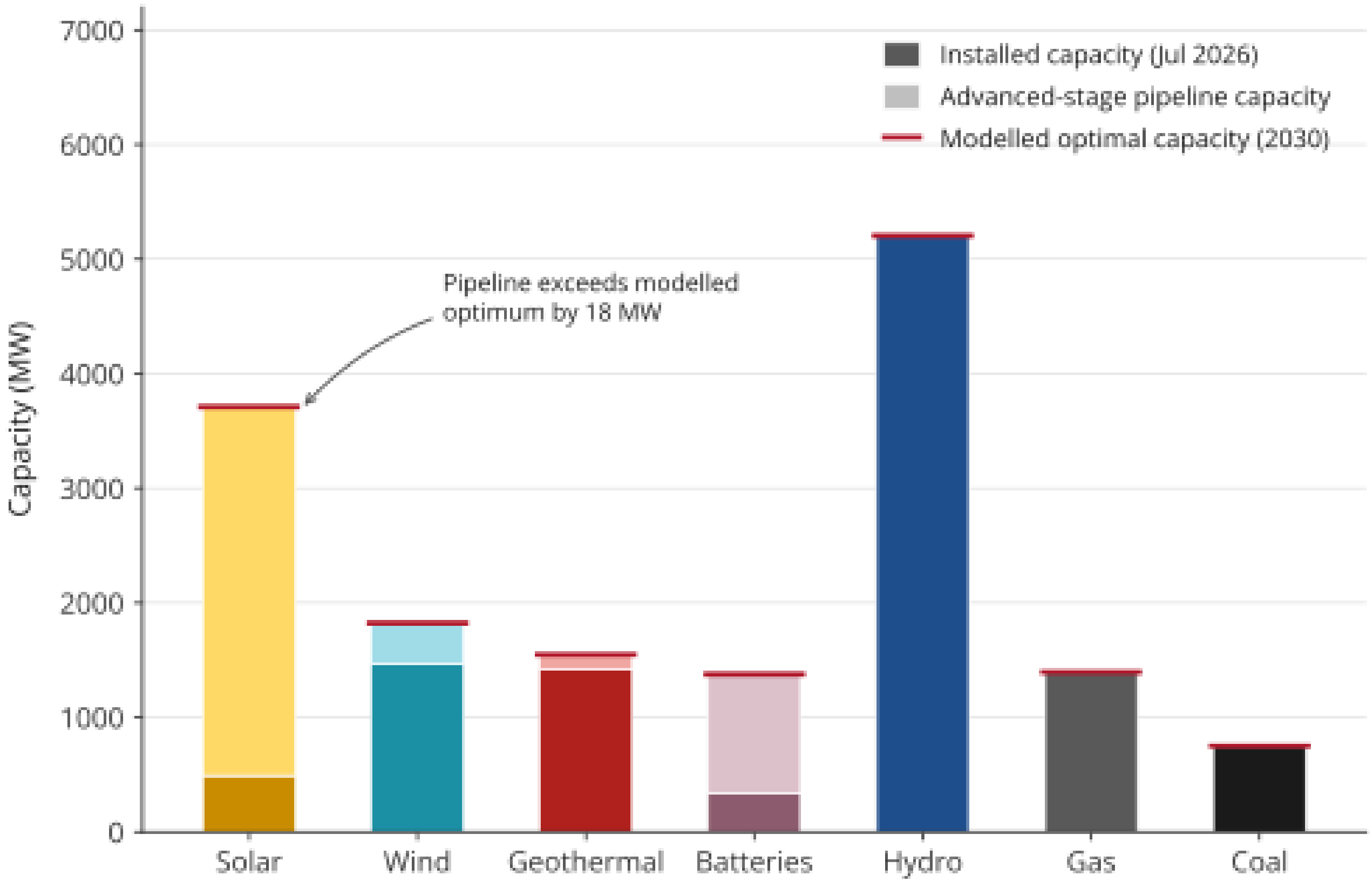
$$f_{l,t} = B_l \cdot (\theta_{n,t} - \theta_{m,t})$$

- **B_l:** Susceptance of line **l**
- **$\theta_{n/m,t}$:** Voltage phase angle at bus **n** (start of line), and bus **m** (end of line)

https://pypsa.readthedocs.io/en/latest/user-guide/optimal-power-flow.html

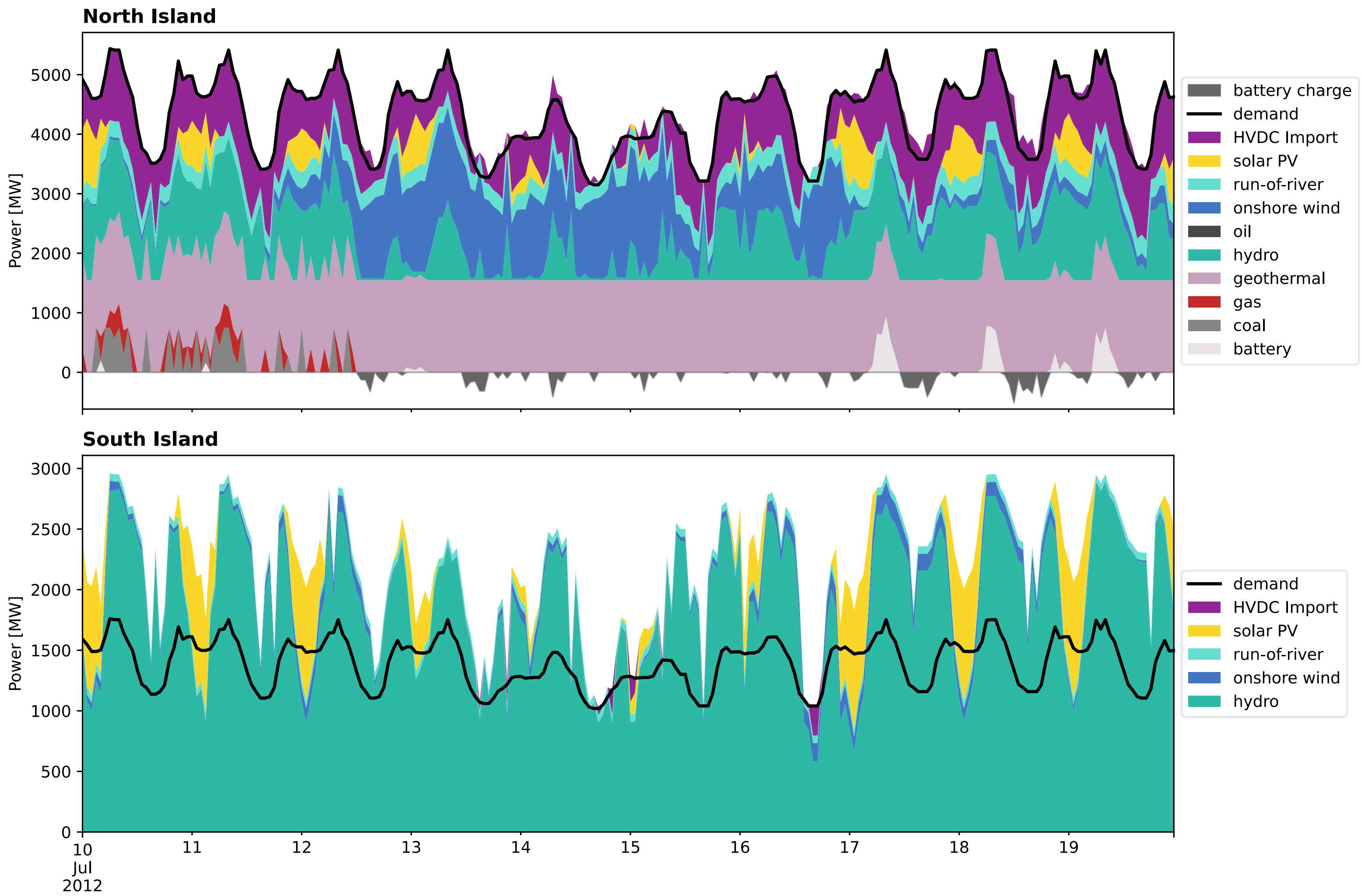
Planned renewable investment meets 2030 demand

Optimised capacities for a severe (2012) dry year meet the planned investment pipeline capacities



When hydro is low, we see gas, coal, and batteries

Modelled 2030 hurly electricity supply and demand in July, when hydro storage is lowest



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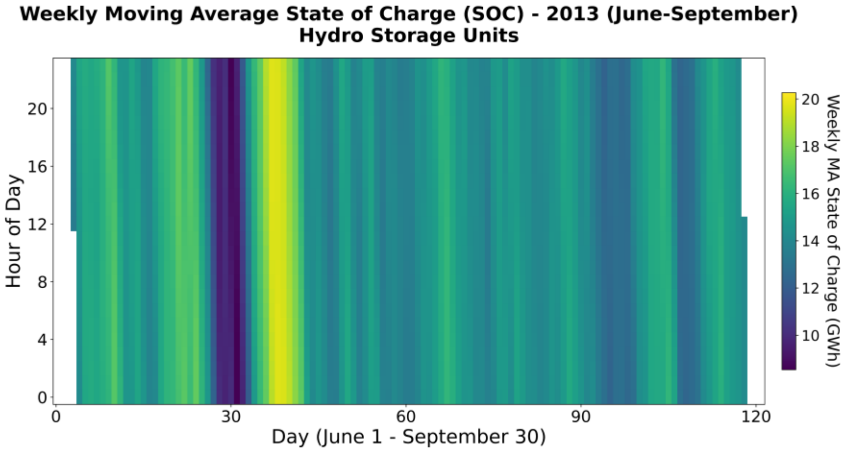
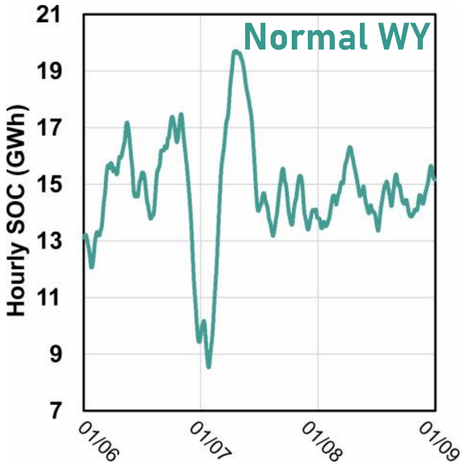
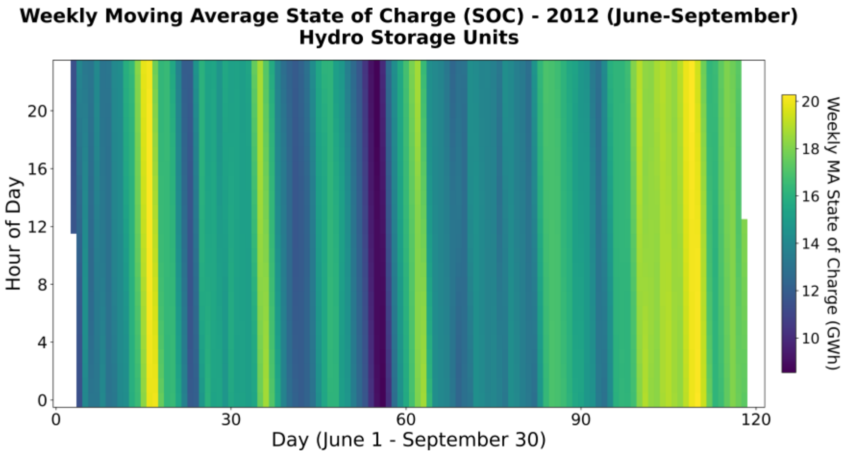
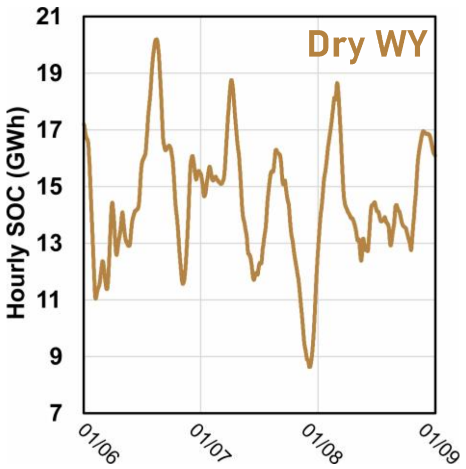
In a dry year, hydro operation is more volatile*

Hydro reservoir state of charge (SOC) shows more dynamic operation in dry years









Notable Operational Changes:

- BESS utilisation rate:

  +15%

  more in 2012

- Run-of-River CF:

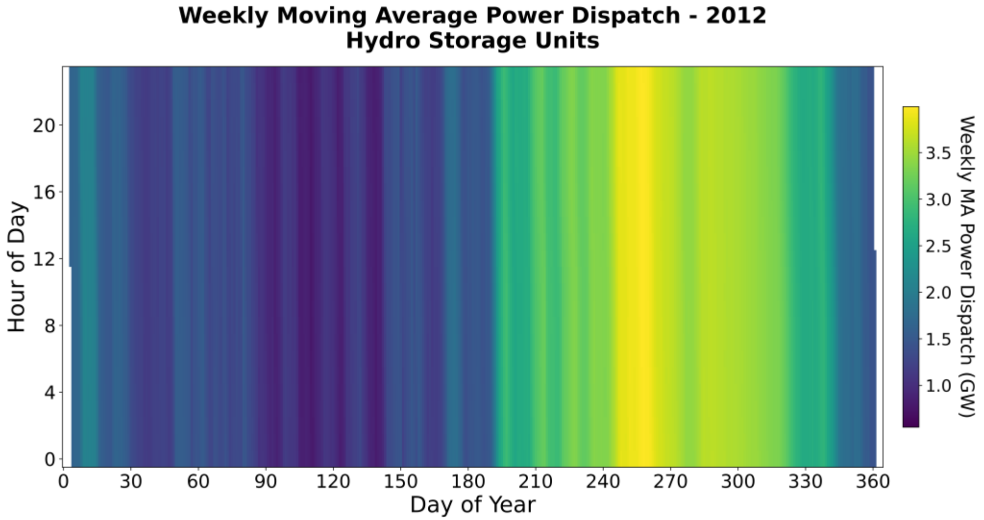
  ~99%

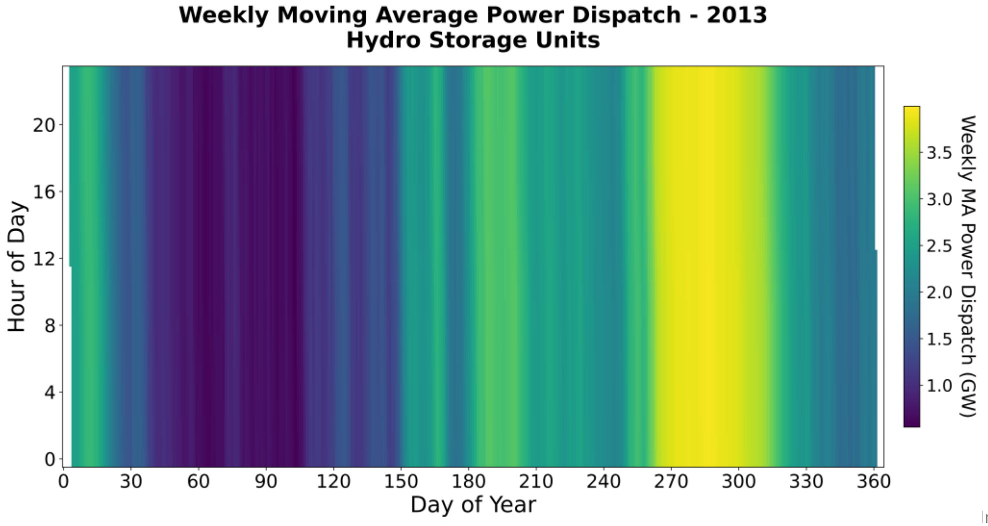
  in 2012

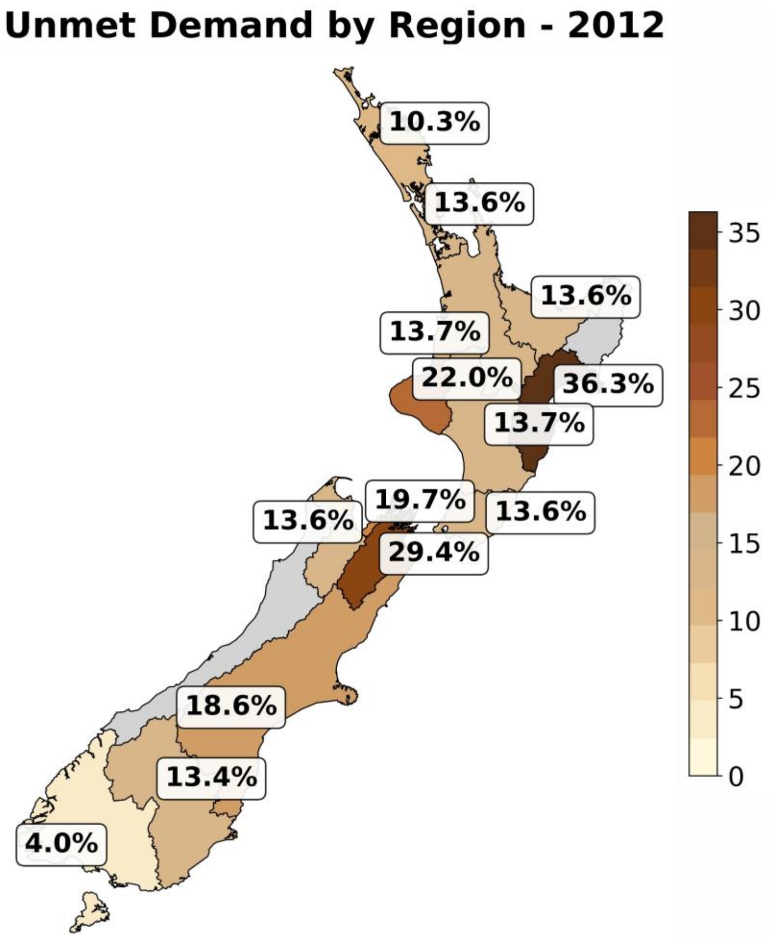
*In a least-cost optimised system with perfect foresight

Potential adequacy risk when planning for “normal”

~8 TWh of unmet demand if a system optimised by a normal weather year faces a dry winter







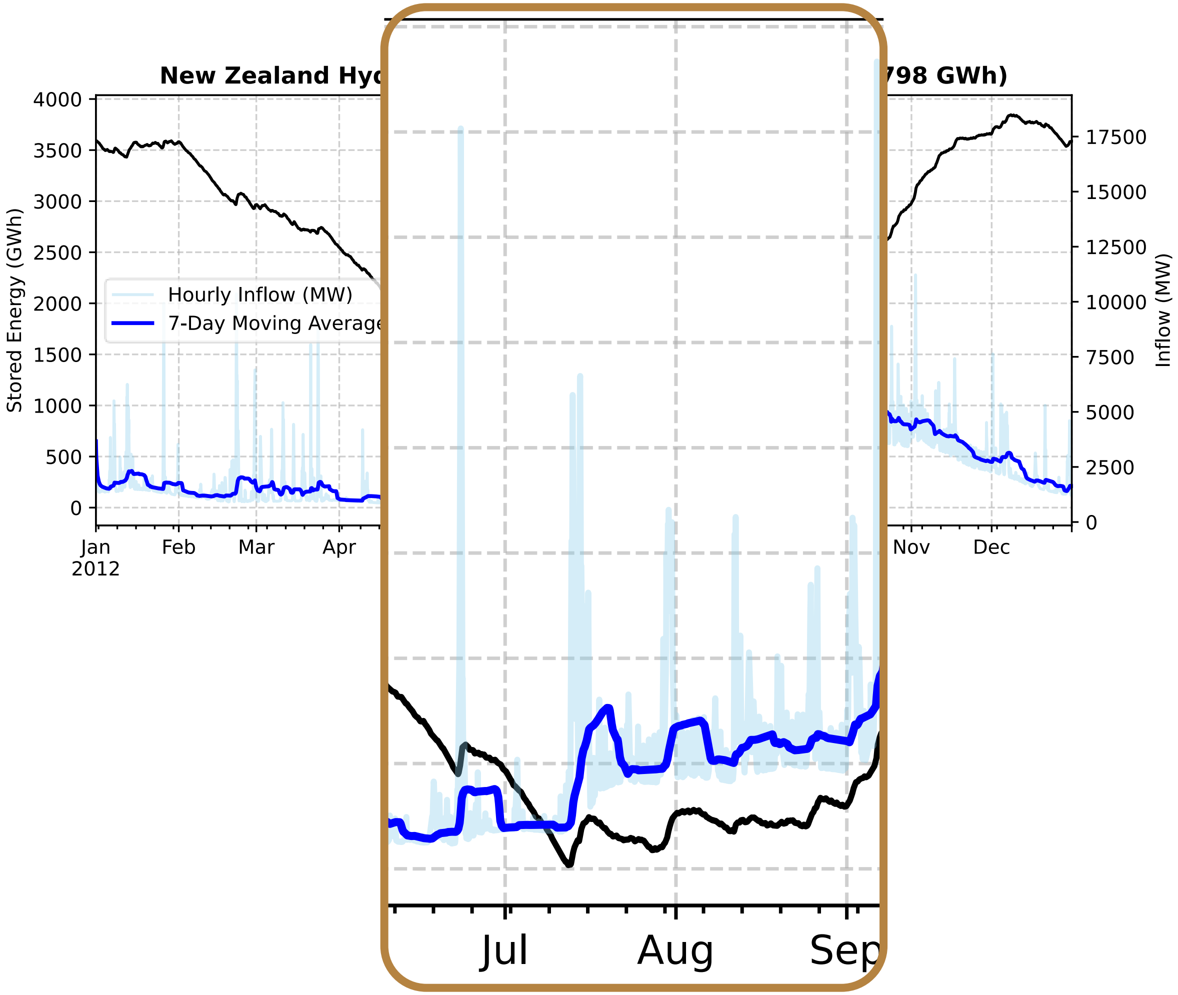
UC

BUT… We are assuming perfect foresight

How robust are these results under more realistic system operation?

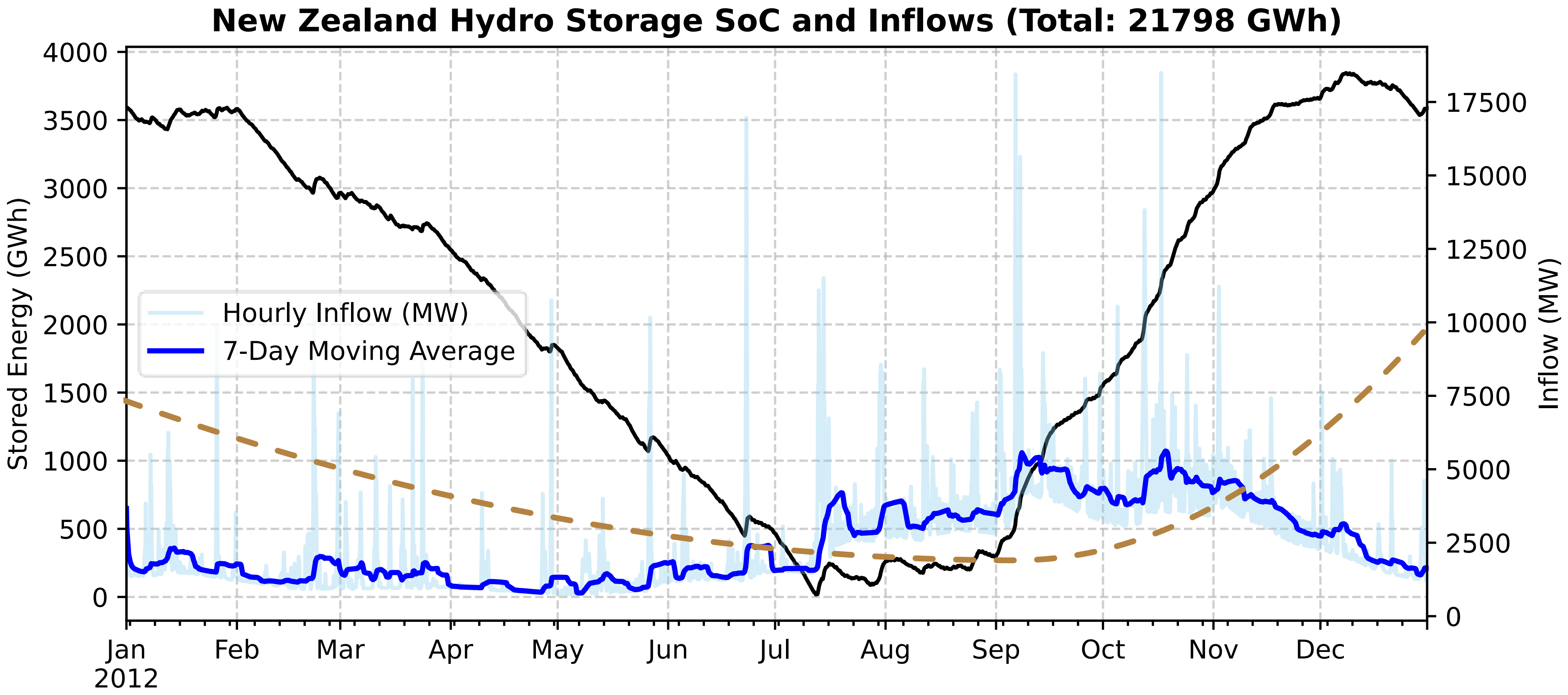
This approach has limitations:

- Perfect foresight optimises both investment and dispatch for a single representative year
- Perfectly centralised least-cost dispatch and coordinated actors may overstate the practical benefits of hydro flexibility
- Unrealistic operations, such as full depletion of hydro reservoirs



In the optimal solution hydro reservoirs are depleted

Reservoirs are depleted below the historical average minimum storage; zero in mid-July



We are working to better represent hydro operation

Combining reservoir operation (SDDP) modelling with long-term capacity expansion

Enhanced hydropower representation in PyPSA-NZ:

- Inter-seasonal storage constraints
- Stochastic hydro-scheduling insights
- Multiple weather years
- Alternative demand trajectories
- Different reliability technology portfolios

To help determine:

- Adequacy risk in future electricity systems
- Whether system diversification mitigates or amplifies traditional dry-year vulnerabilities
- Least-cost portfolios of flexibility and firming resources that improve reliability

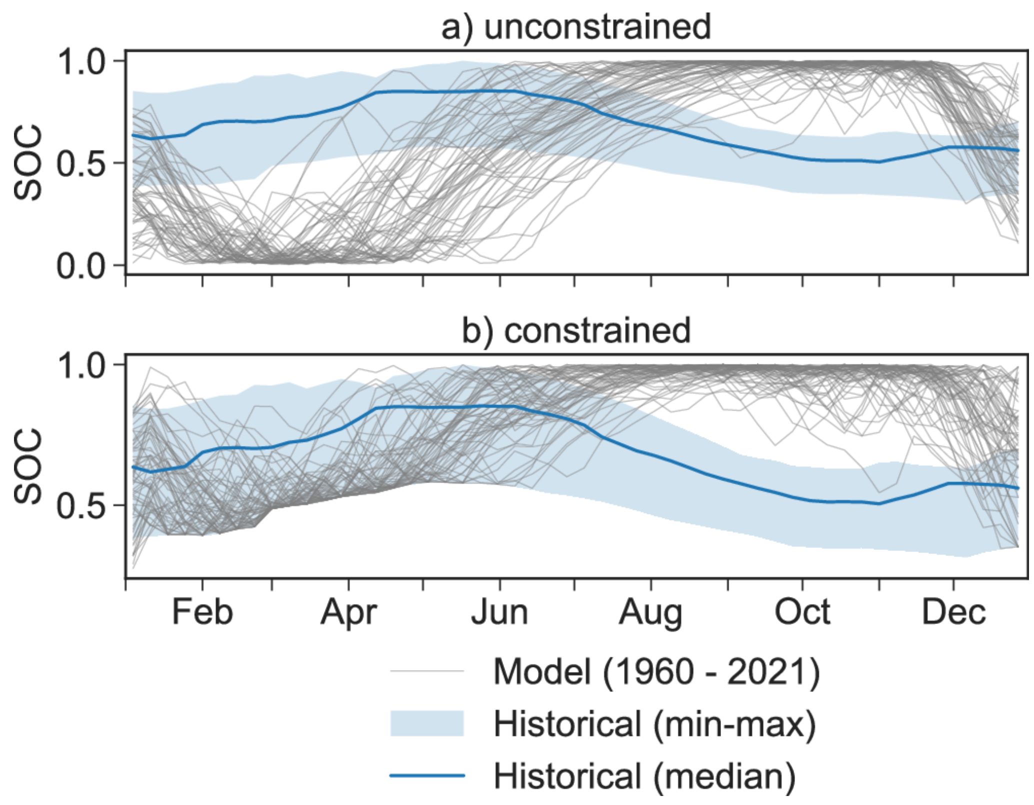
So we can answer: Are our results robust under different demand, technology, and inflow scenarios?

Previous studies use only **historical** reservoir storage data as a lower bound (e.g., Gøtske et al., 2024)

Our ongoing work uses **Stochastic Dual Dynamic Programming (SDDP)** to:

- Simulate weekly reservoir storage under future weather conditions and renewable integration
- Inform parameterisation in long-term (capacity expansion) planning contexts

Goal: Reflect realistic operational behaviour in high-resolution expansion models



Gøtske, E. K., Andresen, G. B., Neumann, F., & Victoria, M. (2024). Designing a sector-coupled European energy system robust to 60 years of historical weather data. *Nature Communications*.

Q & A

Thanks!

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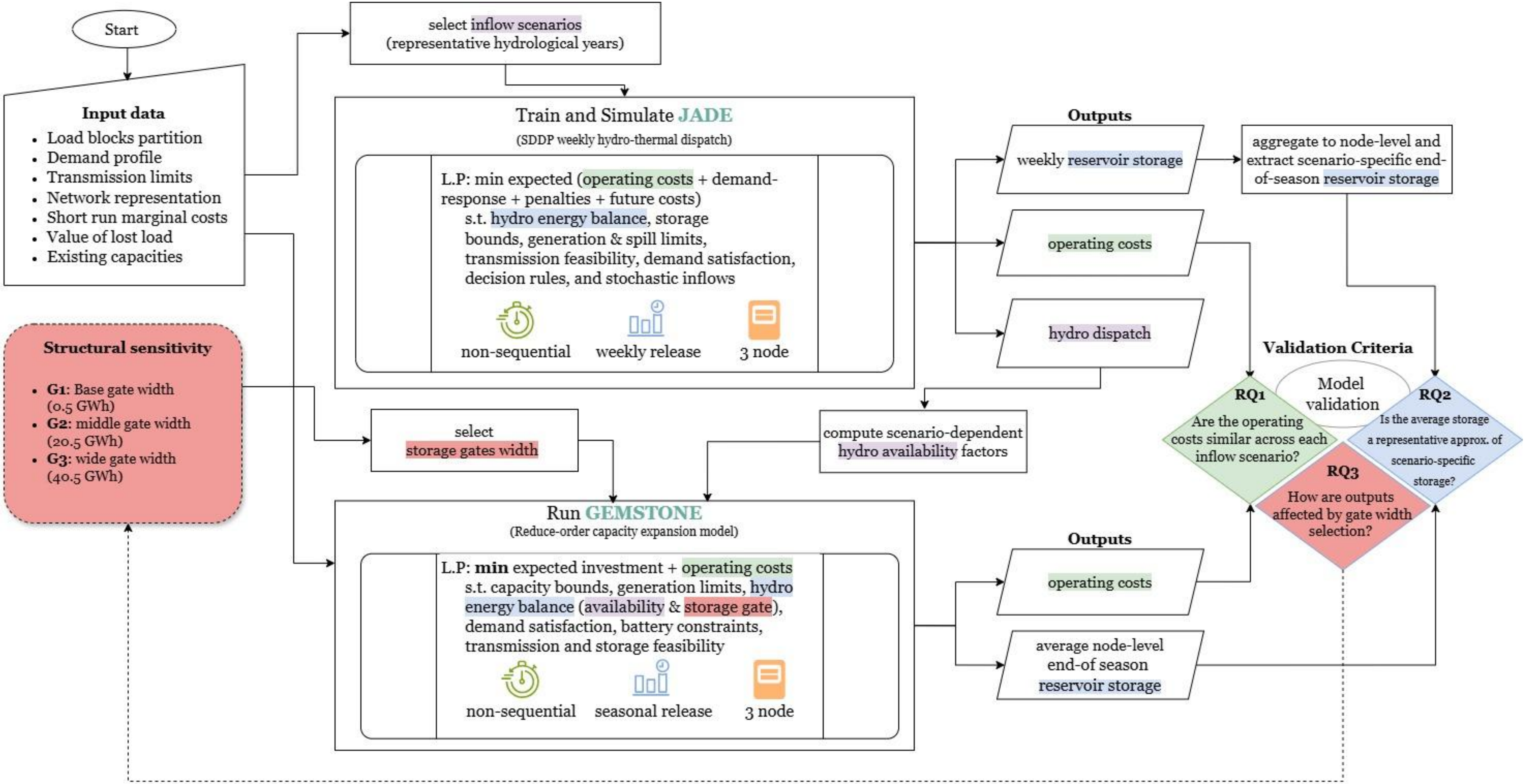
SERG Sustainable Energy Research Group

UC UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND


Start
Input data
Load blocks partition
Demand profile
Transmission limits
Network representation
Short run marginal costs
Value of lost load
Existing capacities
select inflow scenarios
(representative hydrological years)
Train and Simulate JADE
(SDDP weekly hydro-thermal dispatch)
L.P: min expected (operating costs + demand-response + penalties + future costs)
s.t. hydro energy balance, storage bounds, generation & spill limits, transmission feasibility, demand satisfaction, decision rules, and stochastic inflows
non-sequential
weekly release
3 node
Outputs
weekly reservoir storage
operating costs
hydro dispatch
aggregate to node-level and extract scenario-specific end-of-season reservoir storage
Structural sensitivity
G1: Base gate width (0.5 GWh)
G2: middle gate width (20.5 GWh)
G3: wide gate width (40.5 GWh)
select
storage gates width
compute scenario-dependent
hydro availability factors
Run GEMSTONE
(Reduce-order capacity expansion model)
L.P: min expected investment + operating costs
s.t. capacity bounds, generation limits, hydro energy balance (availability & storage gate), demand satisfaction, battery constraints, transmission and storage feasibility
non-sequential
seasonal release
3 node
Outputs
operating costs
average node-level
end-of season
reservoir storage
Validation Criteria
Model validation
RQ1
Are the operating costs similar across each inflow scenario?
RQ2
Is the average storage a representative approx. of scenario-specific storage?
RQ3
How are outputs affected by gate width selection?

If stochastic models already exist… what's new here?

Integrating stochastic insights into high-resolution capacity expansion models (CEMs)

GEMSTONE (Ferris & Philpott, 2023)
Reduced-order stochastic model capturing hydropower uncertainty with a seasonal storage-*gate* formulation

PyPSA – NZ
High-resolution capacity expansion model for planning the energy transition

VALIDATION CRITERIA
(1) Operating Costs (SRMC)
(2) End-of-season storage

VALIDATION

JADE (Electricity Authority, 2025)
Stochastic dual dynamic programming model (SDDP) for hydropower operation in New Zealand

Ferris, M. & Philpott, A. (2023). Renewable electricity capacity planning with uncertainty at multiple scales. Computational Management Science.
Electricity Authority. (2025). *JADE: Stochastic optimization model for New Zealand's electricity generation sector.* EMI
Canessa, R. et al (2025). From hydro nation to solar giant: New Zealand's renewable build-out and hydrogen export scenarios.