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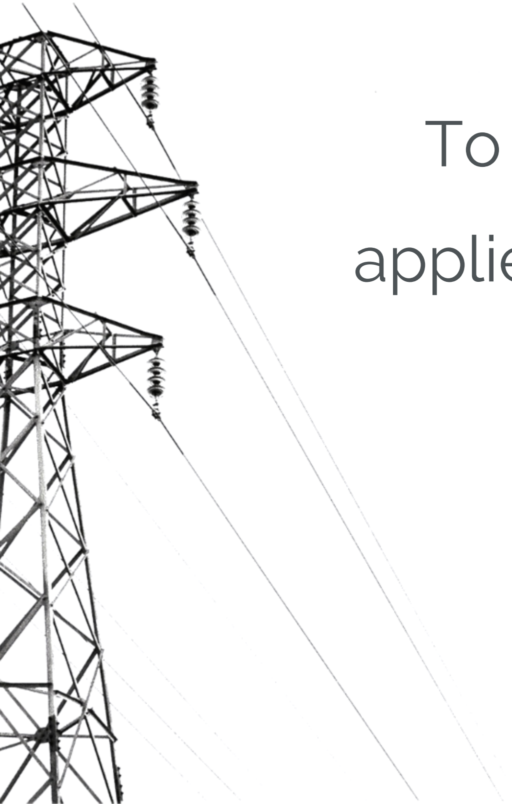
Optimising Renewable Energy: Intelligent Siting and Predictive Power

Dept. Electrical & Electronic Engineering

By: Drs Armand du Plessis and Chantelle van Staden

Photo by Ignus Dreyer

Goal of this presentation = application



To show how researchers at Stellenbosch University have applied machine learning and data in the context of renewable energy.

Applying Machine Learning to Renewable Energy Challenges

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Renewable Energy (solar, wind) = intermittent and stochastic power source

- More renewables = More uncertainty & stress onto the electrical grid
- Biases power utilities against dominant grid connection of renewables

Solution: Reduce uncertainty with Forecasting

- Aids both grid operators and power producers with:
  - Supply & demand,
  - Unit commitment (energy markets)

Commercial Solar PV forecasting

- 1st group in SA to deliver a state-of-the-art forecast model for commercial PV

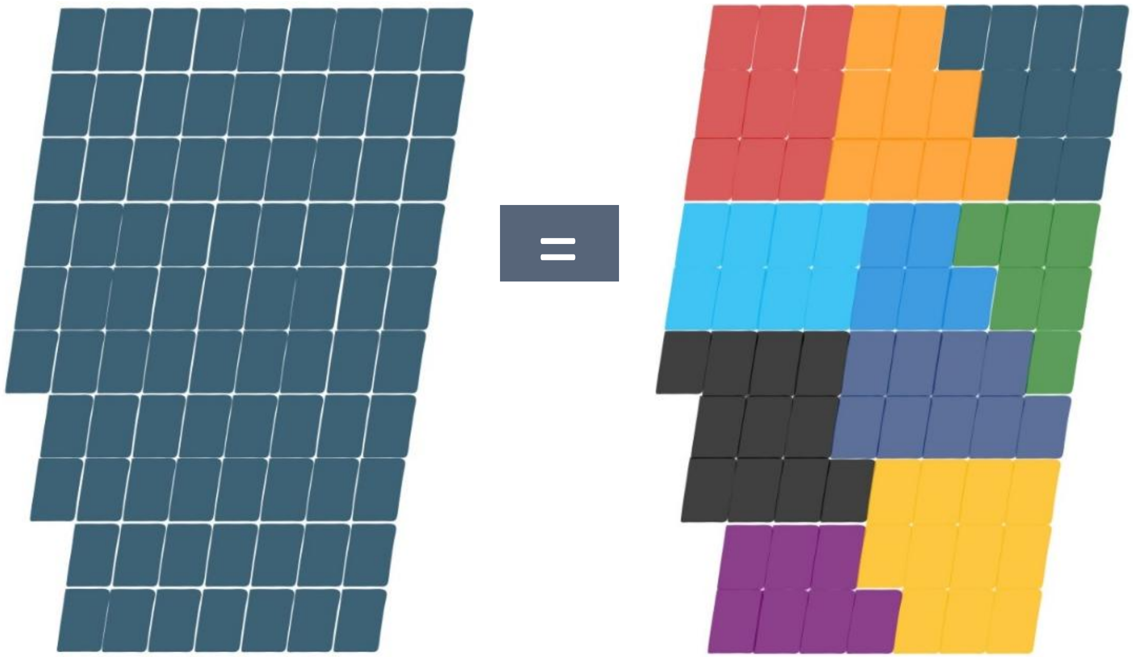
- 75MW PV system
  - 84x 880 kVA inverters
  - 13000+ strings

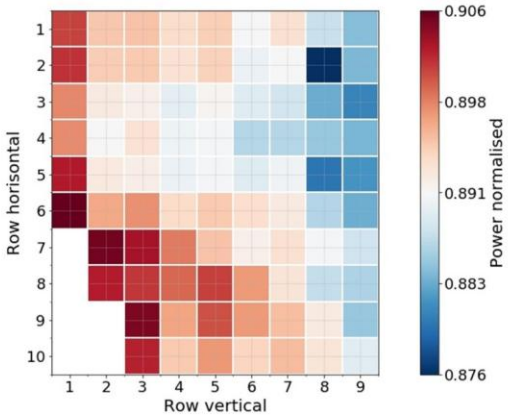
- Successfully delivered 1h – 6h ahead forecasts

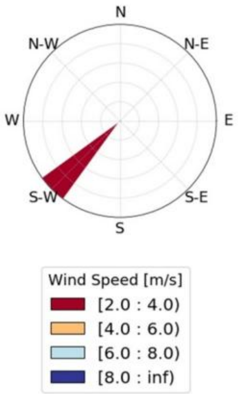
Commercial Solar PV forecasting

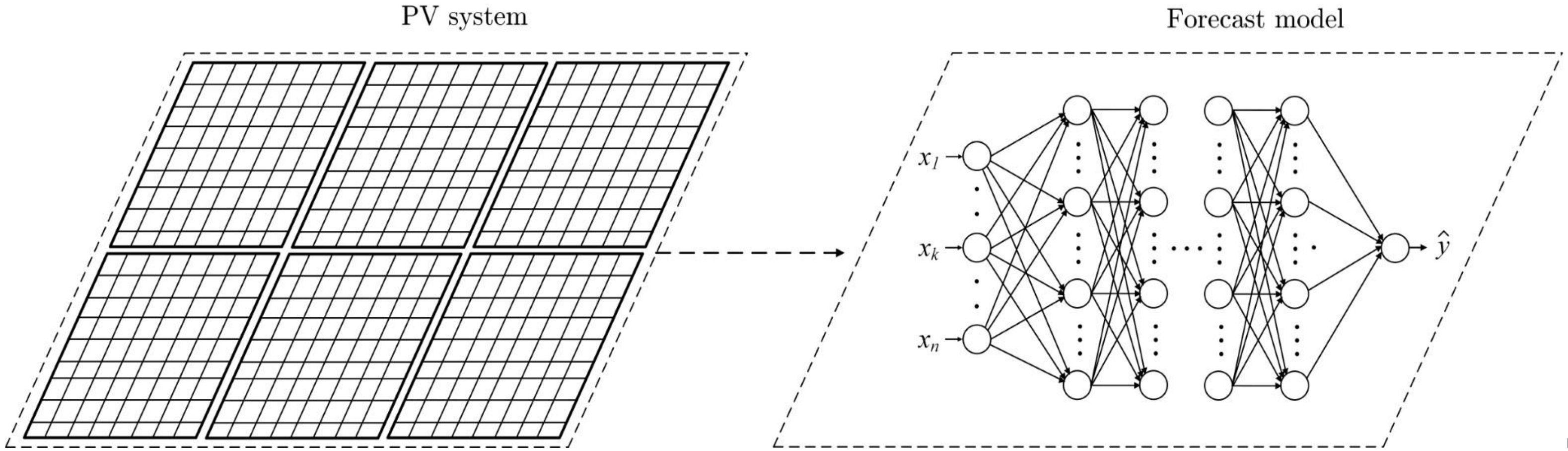
Big question:

- Is one ML model enough to capture PV system dynamics?
- Or should we divide PV system into sections and forecast each section's behaviour?







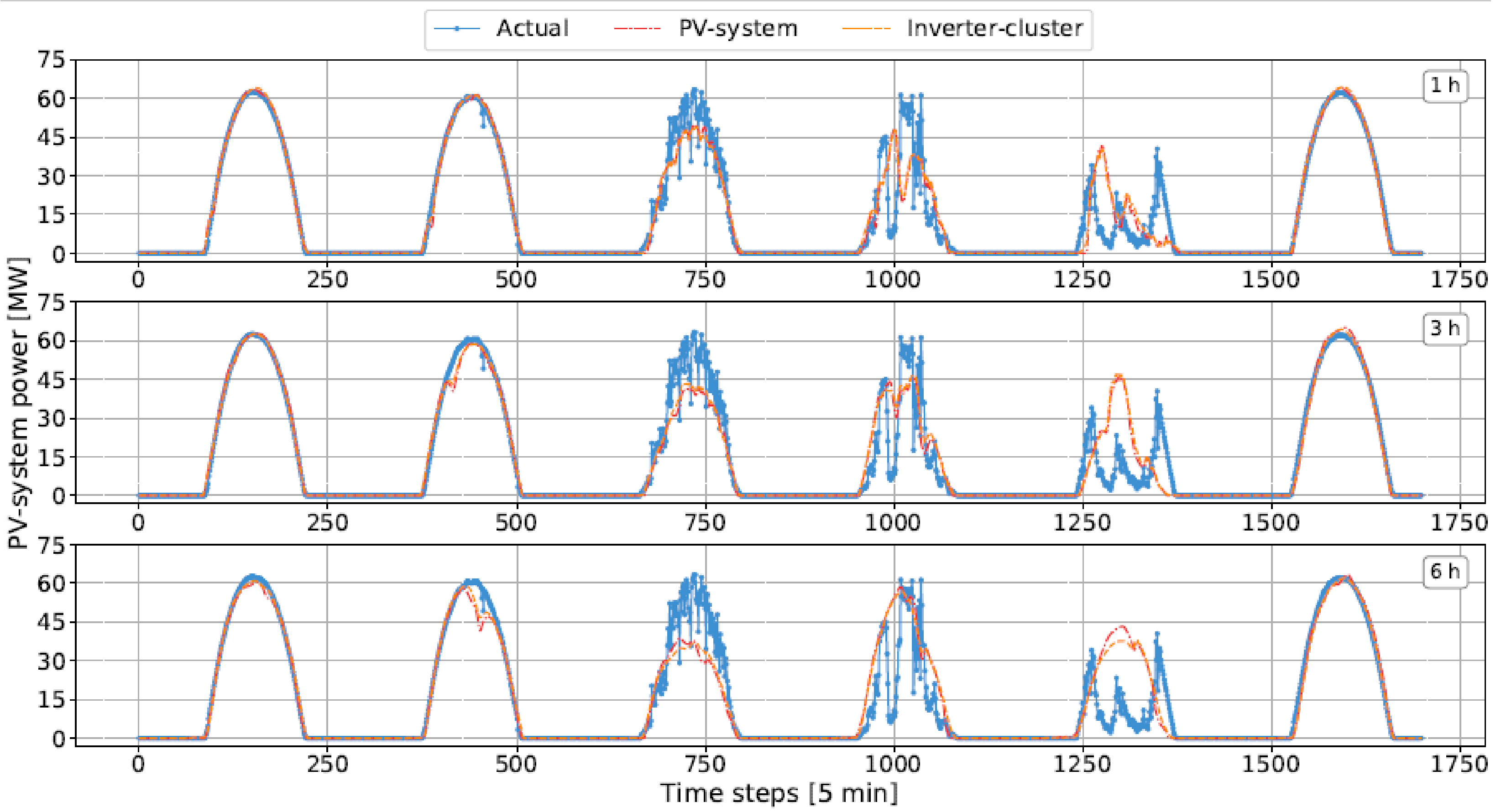


Project: Solar PV Forecasting

Results:

- Machine Learning is powerful enough to capture low-level PV system dynamics
- Solution proven to reduce computational expense without sacrificing accuracy

“You can build…one model to rule them all”



Wind-Power forecasting

Question: We can forecast the wind, but…how can we reduce the energy-market penalties for ‘bad’ unit commitments?

Wind-Power forecasting

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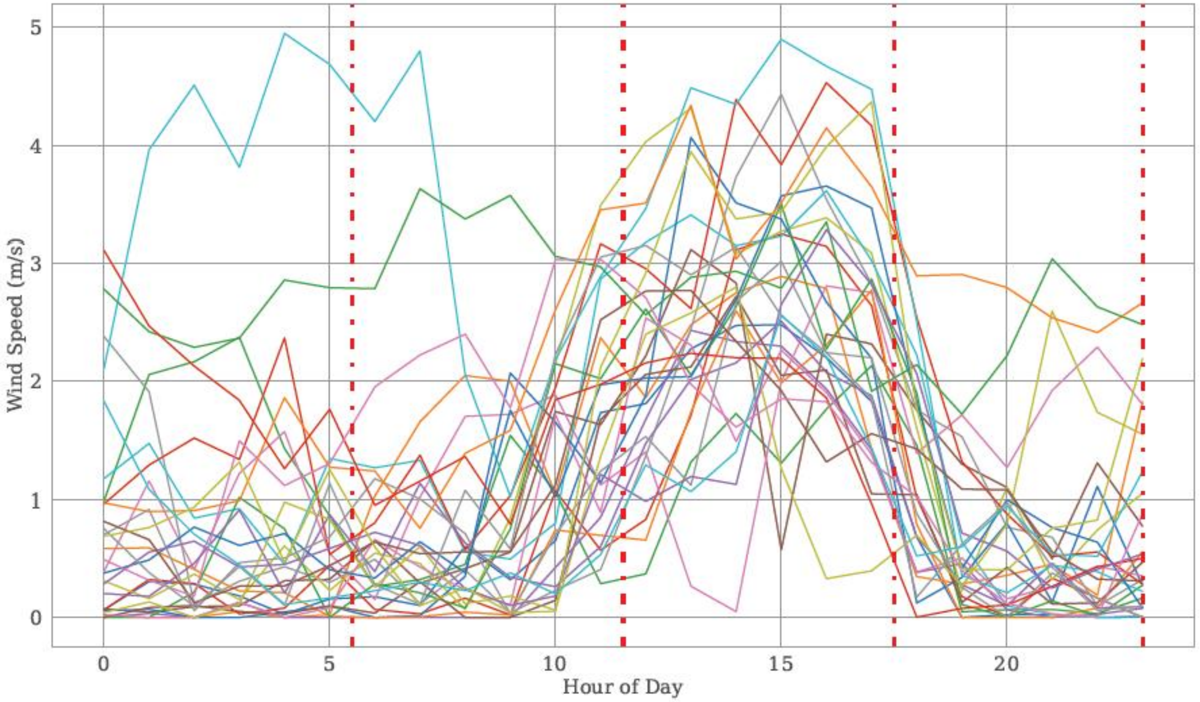
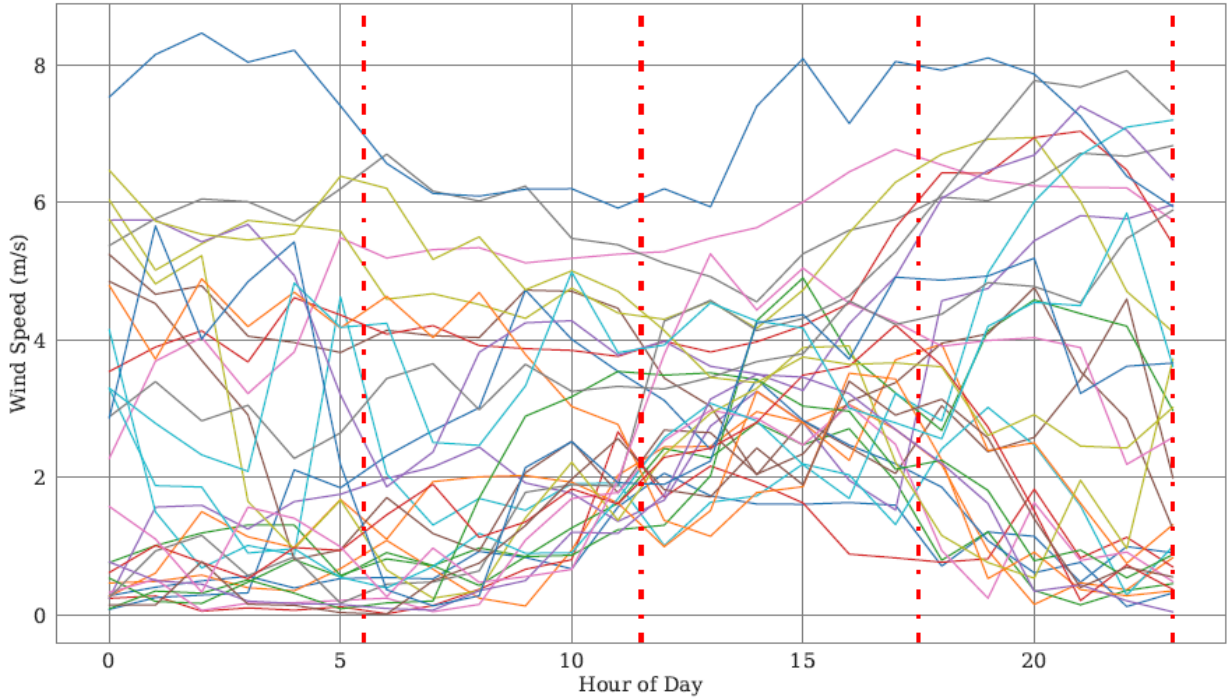
Data:

- Stellenbosch daily wind speed data set



April



August

Wind-Power forecasting

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Challenge:

- Unit commitments are required in day-ahead energy markets.
- If forecasts under-predict, there is a loss of sales.
- If forecasts over-predict, there is a penalty/fine imposed.

Solution:

- Use batteries to supplement unit-commitment errors.
- But how big should this battery be?

Wind-Power forecasting

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Over-prediction

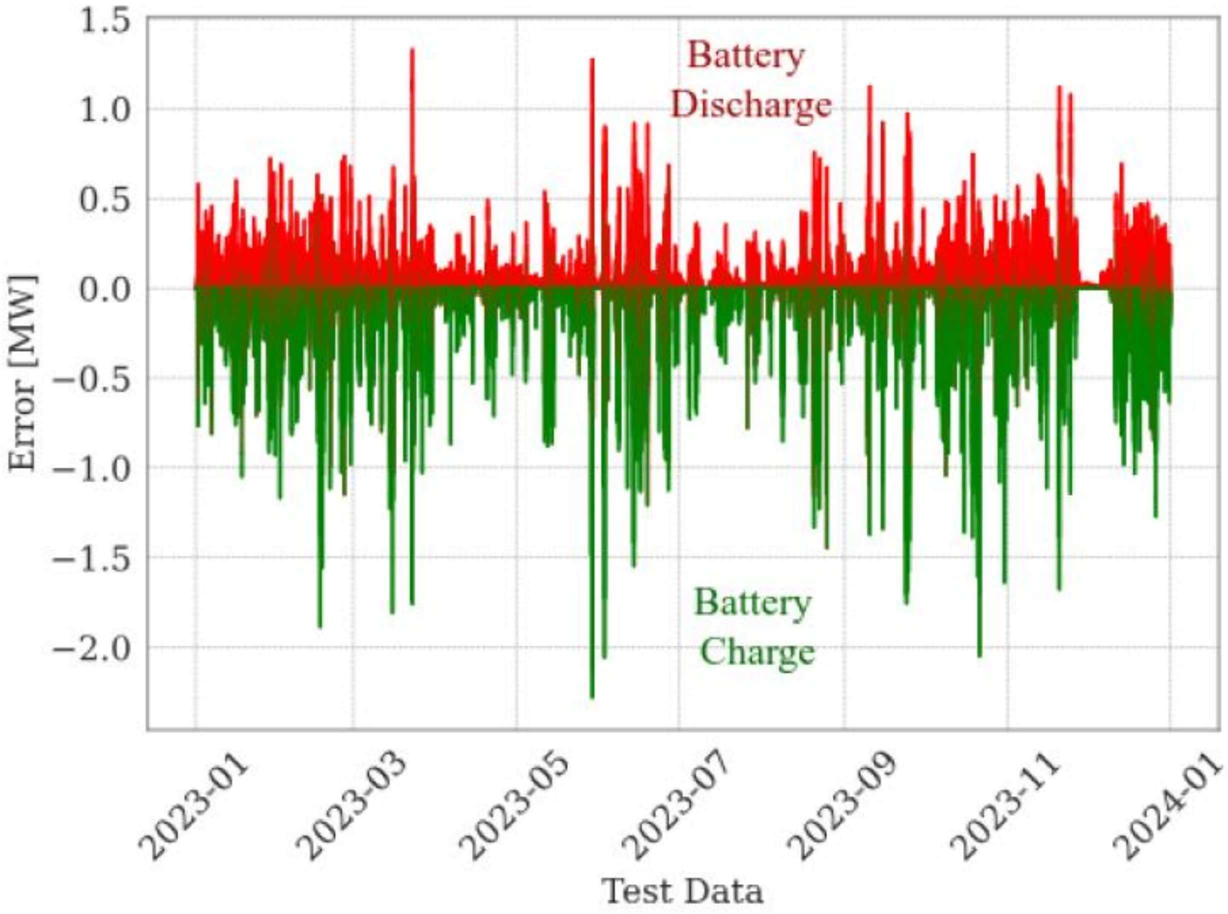
(i.e. less power produced than predicted)

- Energy shortage is supplemented from batteries
- Avoids energy market penalties

Under-prediction

(i.e. surplus power available)

- Surplus wind power is stored into batteries
- Avoids self-imposed curtailment

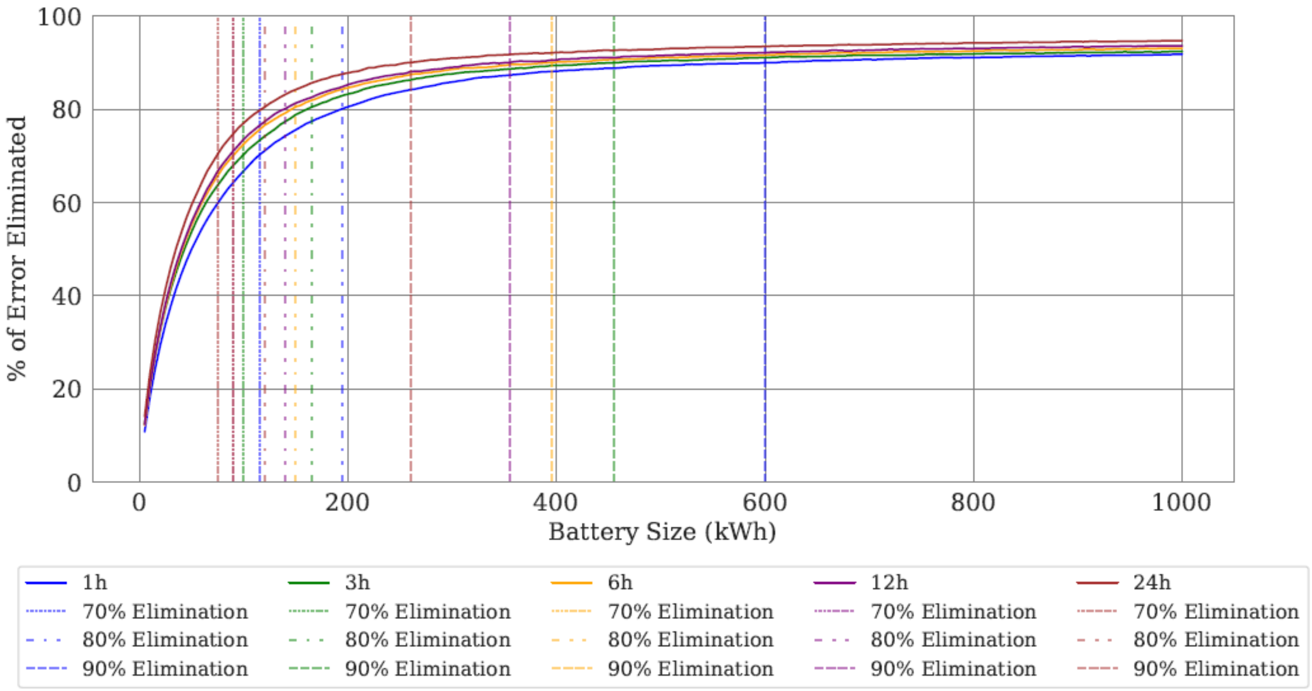


Wind-Power forecasting

Case Study Results (1h – 24h forecast)

- Eliminate **70 %** of forecast errors with battery = ~**5 %** of [rated capacity] x [h]
- Eliminate **80 %** of forecast errors with battery = ~**10 %** of [rated capacity] x [h]
- Elimination of Errors > 80%
  Battery size becomes increasingly impractical

Typical wind forecast error?



Performance monitoring

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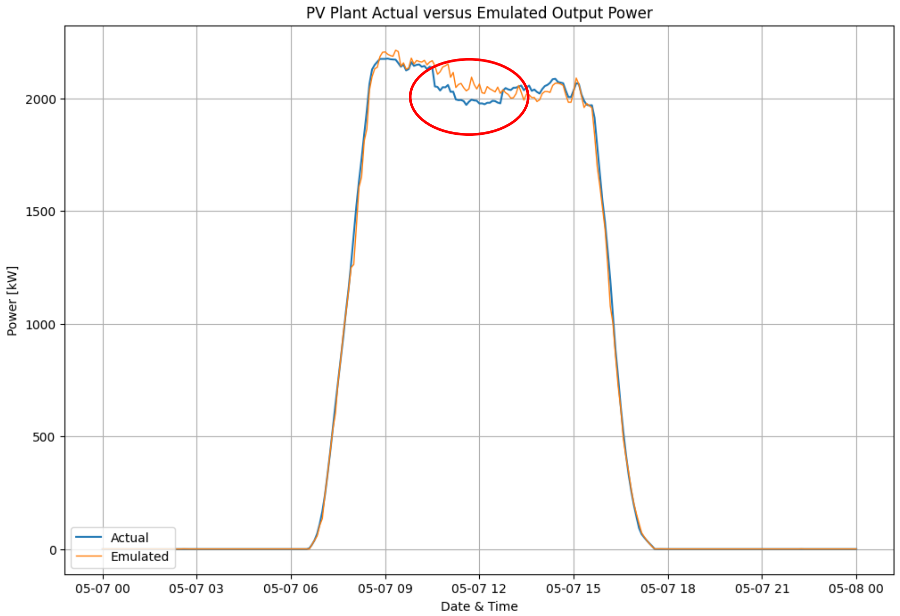
Real-time performance monitoring

Challenge

- Large SA company installed a 3MW PV system
- Issues with automatic & manual system monitoring

Objective:

- Develop a sensitive monitoring tool with machine learning



Real-time performance monitoring

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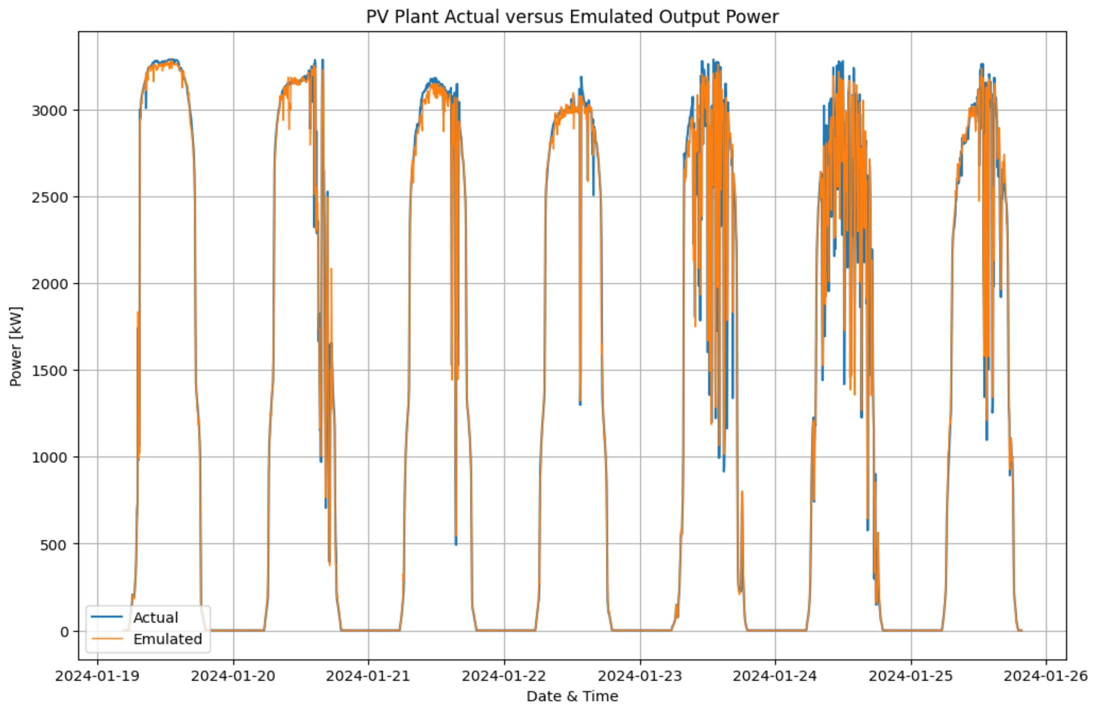
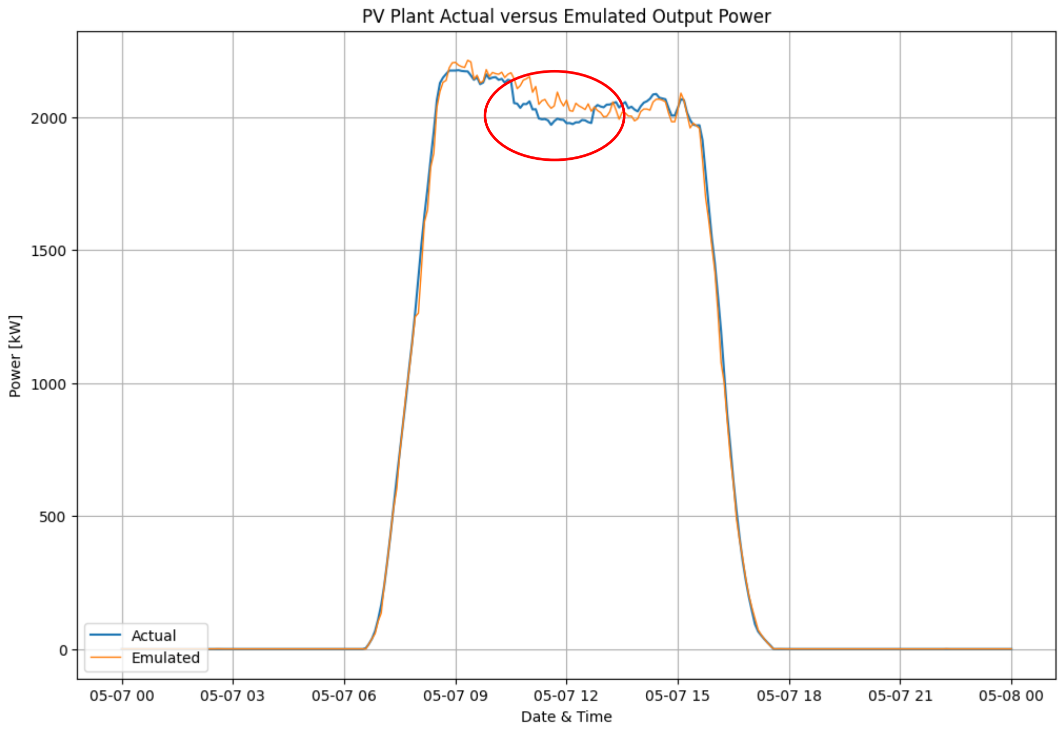
Result

- Real-time system performance executed with little to no dependence on human observation





System deviation identified

Renewables, Batteries, Electric Vehicles & Machine Learning

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Renewables, Batteries, Electric vehicles & Machine Learning

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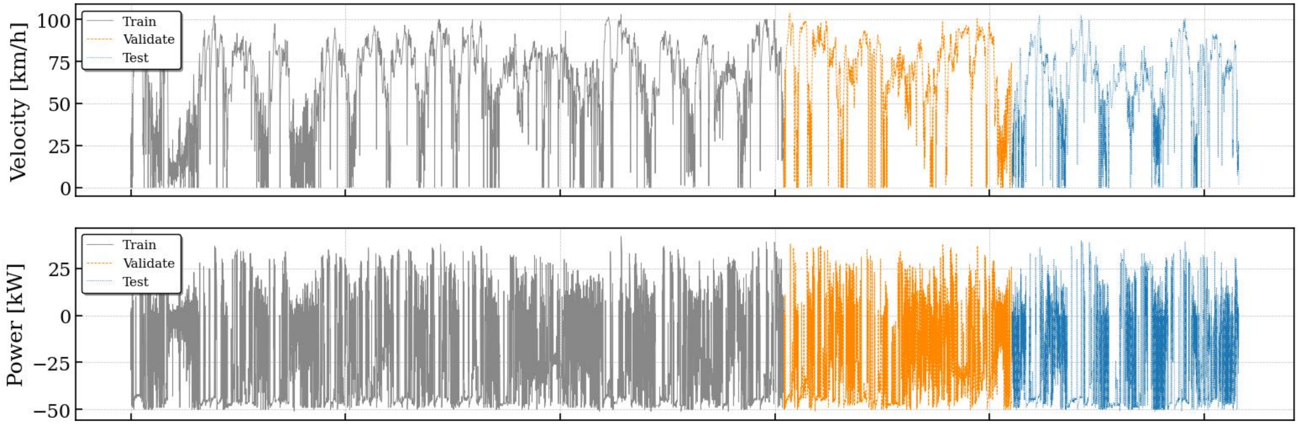
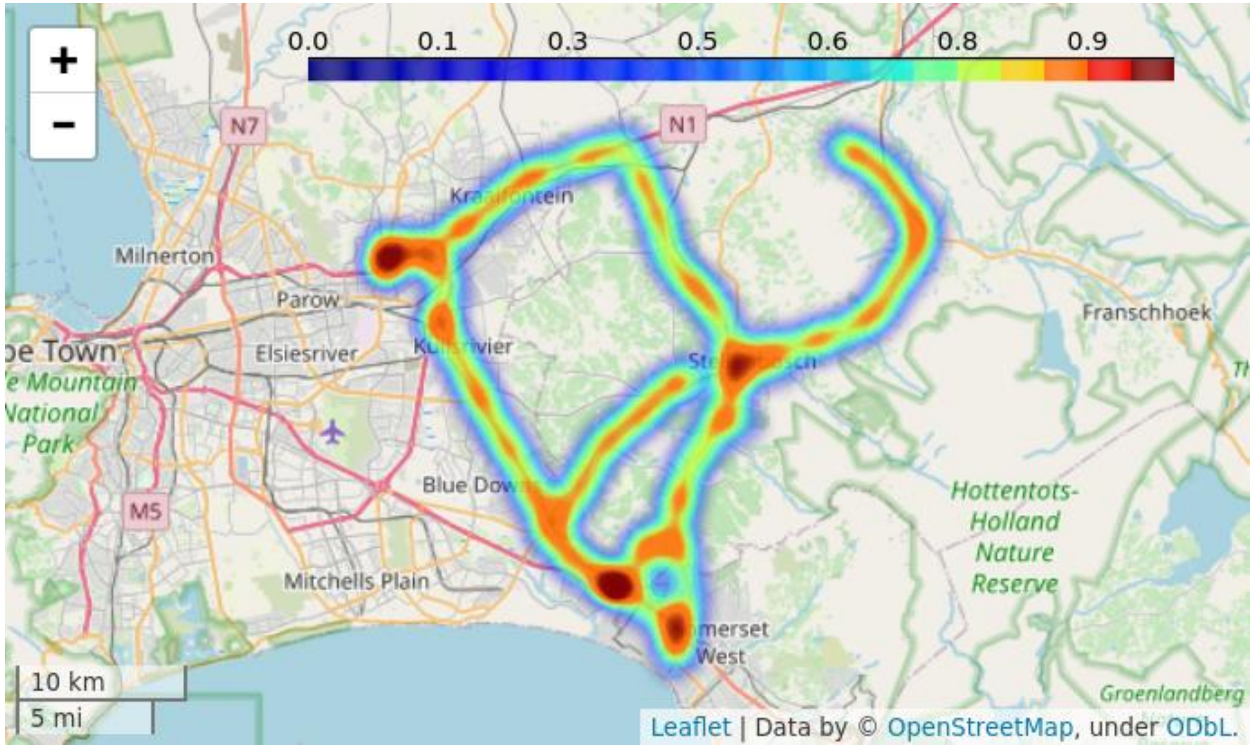
Application:

- Machine learning has proven to be an effective tool to assess EVs efficiency.
- Provided the data of any existing EV, we can emulate any route, anywhere.
- With kWh/km identified, financial feasibility can be determined





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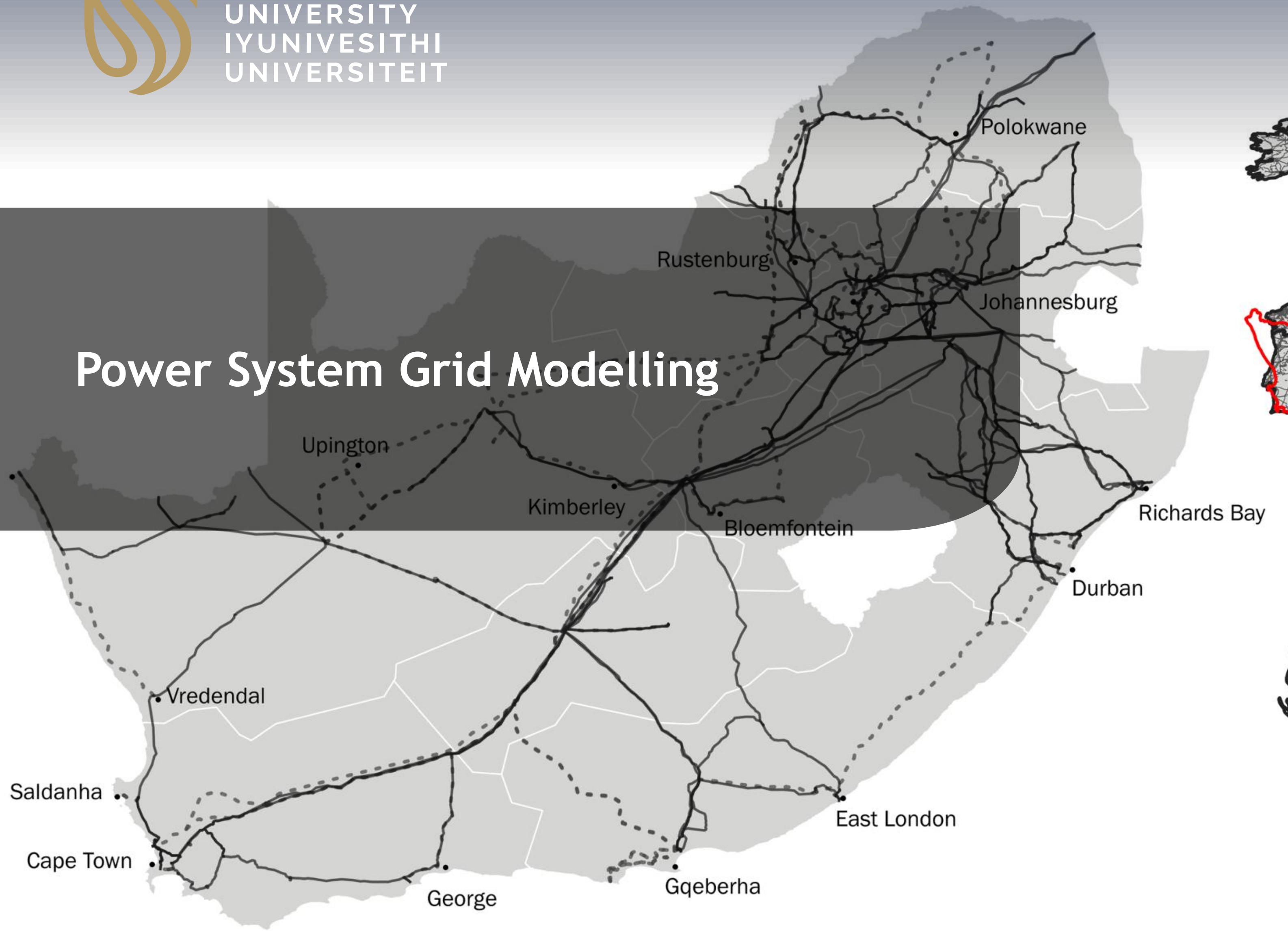
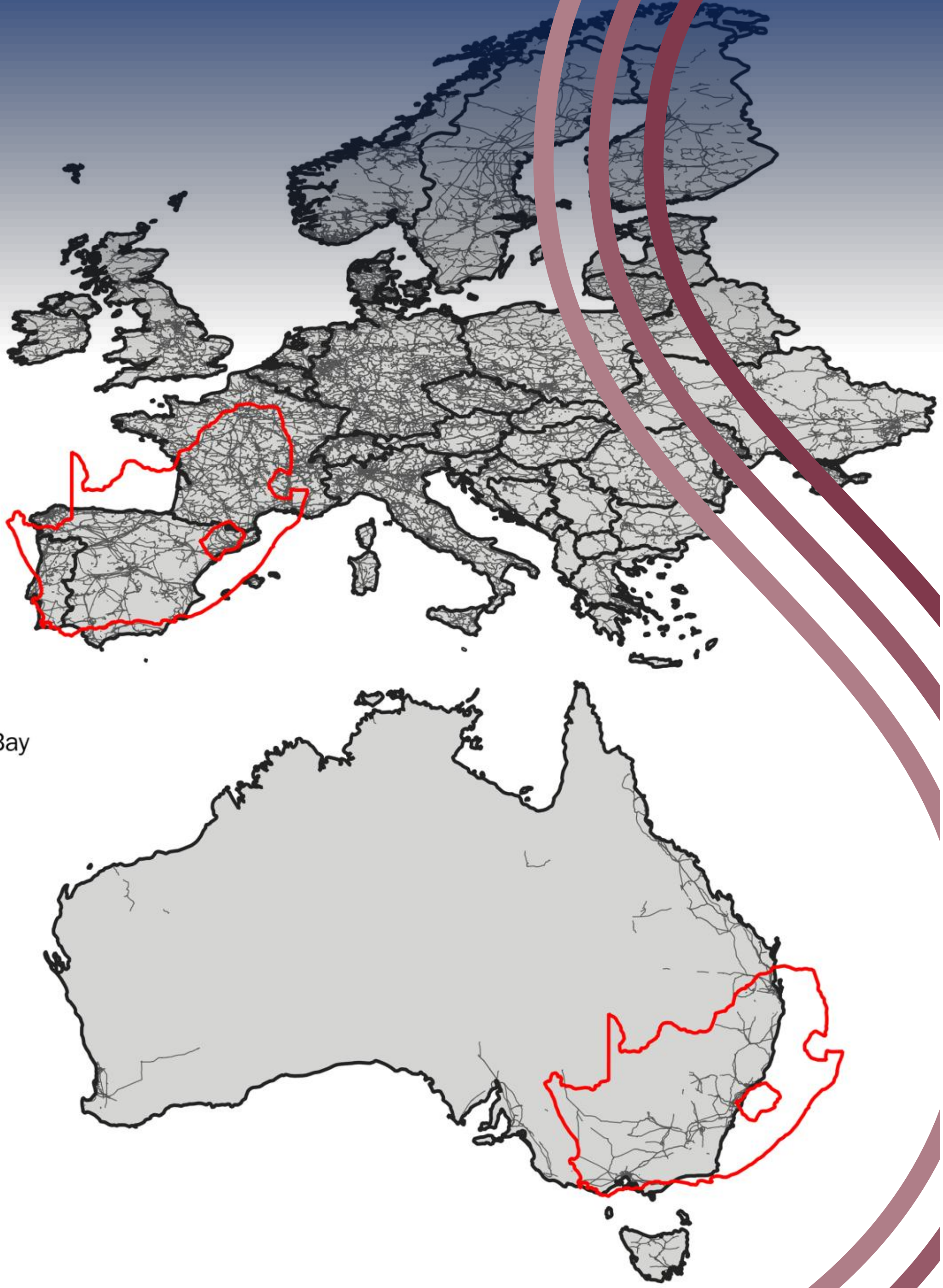
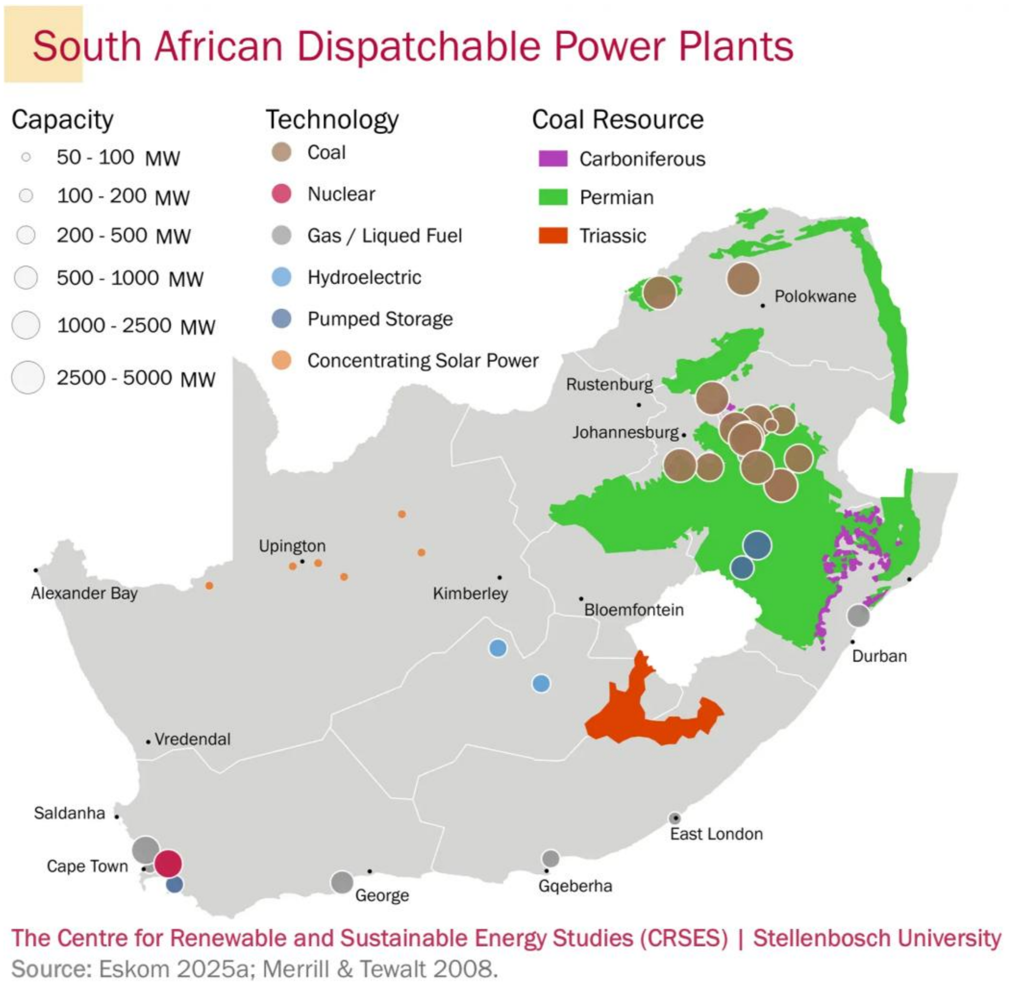
Power System Grid Modelling





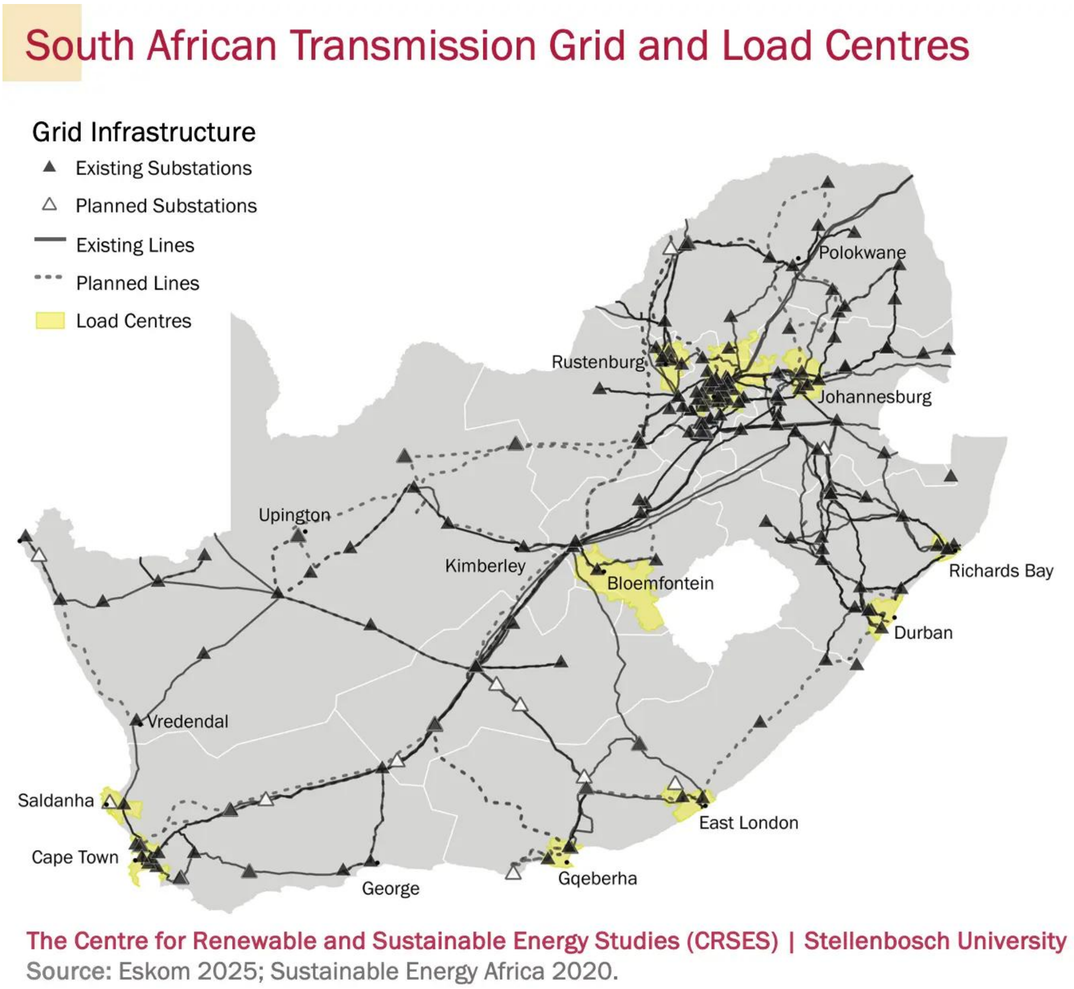
Traditional electricity planning was relatively simple
until… the four D's arrived



CAPACITY EXPANSION MODEL (least-cost generation mix, years resolution)

+

UNIT COMMITMENT MODEL (validation of generation mix, hours resolution)



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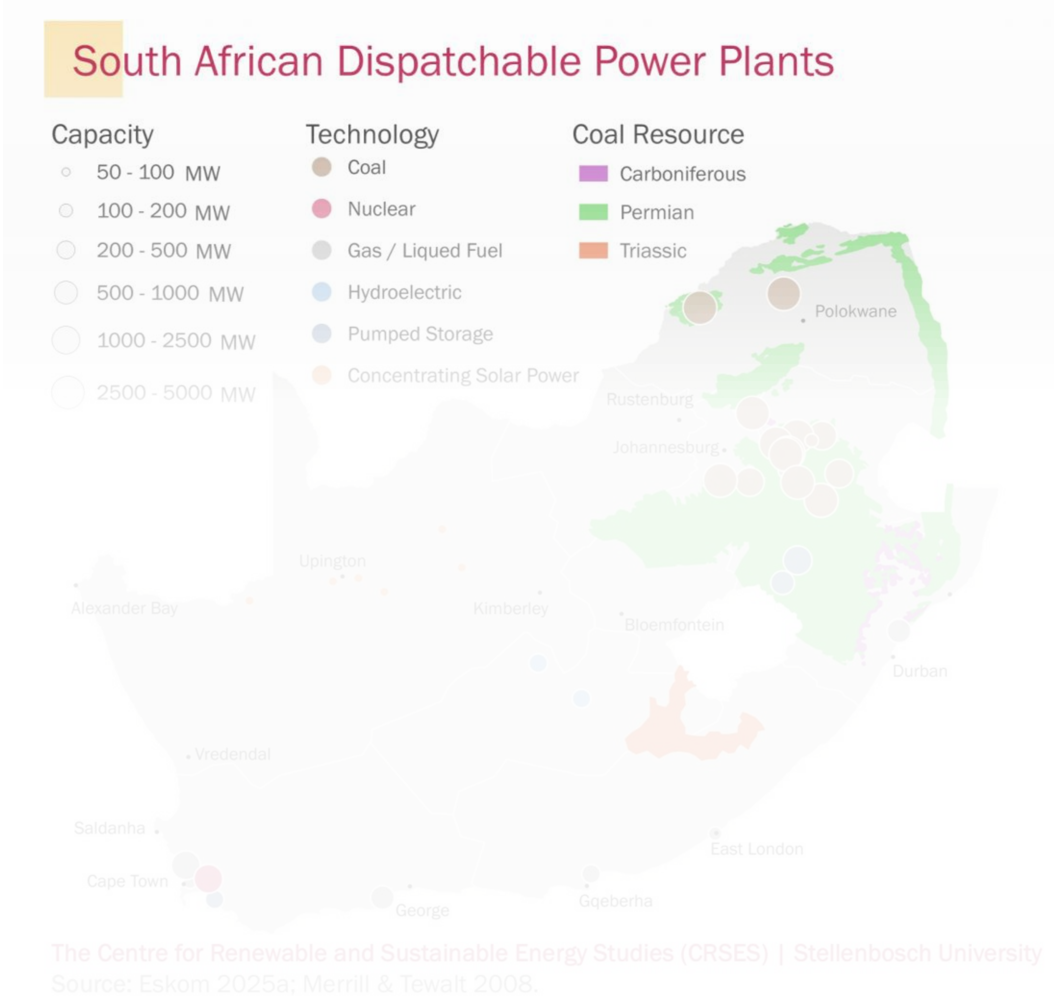

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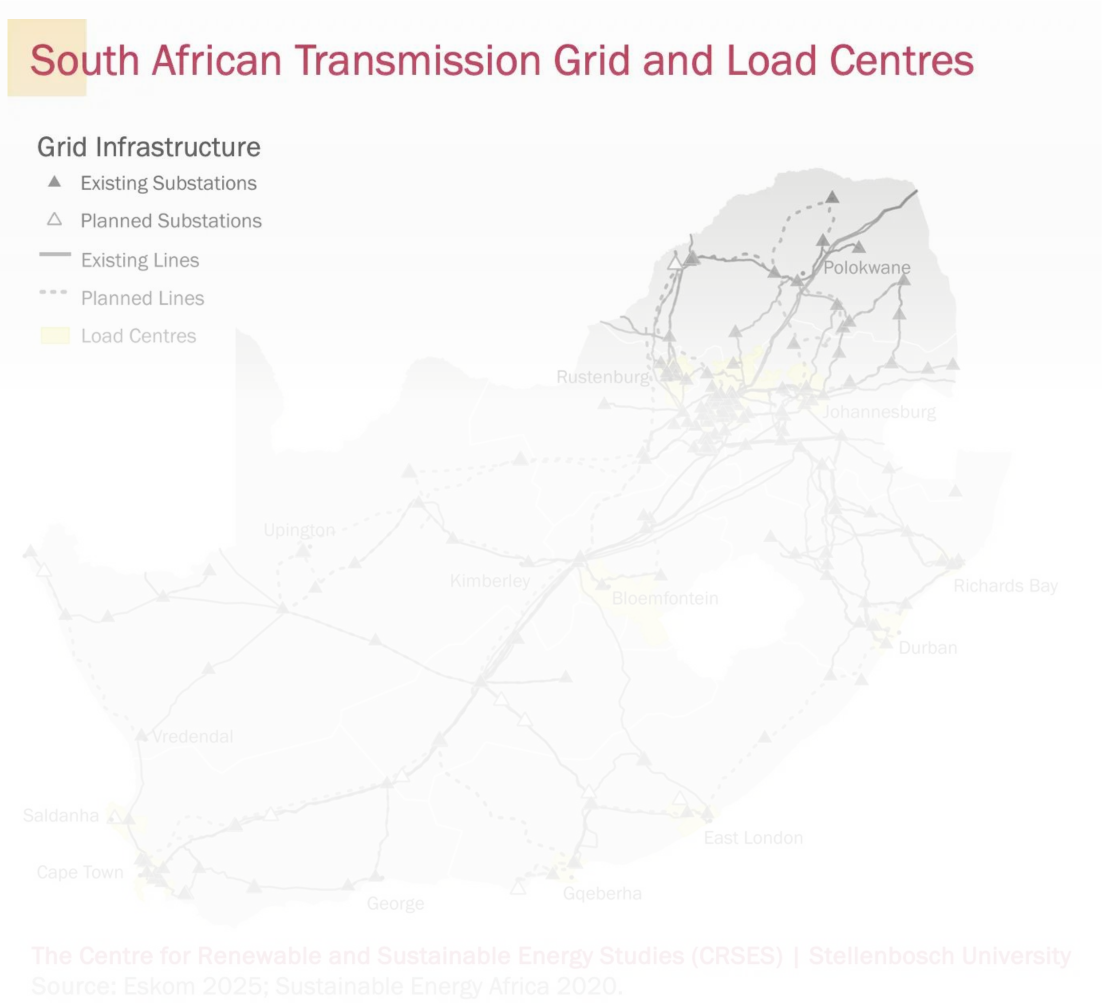

Decarbonised, Distributed, Deregulated, Datafied electricity

Traditional electricity planning was relatively simple
until… the four D's arrived

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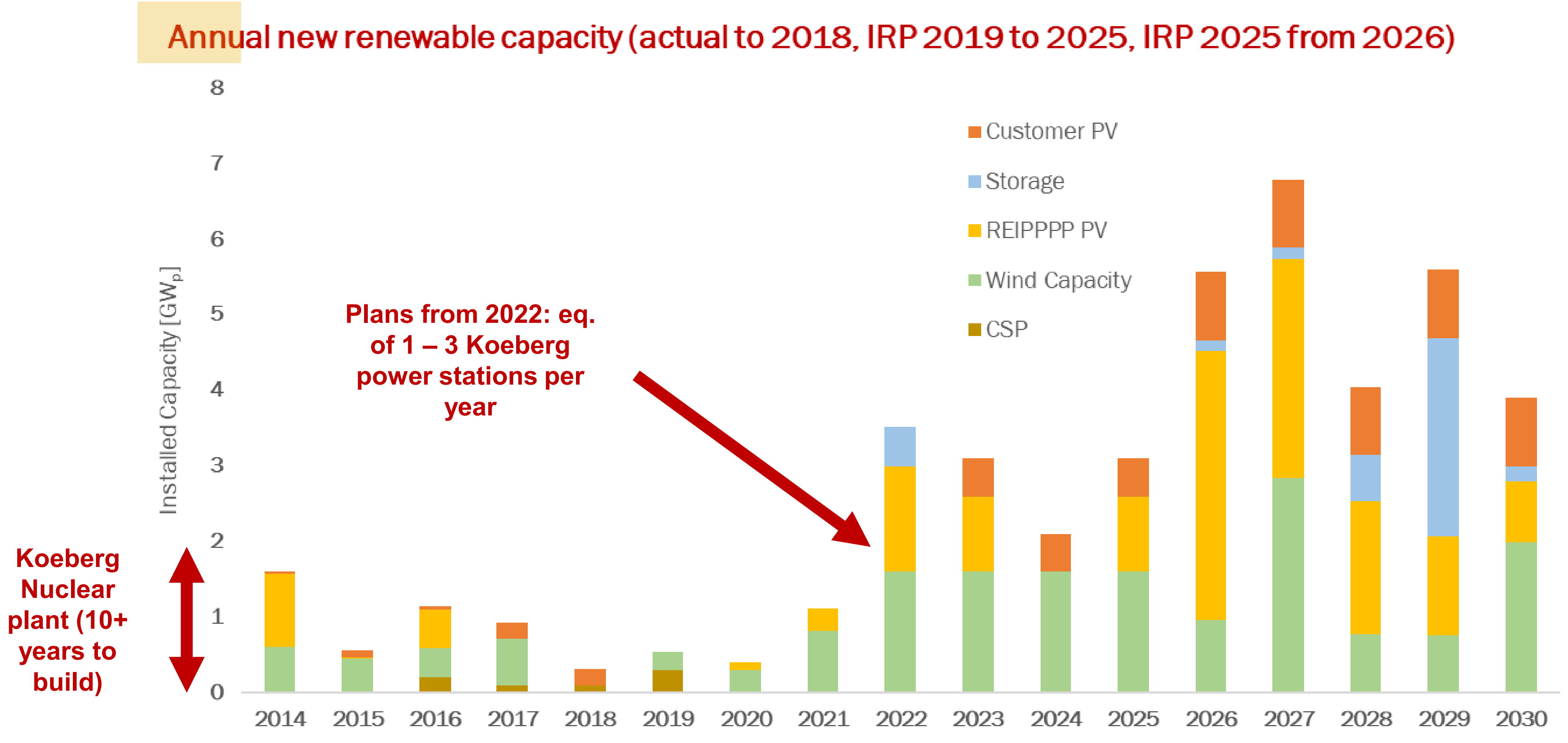

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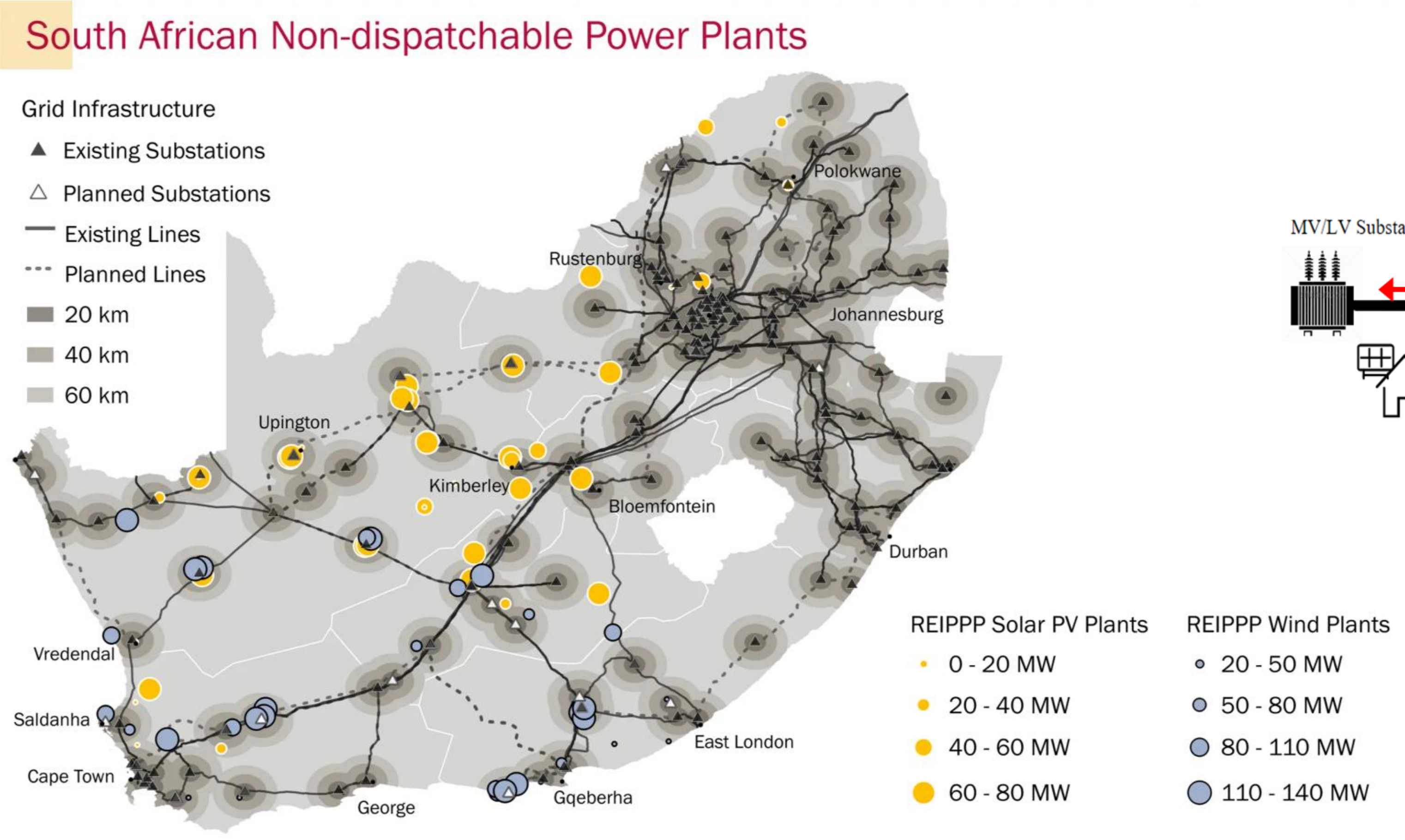
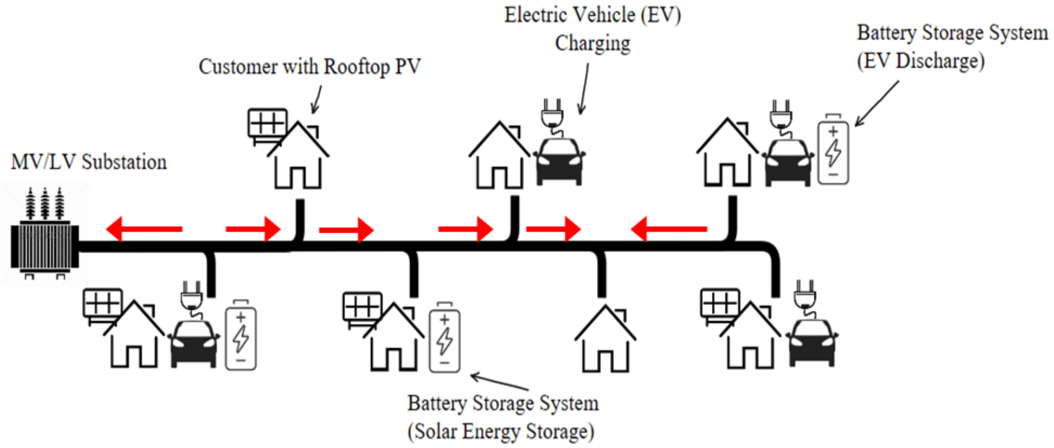


The Centre for Renewable and Sustainable Energy Studies (CRSES) | Stellenbosch University
Source: Eskom 2025a. Notes: REIPPPP: Renewable Energy Independent Power Producer Procurement Programme.



Decarbonised, <u>Distributed</u>, Deregulated, Datafied electricity

Why does electricity planning need to adapt?

Why does electricity planning need to adapt?
The grid is not adequately acknowledged

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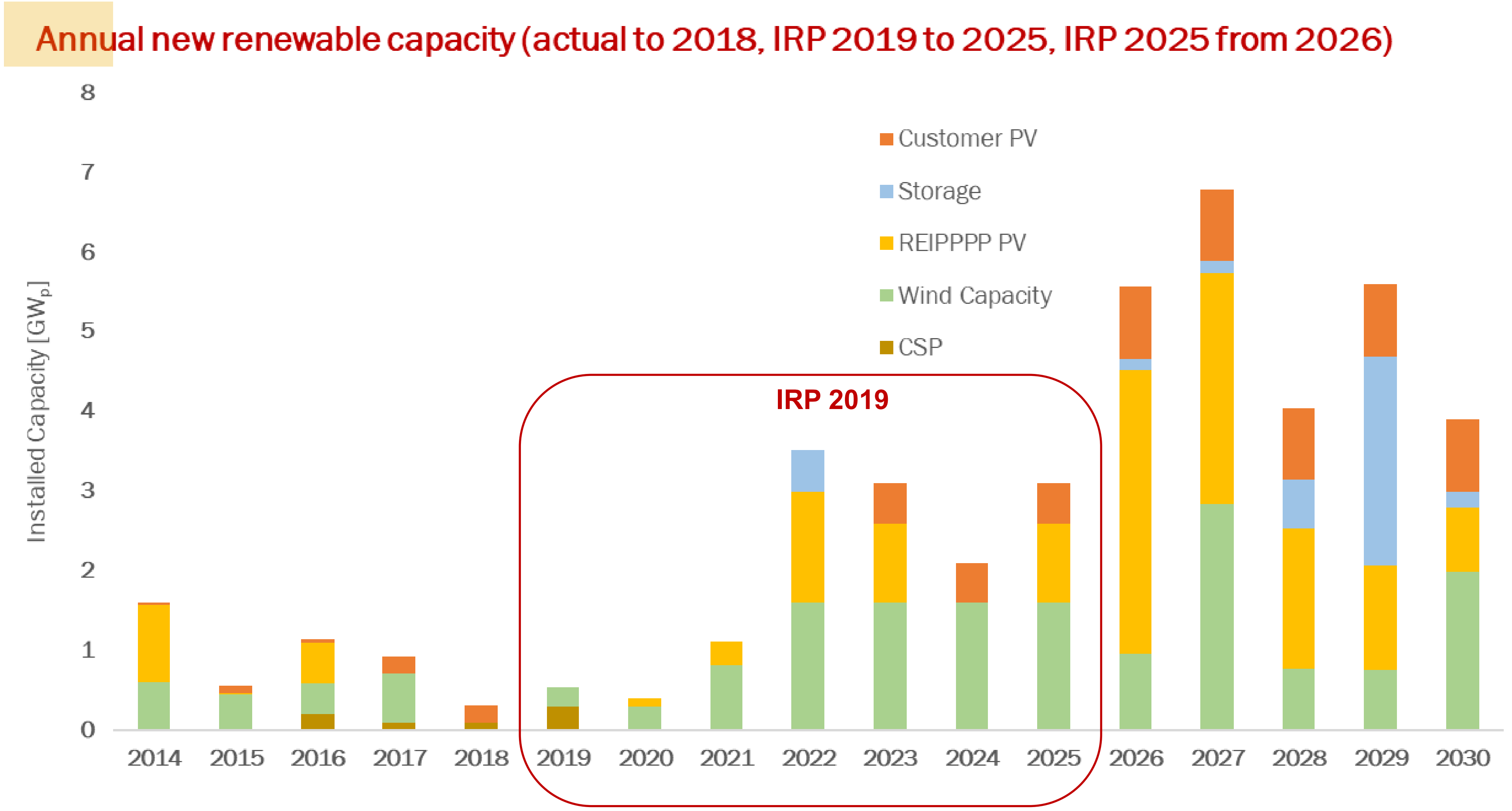

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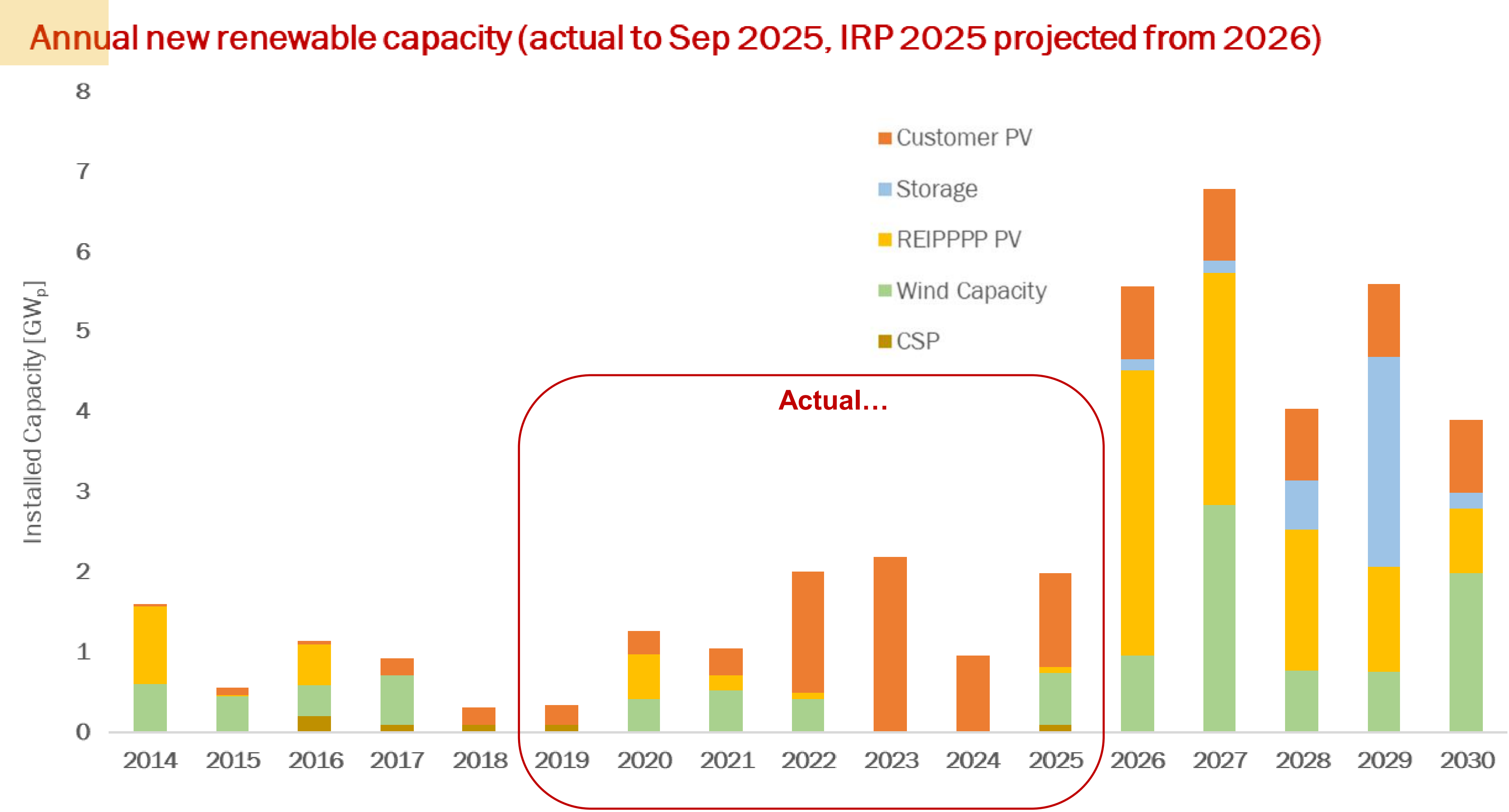
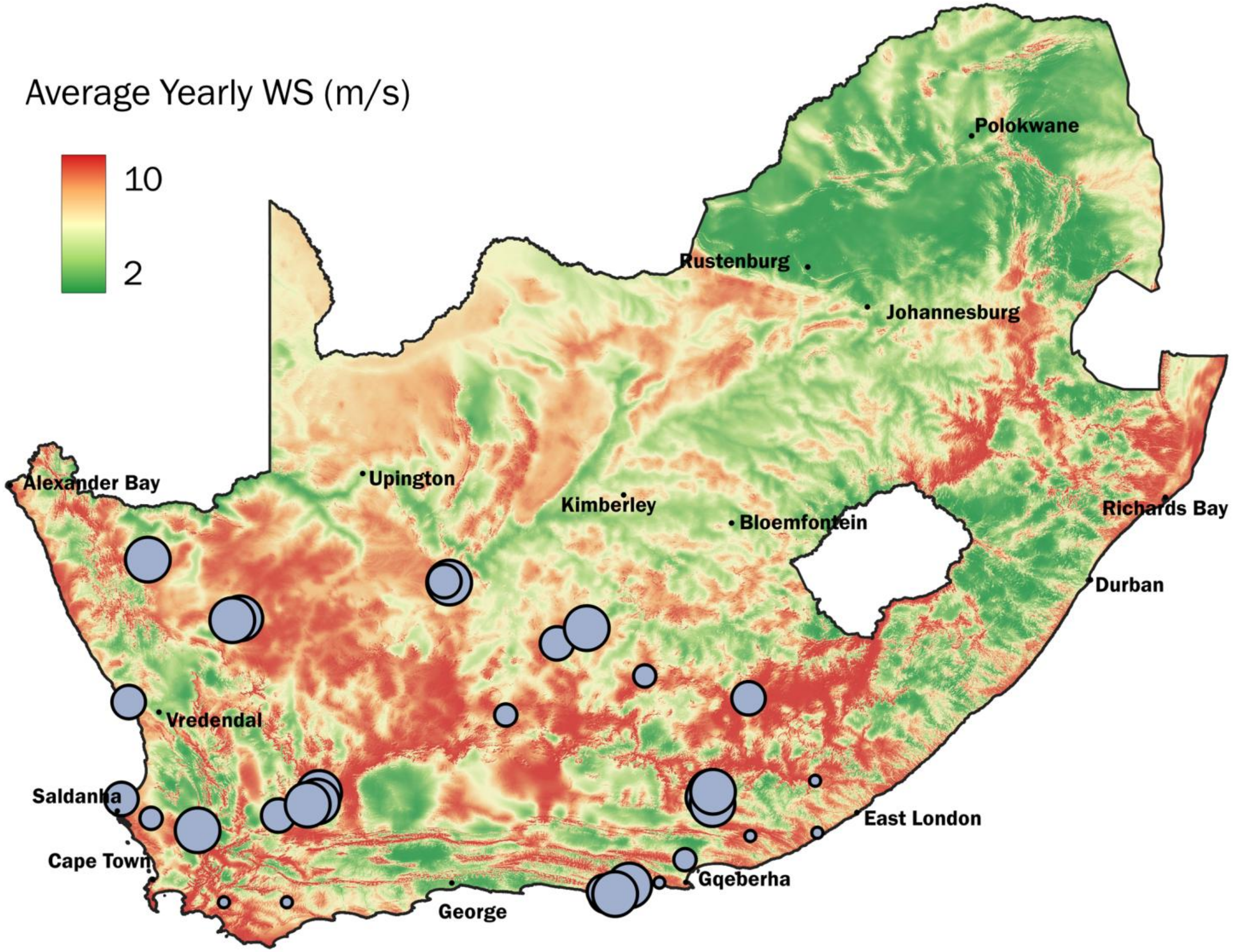


Why does electricity planning need to adapt?

Inadequate geospatial and temporal representation of wind and solar



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Inadequate geospatial and temporal representation of wind and solar

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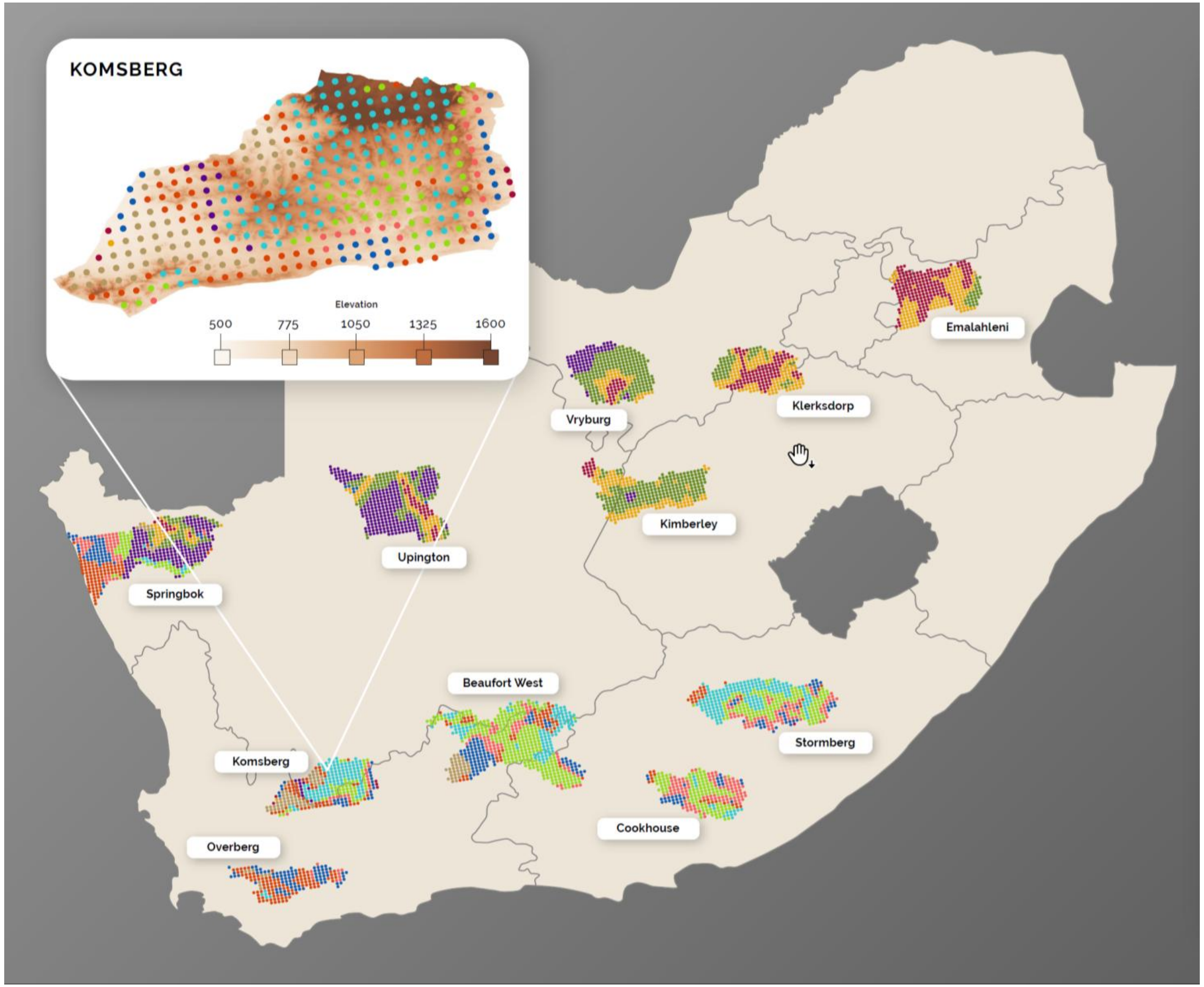
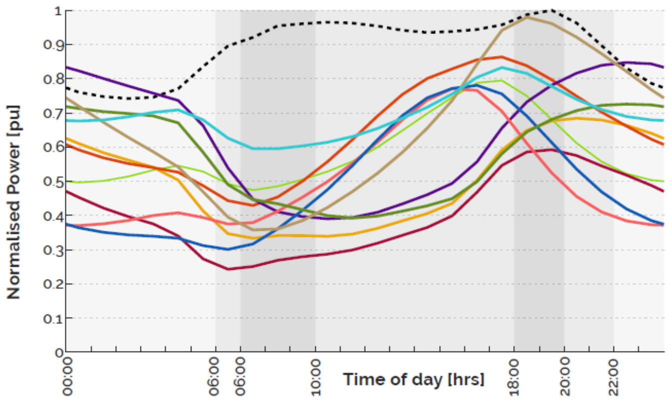
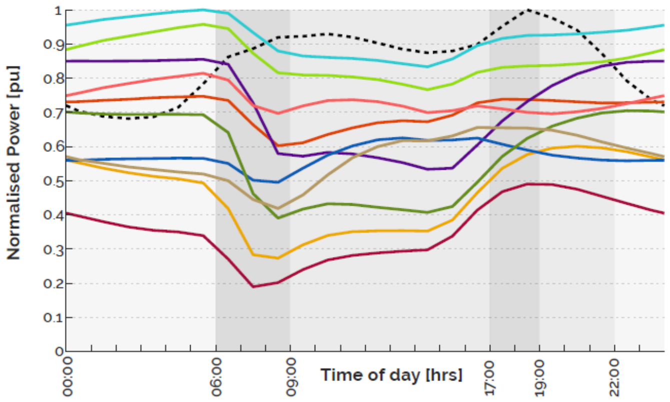


AVERAGE WIND POWER DAILY PROFILES

Low demand season (Sept-May)



High demand season (Jun-Aug)



Why does electricity planning need to adapt?

Inadequate geospatial and temporal representation of wind and solar

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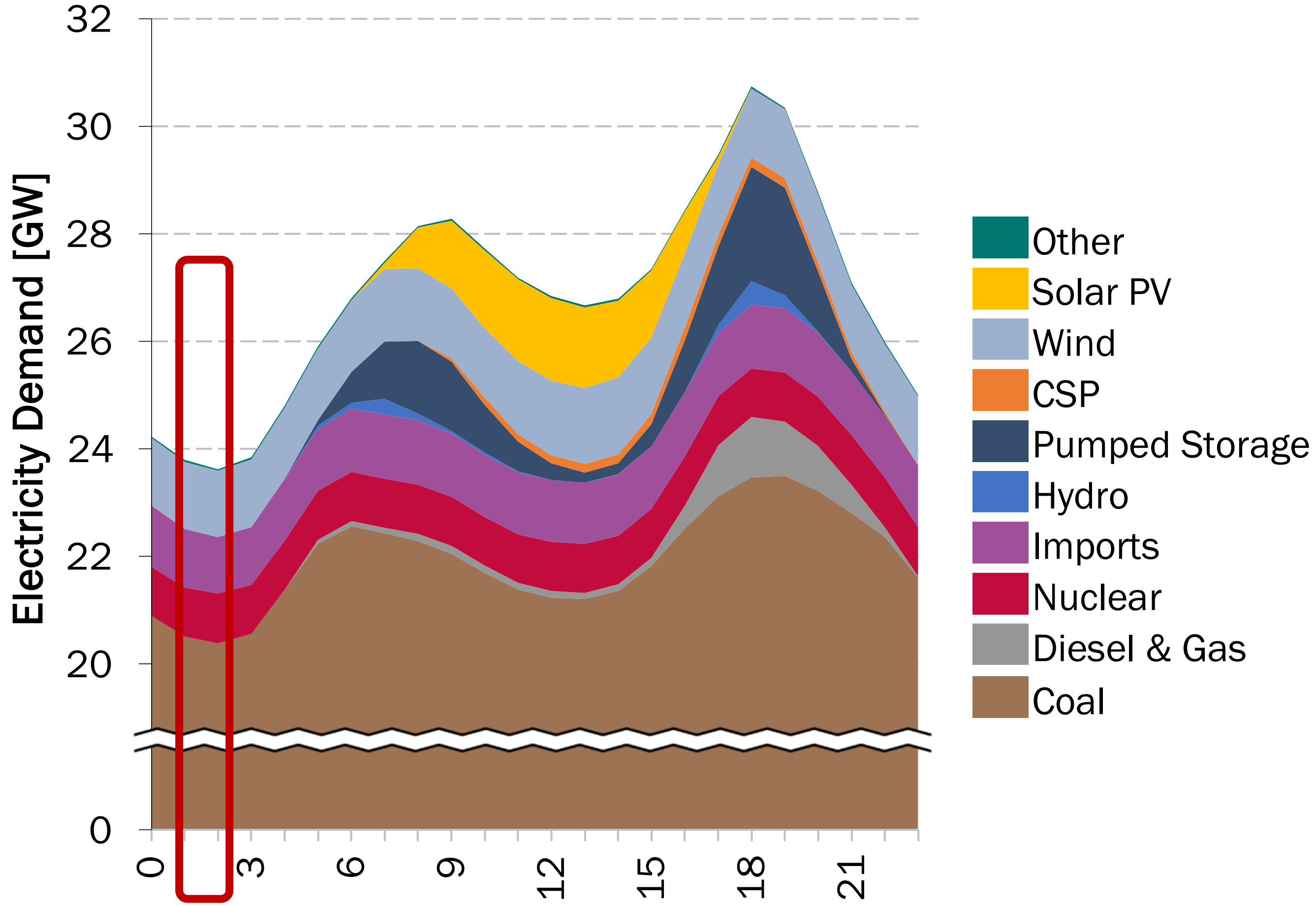
Typical-Day Electricity Production

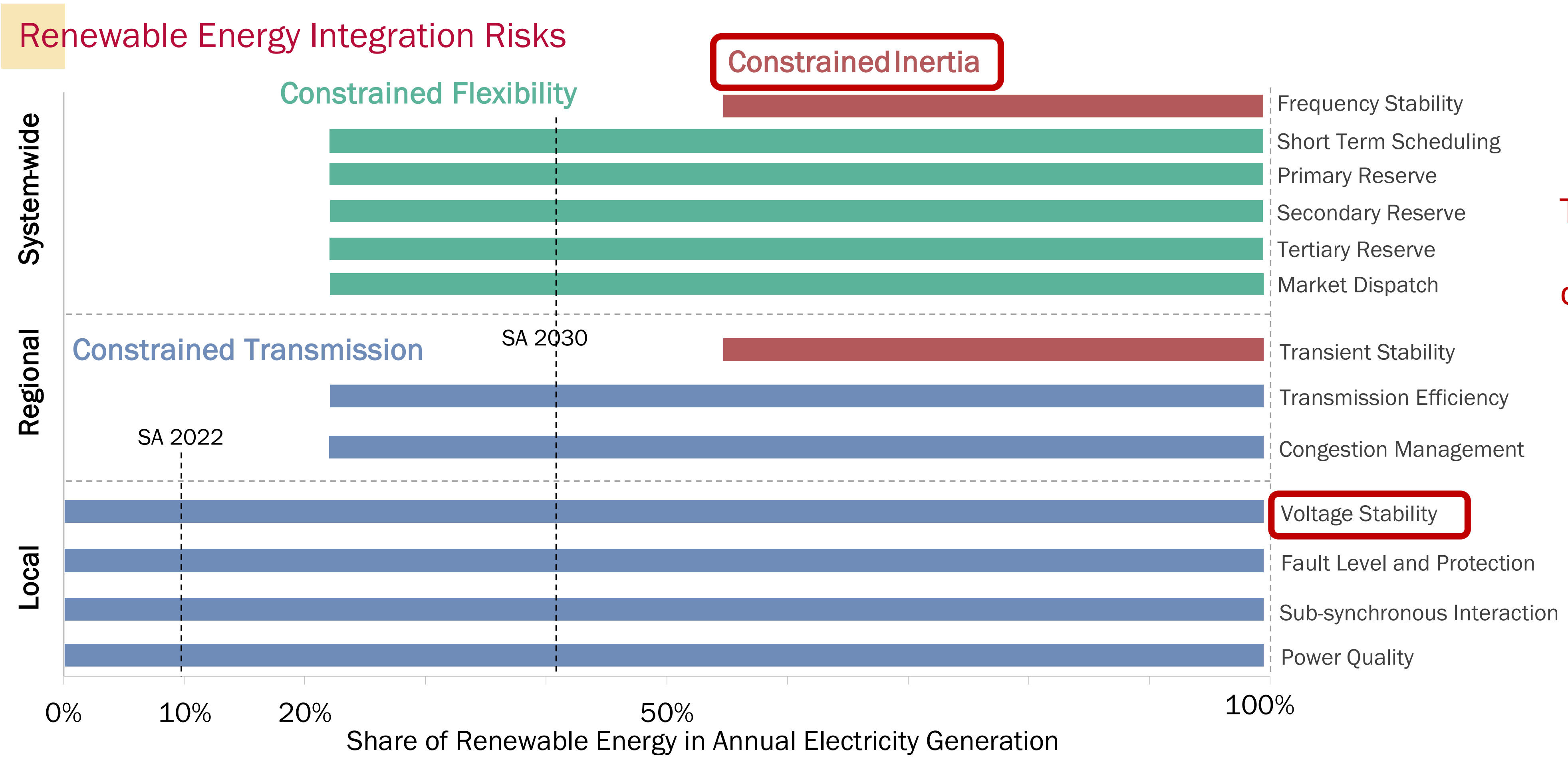


Curtailment of wind due to coal's minimum generation levels, even at the current low penetration of wind.

The Centre for Renewable and Sustainable Energy Studies (CRSES) | Stellenbosch University

Source: Eskom 2025a. **Notes:** Winter daily average uses data from June, July, and August 2024

Why does electricity planning need to adapt?
Stability costs as variable renewables increase are not considered



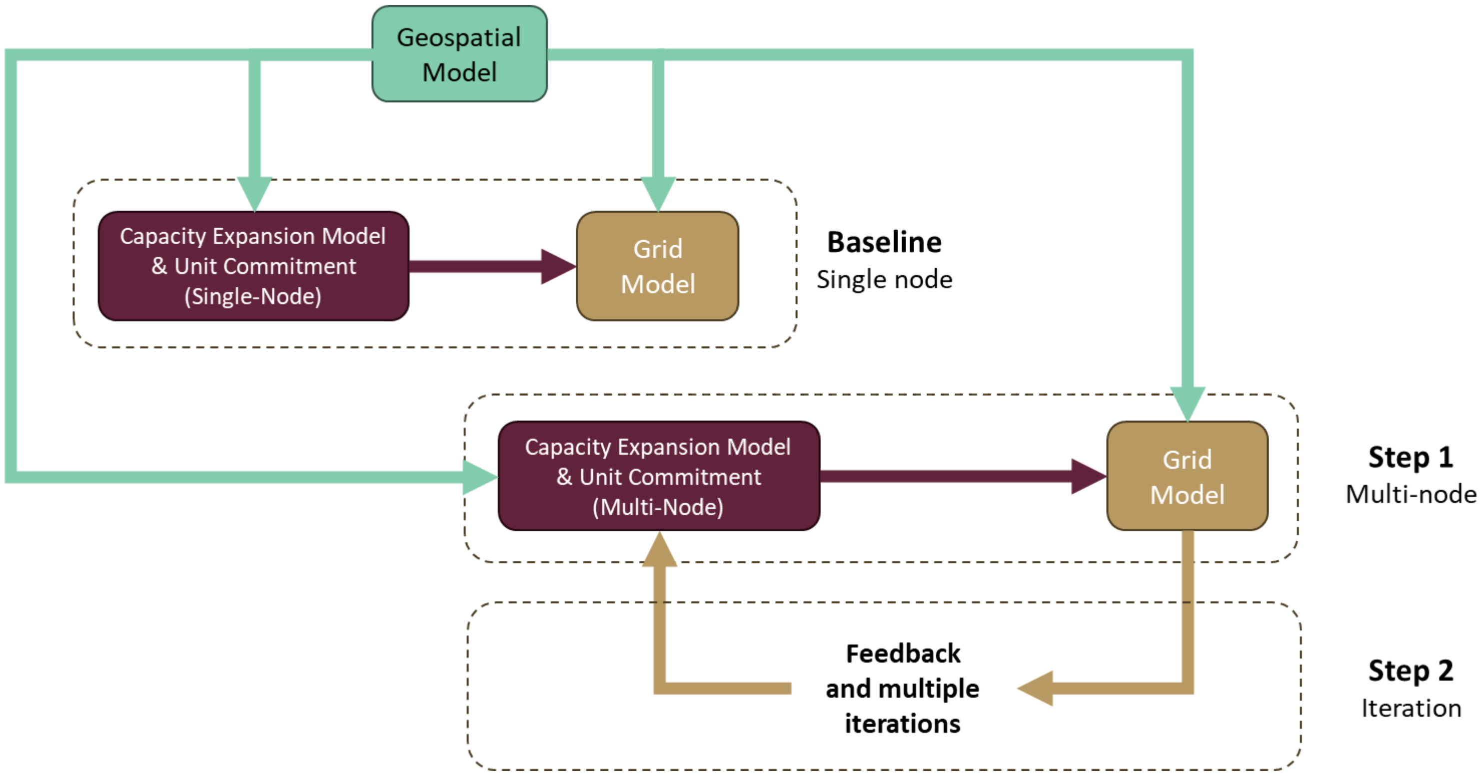
Complications:
The required stability data, if available, is typically confidential and unlikely to be released by the utility.

The Centre for Renewable and Sustainable Energy Studies (CRSES) | Stellenbosch University

Source: Mararakanye & Bekker 2019 | Eskom 2022 (TDP 2023– 32).

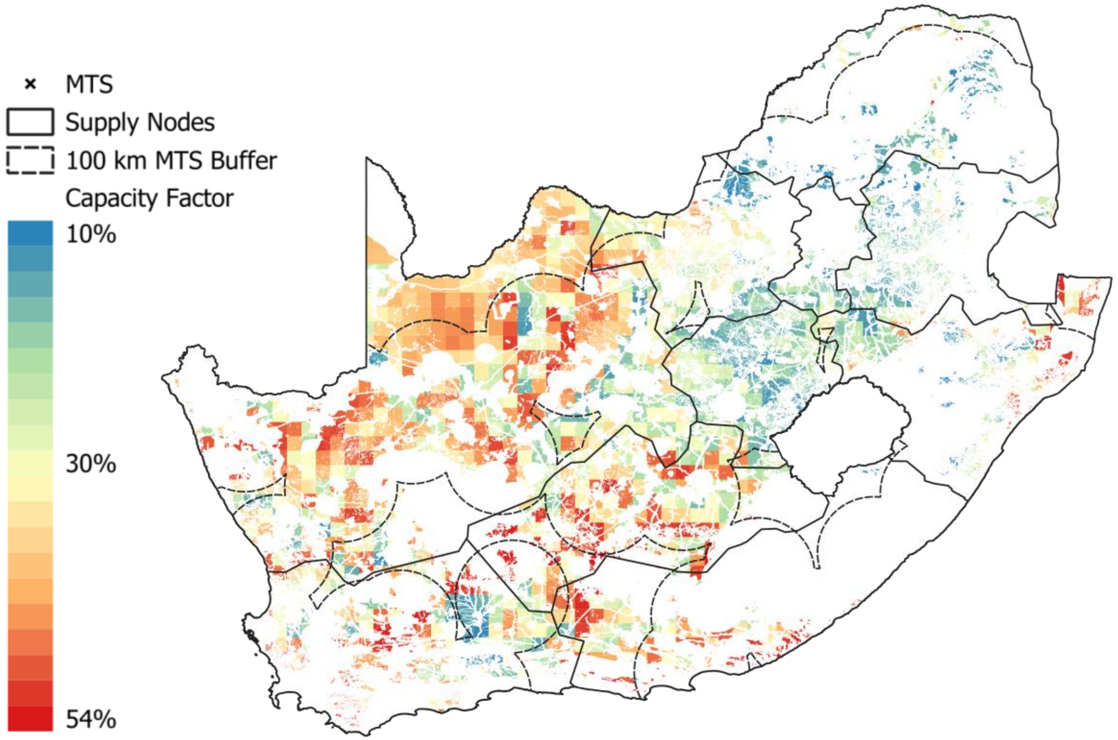
What are we working on?
University grid modelling project

- Utilise high-resolution wind and solar resource data to **produce technology-specific geospatial and temporal inputs.**
- **Develop and demonstrate an iterative soft-linking approach** that explicitly incorporates transmission constraints and resource sensitivities into expansion planning.
- **Evaluating the use of steady-state proxy metrics** for voltage stability and inertia requirements.

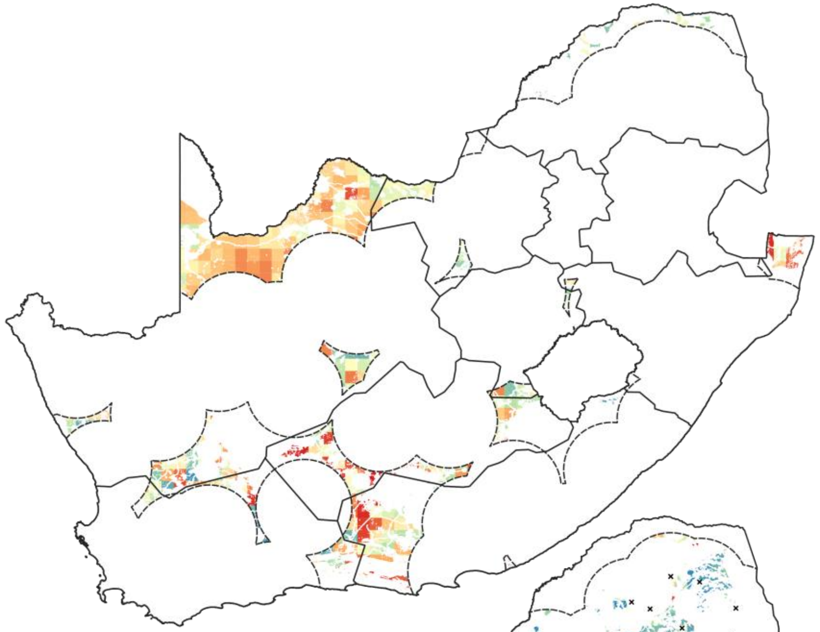


Renewable Candidate Technologies
Onshore Wind

- Wind capacity factors are derived from ERA5 and bias-corrected using WASA. Candidate locations are graded by capacity factor and used as inputs to the multilayer modelling framework.



Main Transmission Station outside of the 100km Buffer



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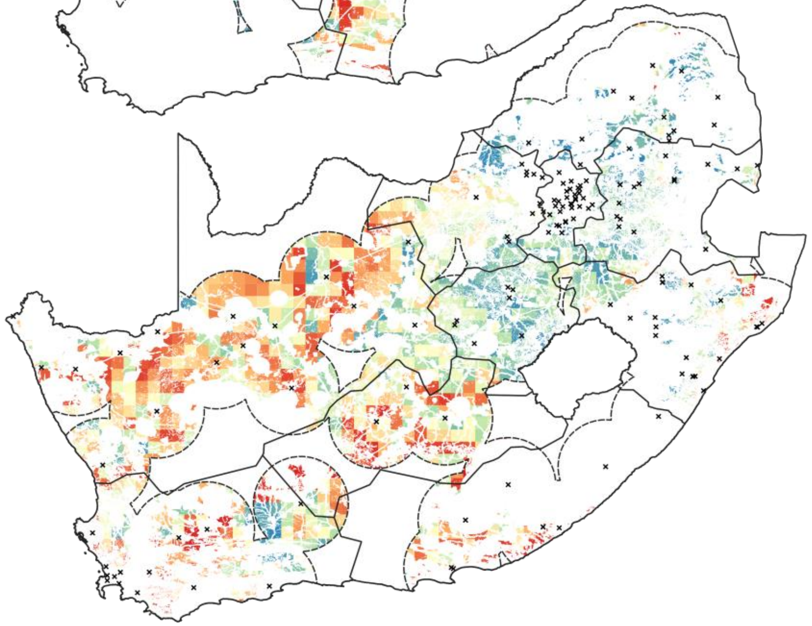
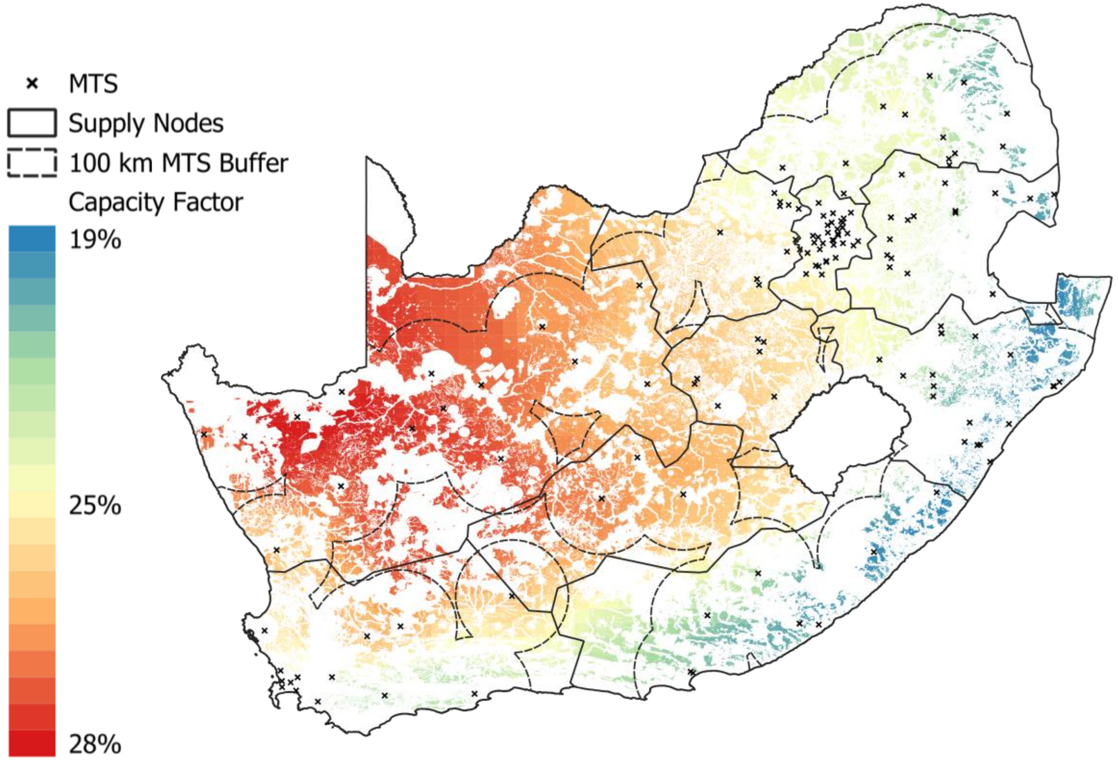
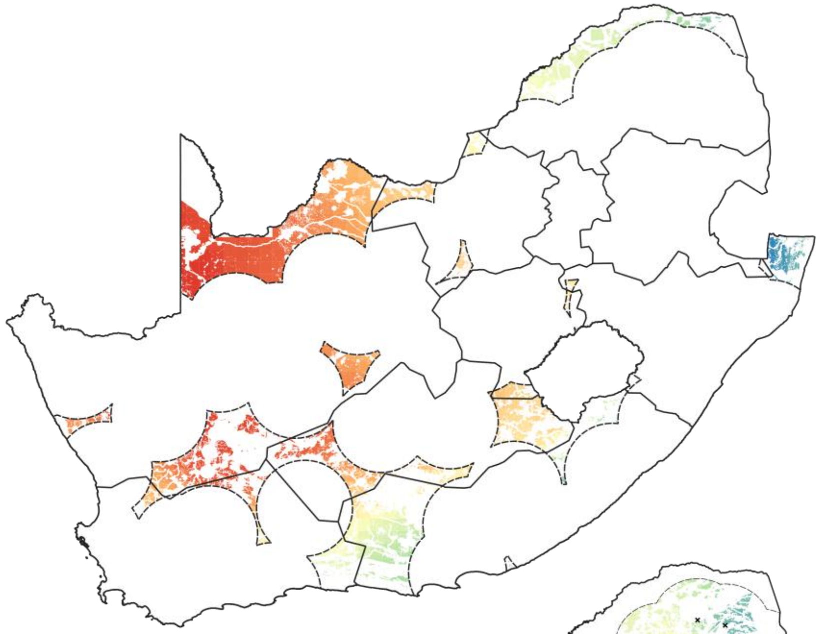


Solar PV capacity factors are derived from ERA5 data. Candidate locations are graded by capacity factor and used as inputs to the multilayer modelling framework.



Main Transmission Station outside of the 100km Buffer



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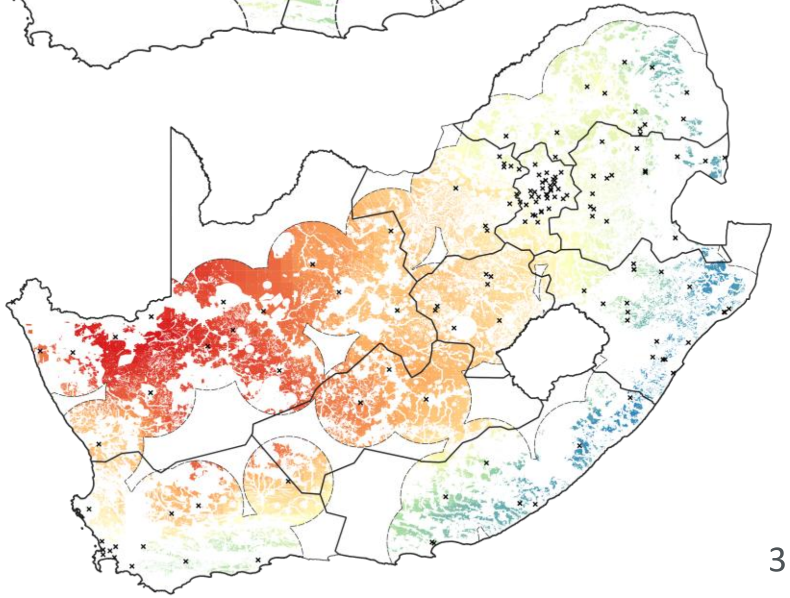

Renewable Candidate Technologies
Concentrated Solar Power

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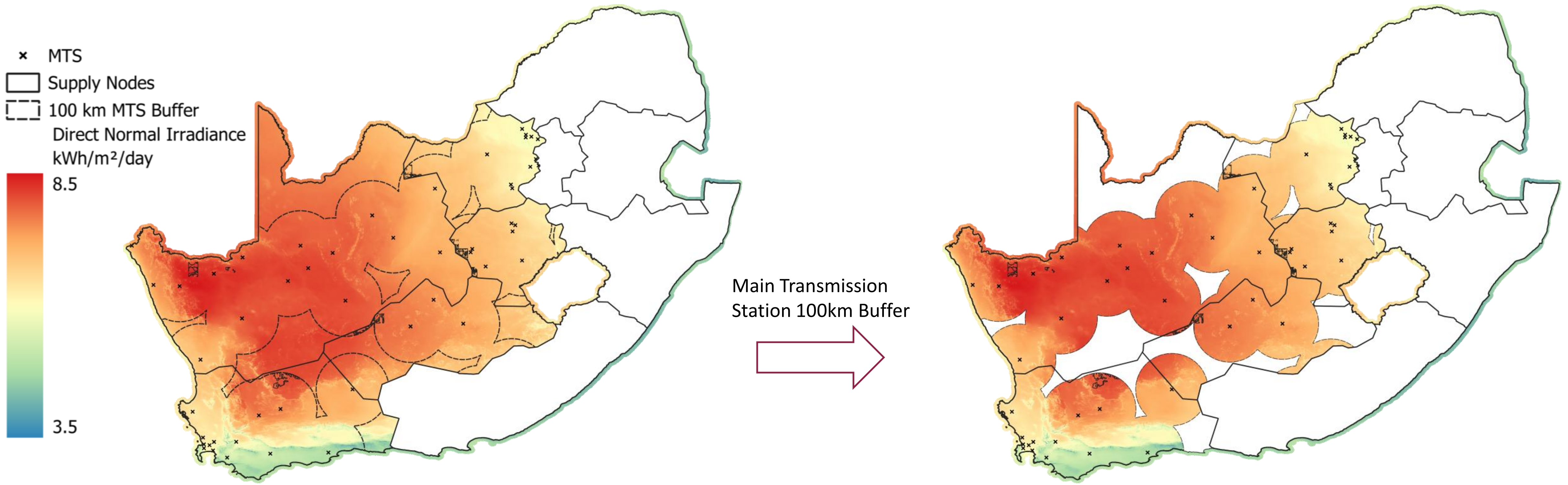
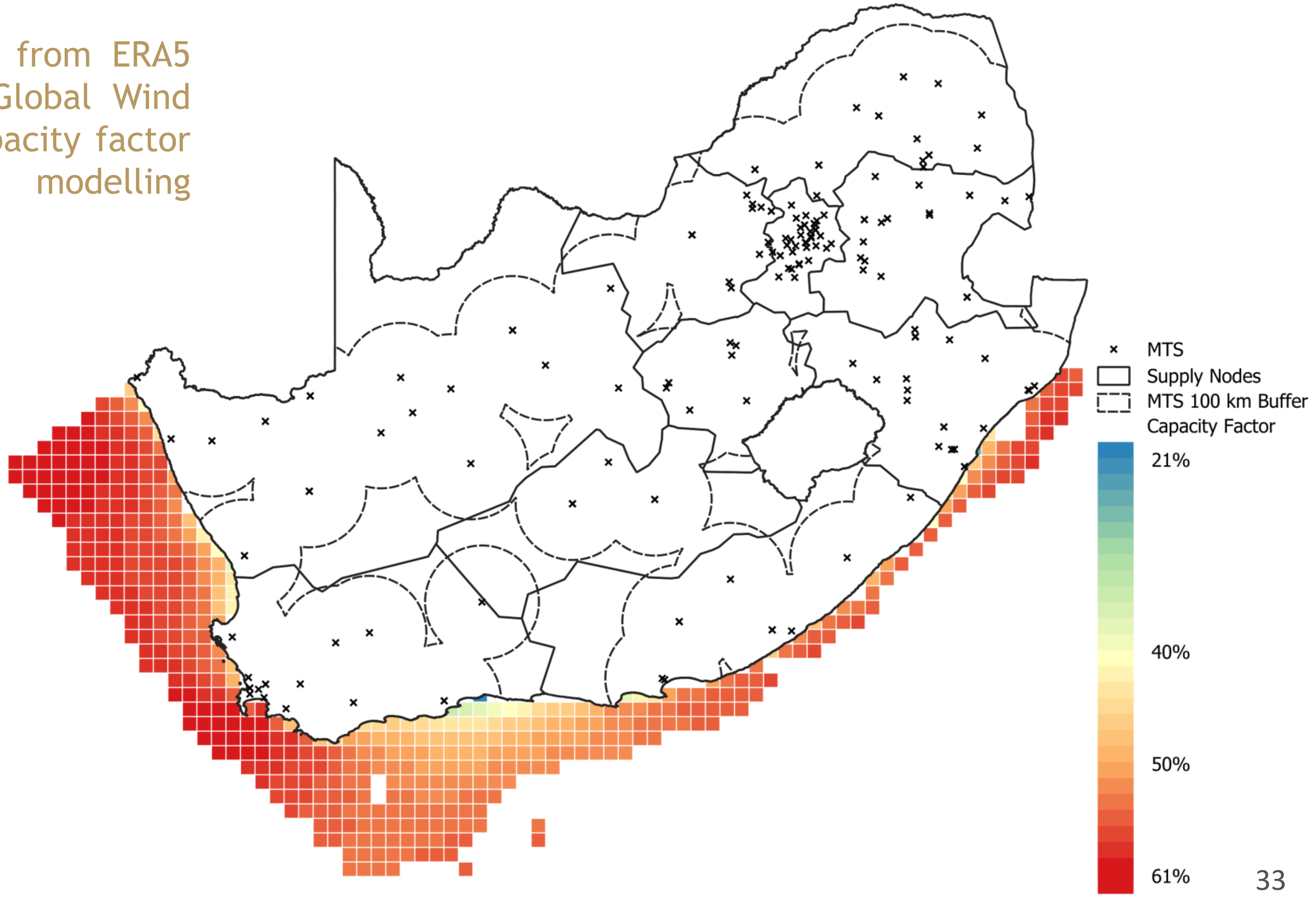
Direct Normal Irradiance (DNI) is derived from ERA5 and used as the Concentrating Solar Power resource input layer. Candidate locations are graded by DNI, and the highest-ranked locations sufficient to supply 5 GW of CSP per supply node are used as inputs to the multilayer modelling framework.



Renewable Candidate Technologies
Offshore Wind

Offshore wind capacity factors are derived from ERA5 wind data with bias correction using the Global Wind Atlas. Candidate locations are graded by capacity factor and incorporated into the multilayer modelling framework.



SU grid modelling project
Objectives and methodology

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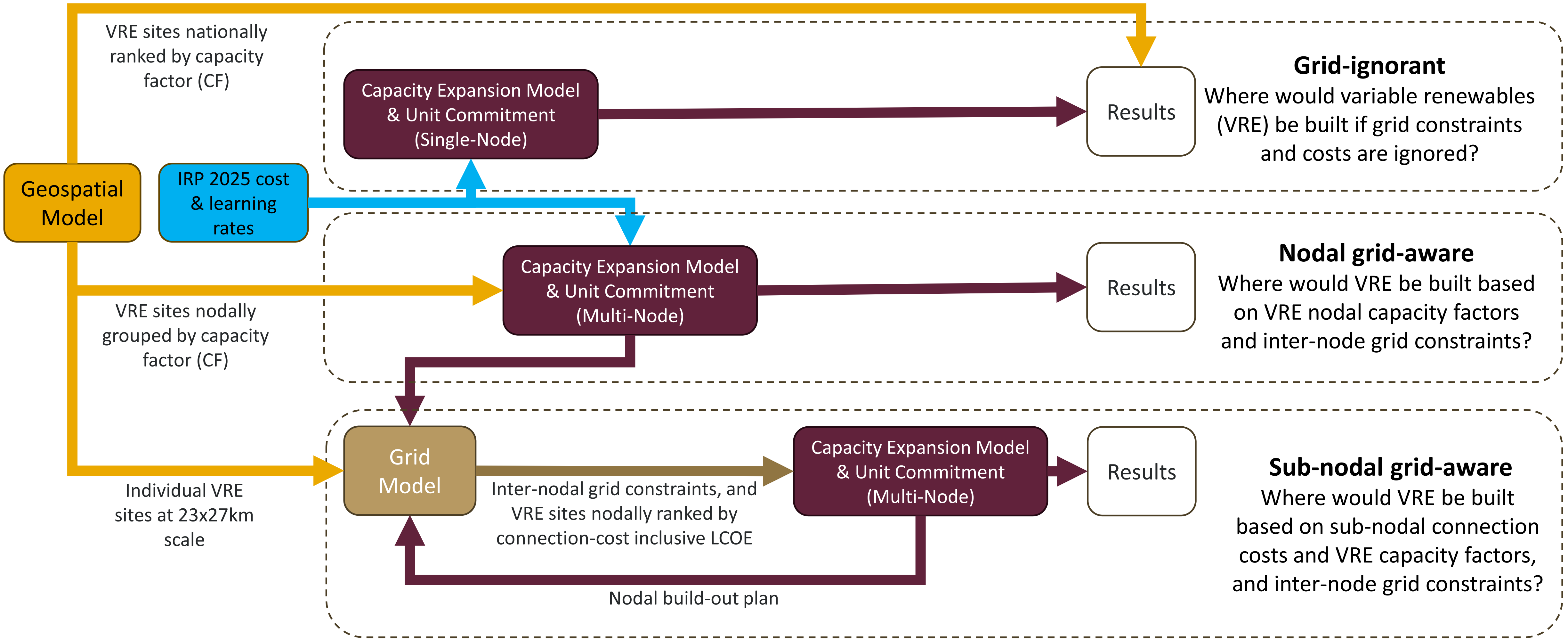

Models alone do not improve planning outcomes

…and academia does not make the decisions that shape SA's future

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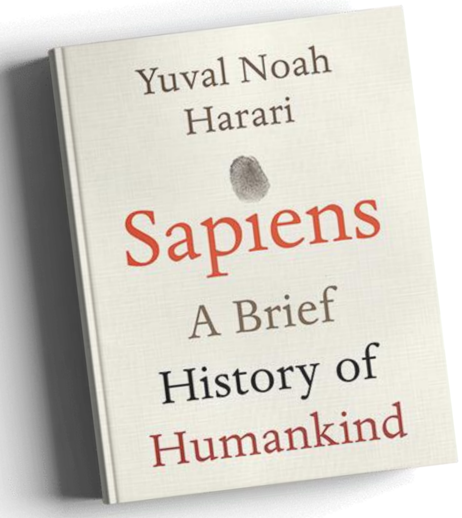


"…an imagined reality is something that everyone believes in, and as long as this communal belief persists, the imagined reality exerts force in the world."

"Storytelling is our superpower"

STORIES SHAPE REALITY + MODELLING INFORMS STORIES = FOR IMPACTFUL MODELS, LEARN TO TELL BETTER STORIES

We can make our models impactful
…by telling these stories to audiences that can effect change

- Everyone likes listening to good stories.
- However, you have limited time and resources to make your models impactful, so choose wisely where you tell these stories.

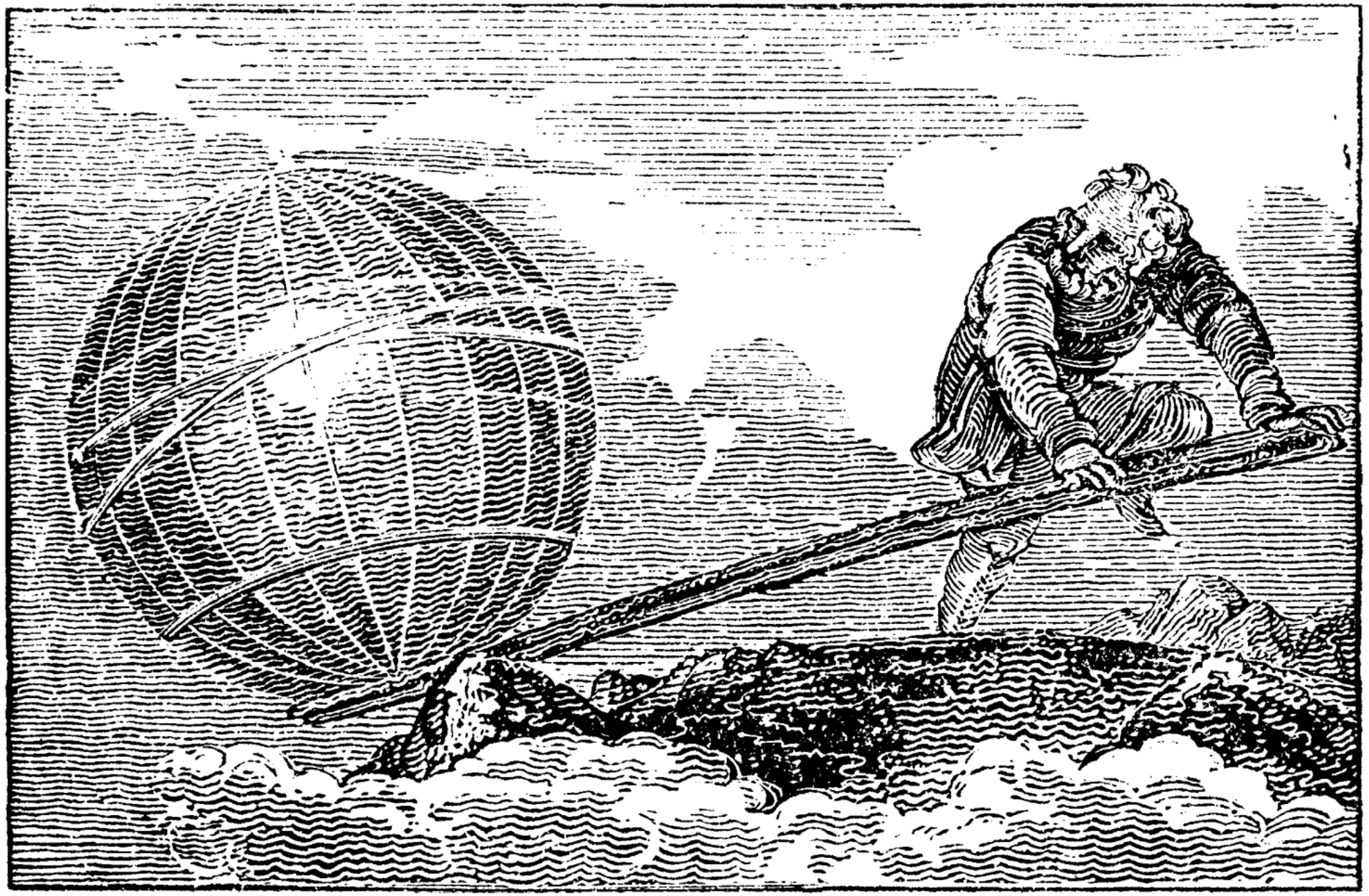
We can make our models impactful
…by building relationships and trust with model recipients

- Decision-makers are more likely to listen to stories from people they know and trust.

- Relationships help you understand the decision-maker's existing knowledge scaffolding.

We can make our models impactful

…by mentoring and inspiring the next generation



https://erickimphotography.com/blog/2017/05/15/archimedes-lever/

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Thank you

Photo by Stefan Els