

AP Hilbers, DJ Brayshaw, A Gandy. Efficient quantification of the impact of demand and weather uncertainty in energy system models. United Kingdom: Imperial College London, University of Reading. Version 1. Creative Commons CC-BY-4.0 license.



Efficient quantification of the impact of demand and weather uncertainty in energy system models

AP Hilbers ¹, DJ Brayshaw ², A Gandy ¹

1: Department of Mathematics, Imperial College London

2: Department of Meteorology, University of Reading

Climate forecasting for
energy workshop

Uncertainty on time series inputs leads to *demand*
and weather uncertainty on model outputs

Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

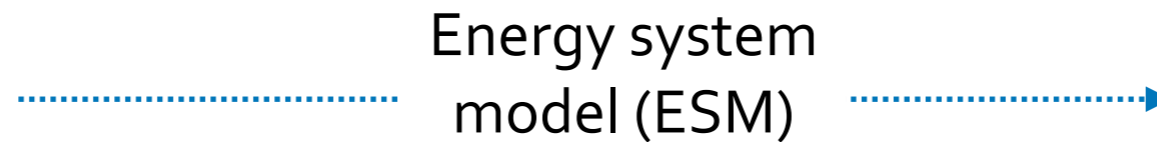
- Demand levels
- Wind speeds
- Solar irradiances

Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

- Demand levels
- Wind speeds
- Solar irradiances

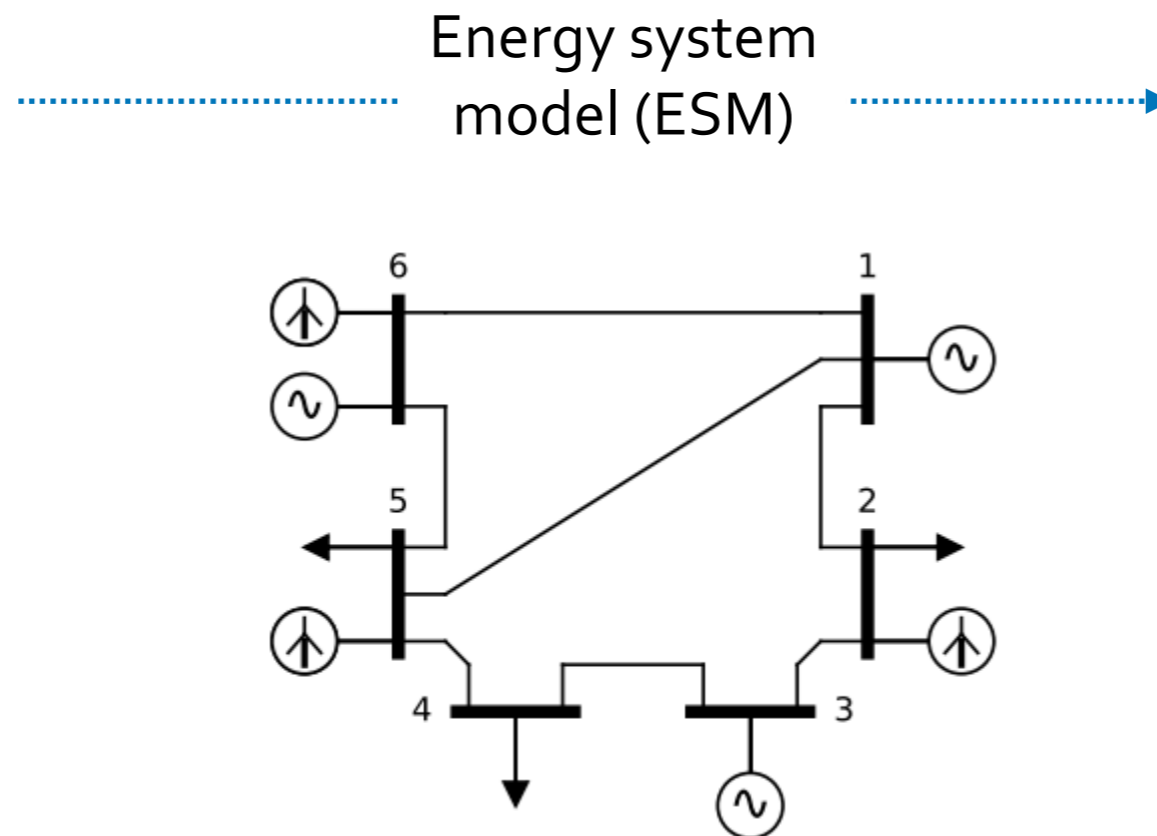


Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

- Demand levels
- Wind speeds
- Solar irradiances



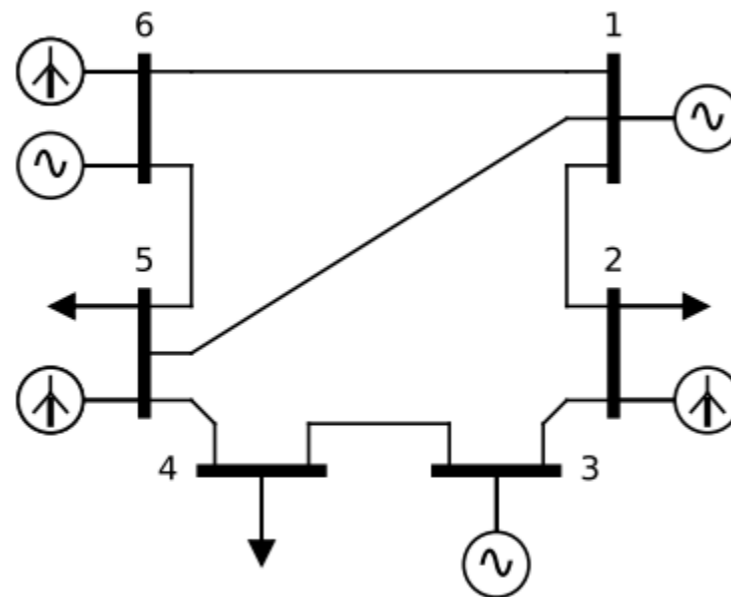
Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

- Demand levels
- Wind speeds
- Solar irradiances

Energy system
model (ESM)



OUTPUTS

- Installed capacities of different technologies
- Hourly generation levels of different technologies
- Total system cost
- Total carbon emissions

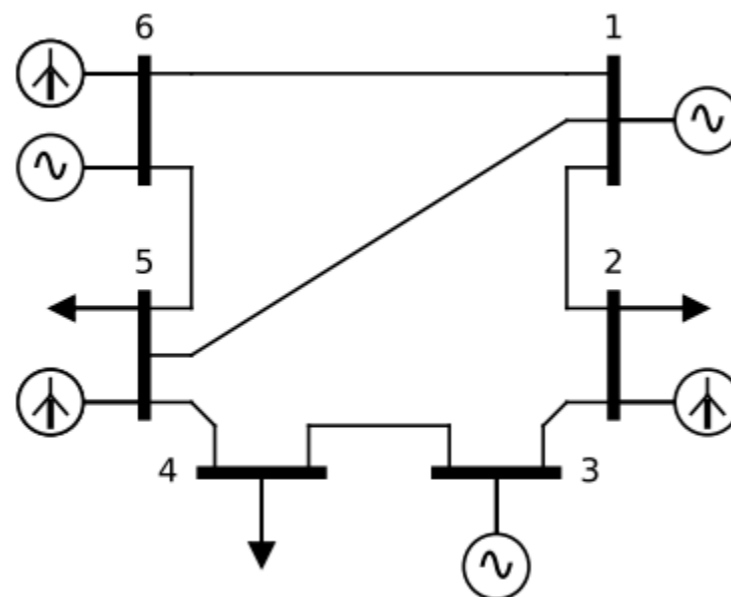
Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

- Demand levels
- Wind speeds
- Solar irradiances

Energy system
model (ESM)



OUTPUTS

- Installed capacities of different technologies
- Hourly generation levels of different technologies
- Total system cost
- Total carbon emissions

Uncertain inputs

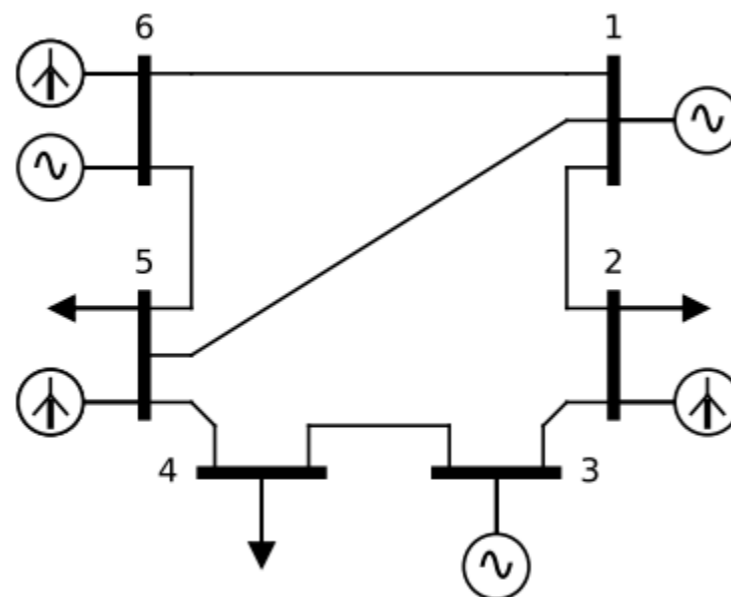
Uncertainty on time series inputs leads to *demand* and *weather uncertainty* on model outputs

INPUTS

Demand & weather data at different locations on the grid

- Demand levels
- Wind speeds
- Solar irradiances

Energy system
model (ESM)



OUTPUTS

- Installed capacities of different technologies
- Hourly generation levels of different technologies
- Total system cost
- Total carbon emissions

Uncertain inputs

Demand and weather
uncertainty on outputs

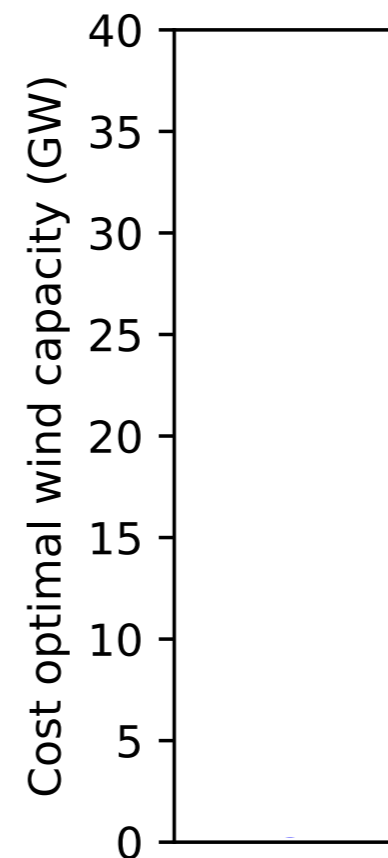
Natural climate variability can lead to large uncertainty on energy system model outputs

Natural climate variability can lead to large uncertainty on energy system model outputs

- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”

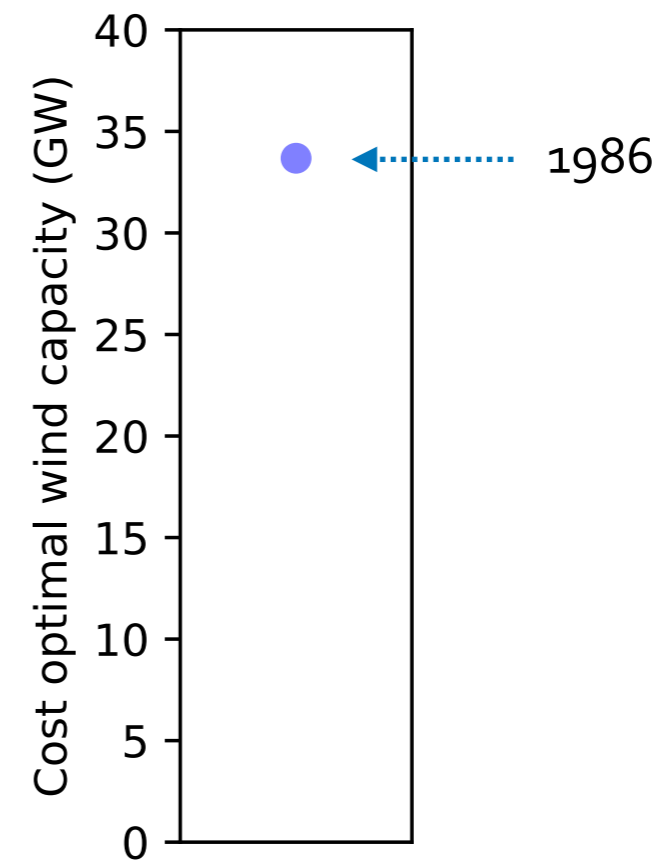
Natural climate variability can lead to large uncertainty on energy system model outputs

- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”



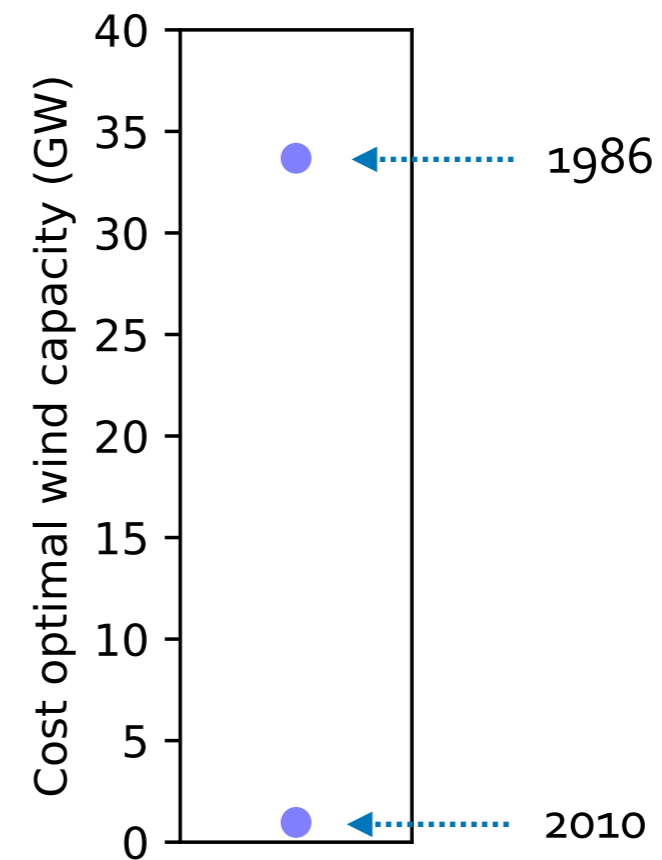
Natural climate variability can lead to large uncertainty on energy system model outputs

- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”



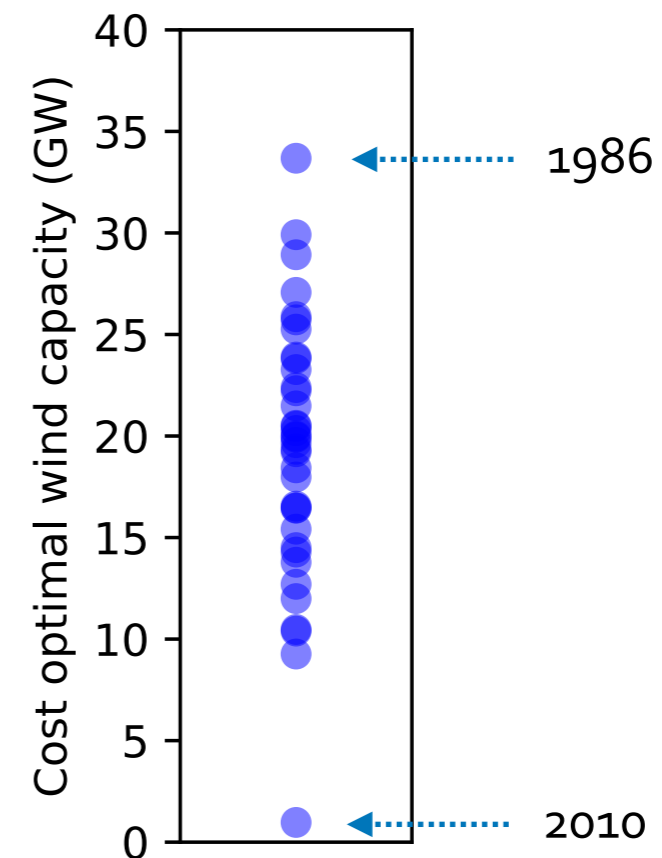
Natural climate variability can lead to large uncertainty on energy system model outputs

- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”



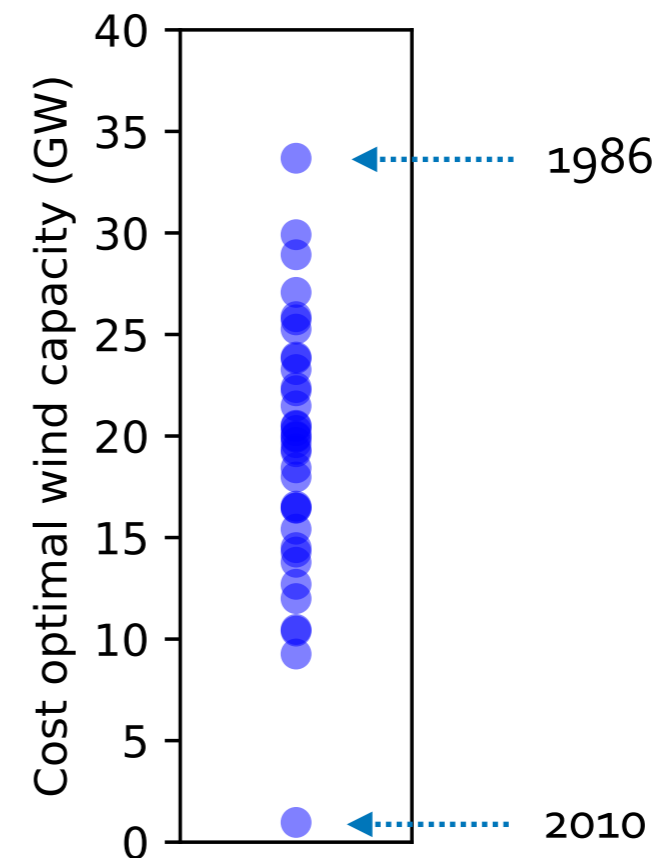
Natural climate variability can lead to large uncertainty on energy system model outputs

- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”



Natural climate variability can lead to large uncertainty on energy system model outputs

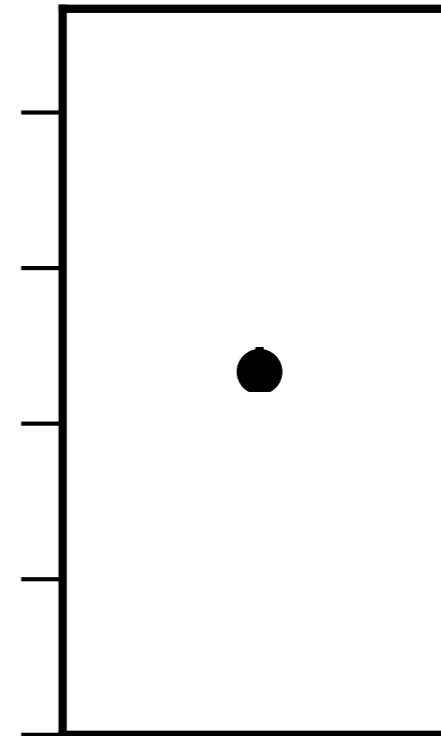
- Spread in model outputs across uncertain demand and weather can be large: risk in “picking wrong year”
- Other studies have shown similar results:
Bloomfield et al (2016), Staffell & Pfenninger (2018) Collins et al (2018), Bothwell & Hobbs (2018), Kumler et al (2019), Bryce et al (2018), Amorim et al (2020).



Can we quantify this *demand*
and *weather uncertainty*?

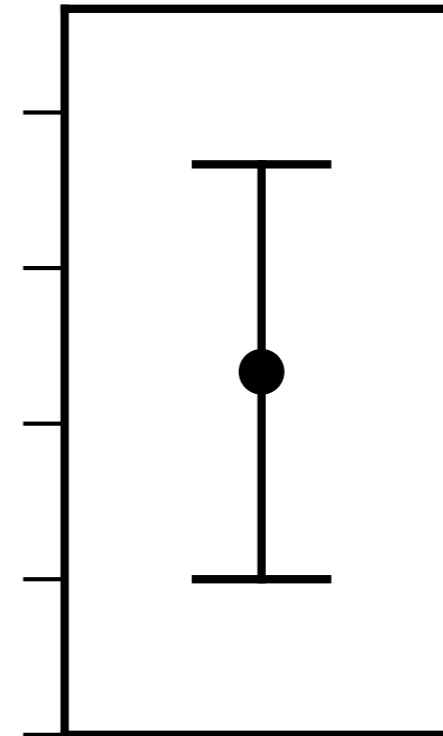
Can we quantify this *demand*
and weather uncertainty?

Model output



Can we quantify this *demand*
and *weather uncertainty*?

Model output



Traditional Monte Carlo methods are inefficient in data and computation

Obtain 100
years of data

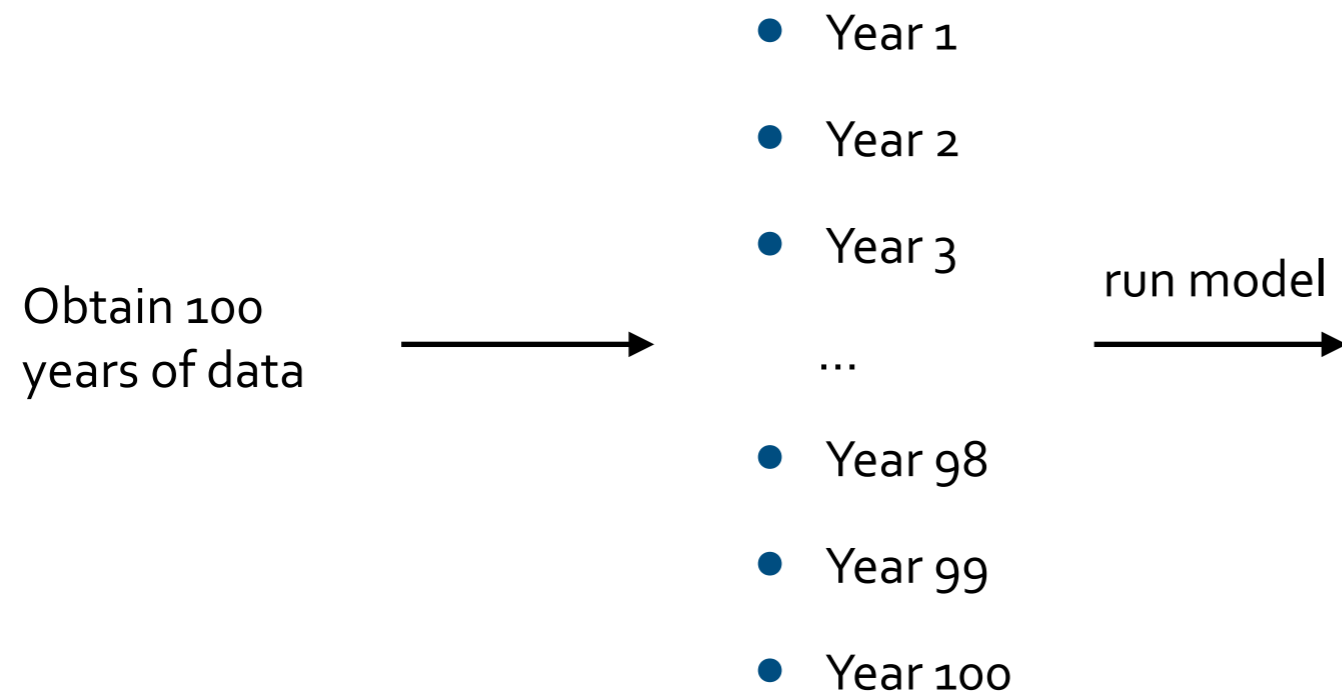
Traditional Monte Carlo methods are inefficient in data and computation

Obtain 100
years of data

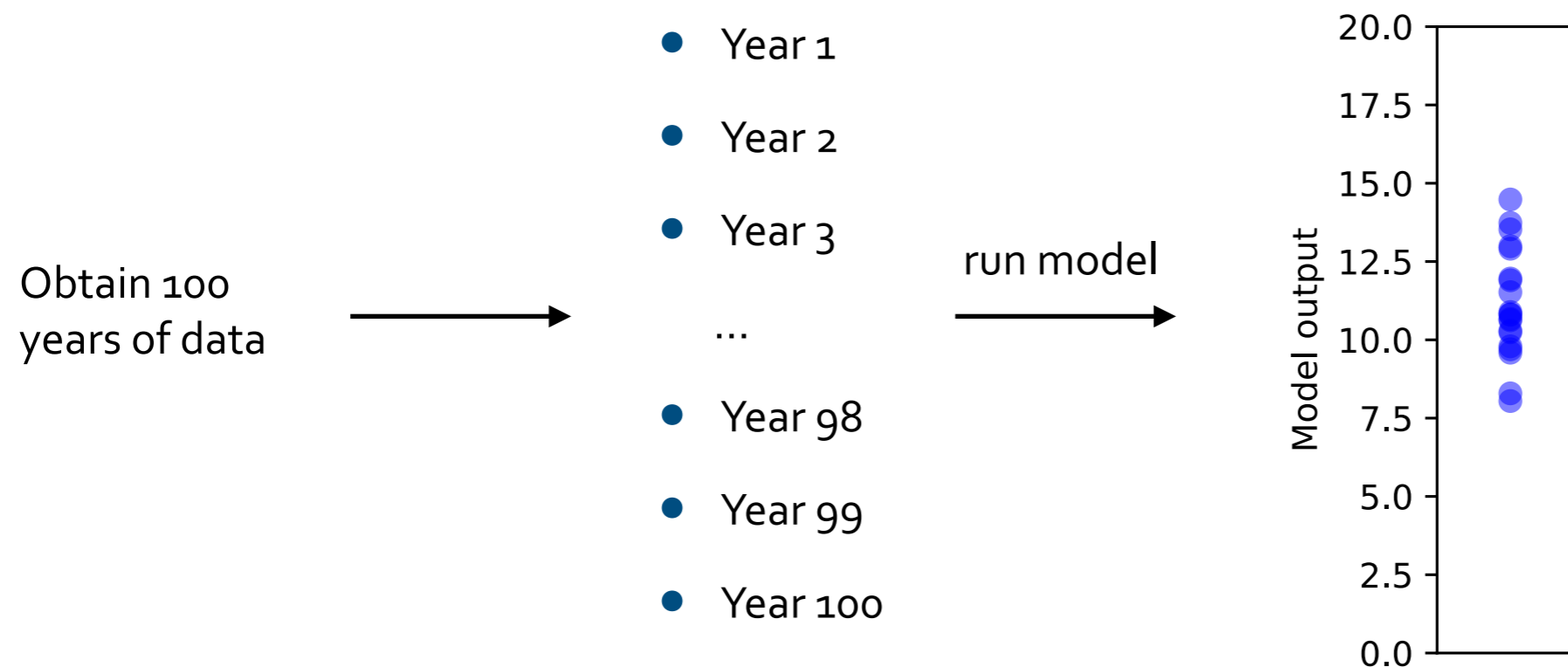


- Year 1
- Year 2
- Year 3
- ...
- Year 98
- Year 99
- Year 100

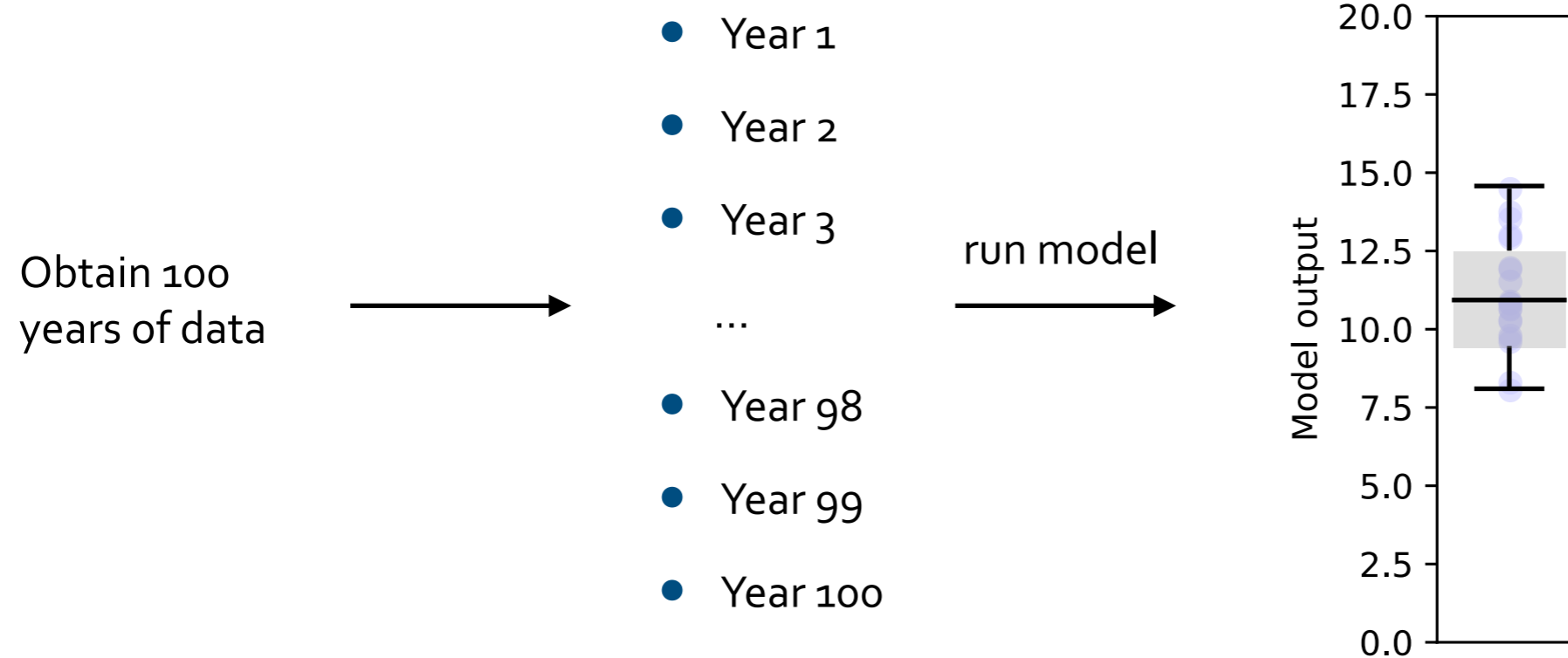
Traditional Monte Carlo methods are inefficient in data and computation



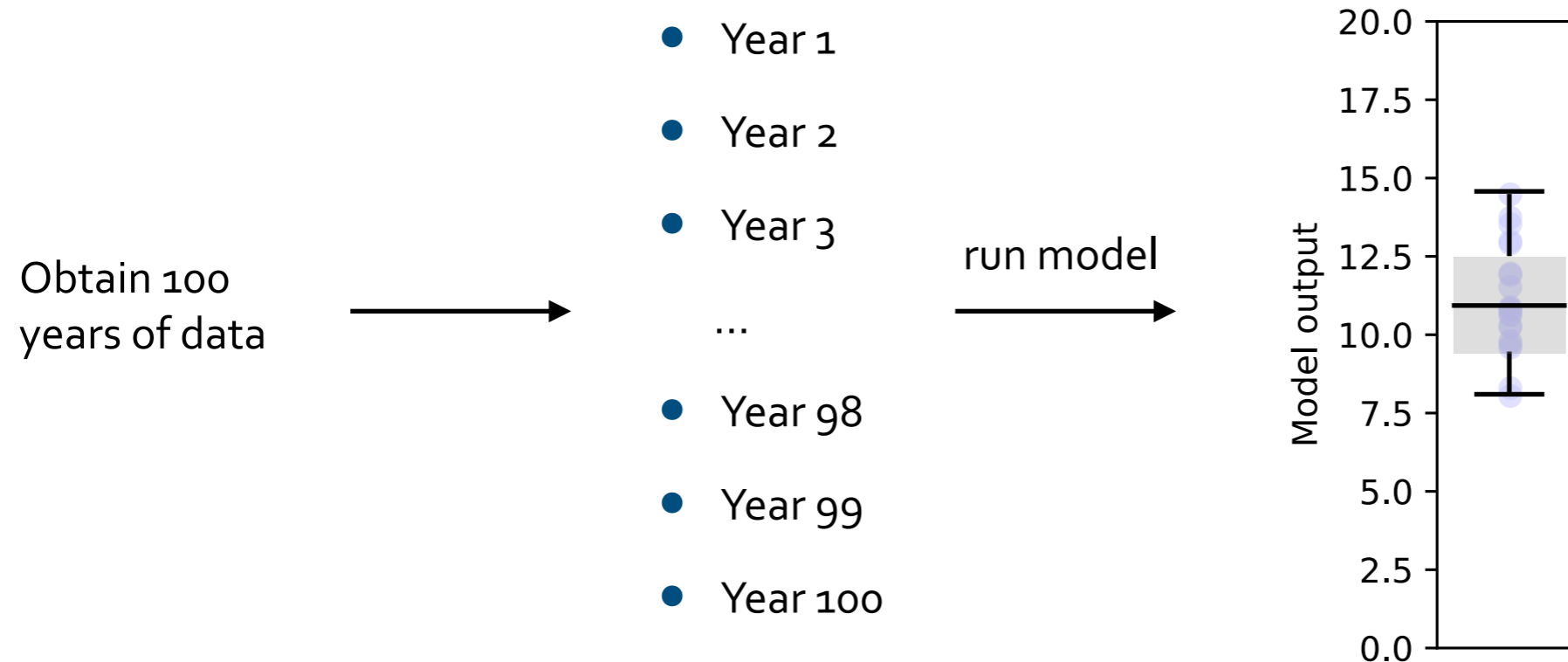
Traditional Monte Carlo methods are inefficient in data and computation



Traditional Monte Carlo methods are inefficient in data and computation



Traditional Monte Carlo methods are inefficient in data and computation



Inefficient in

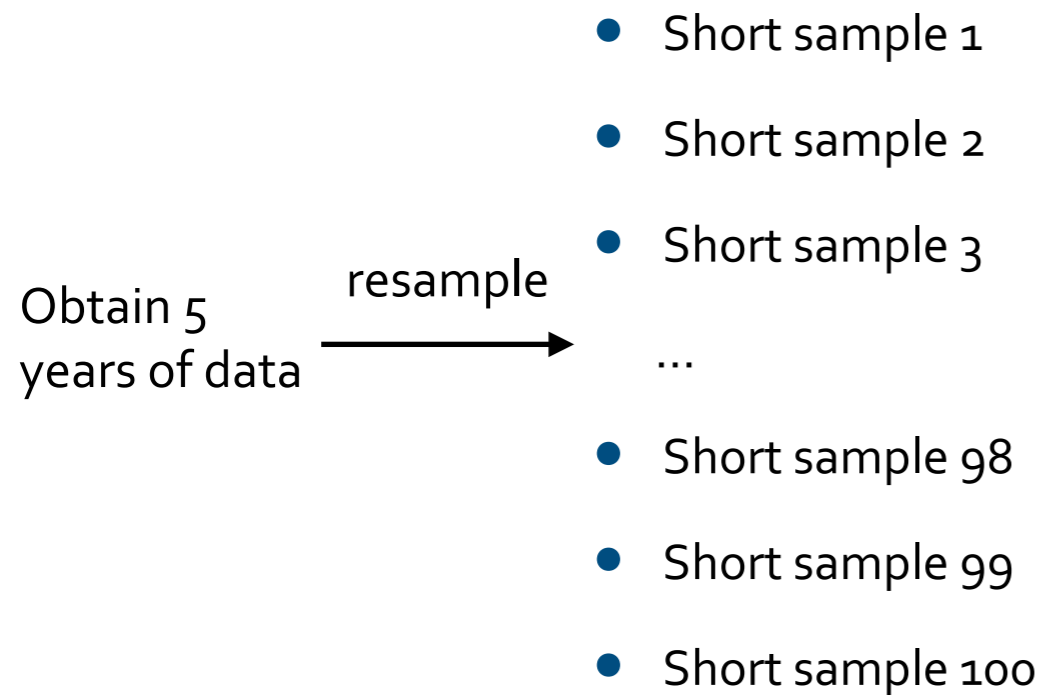
- data: 100 years of demand and weather data
- computation: 100 1-year simulations

New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently

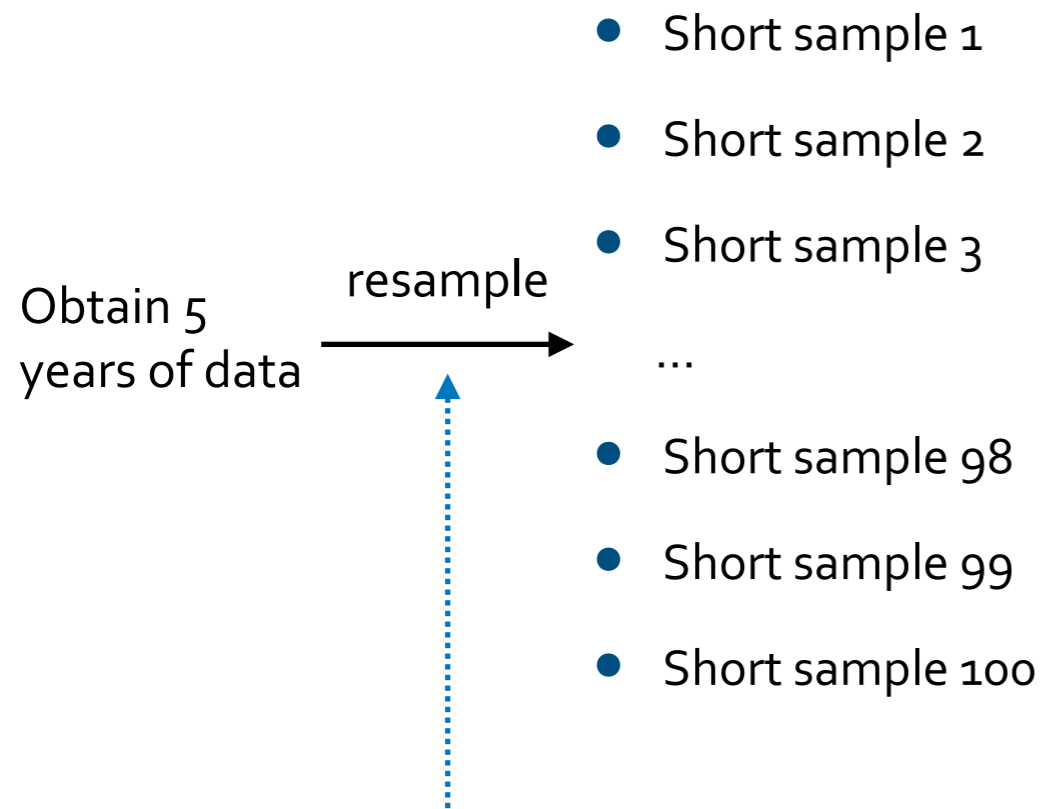
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently

Obtain 5
years of data

New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



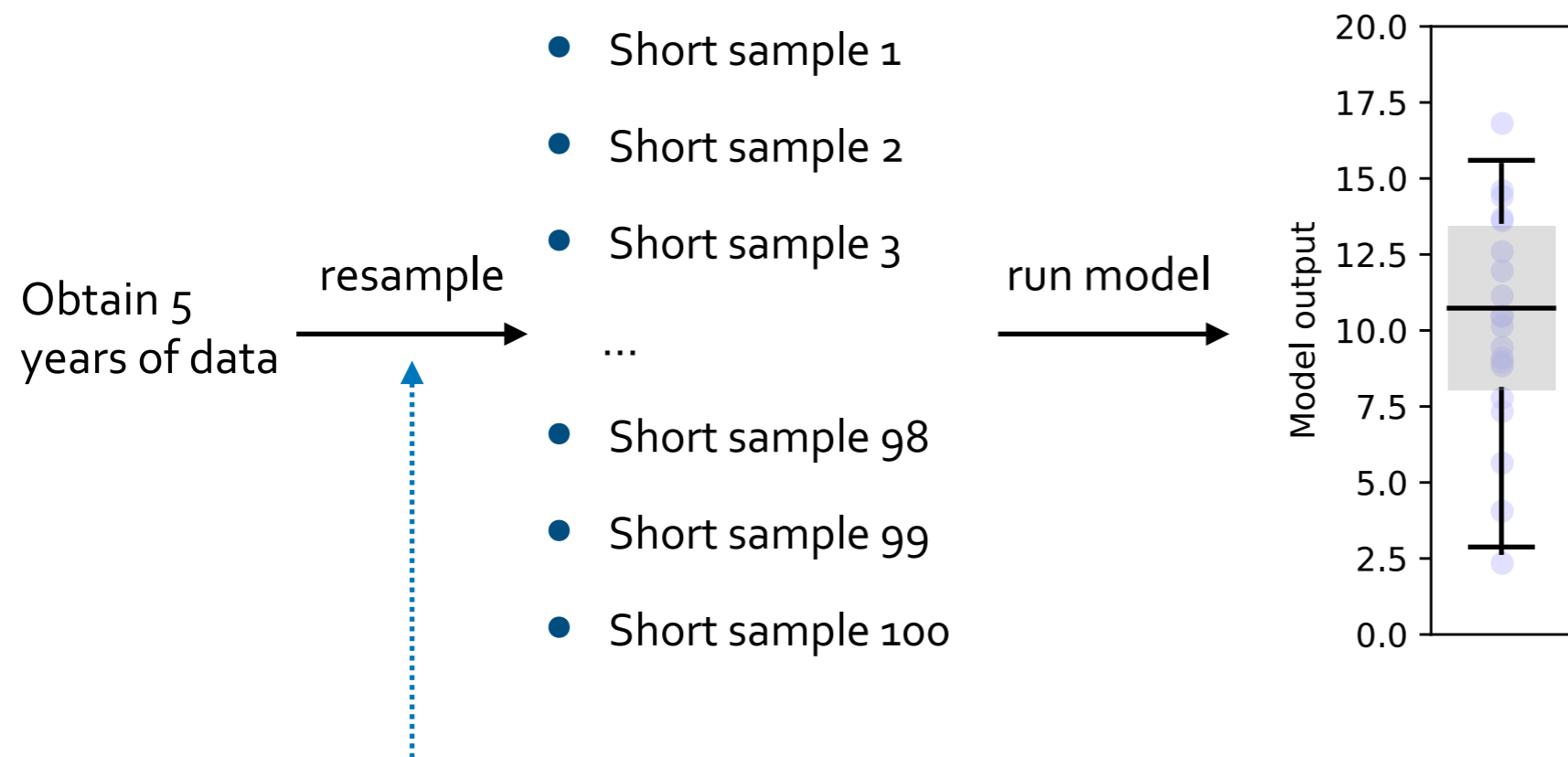
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



Resample weeks from seasons

e.g. one week from winter,
spring, summer, autumn

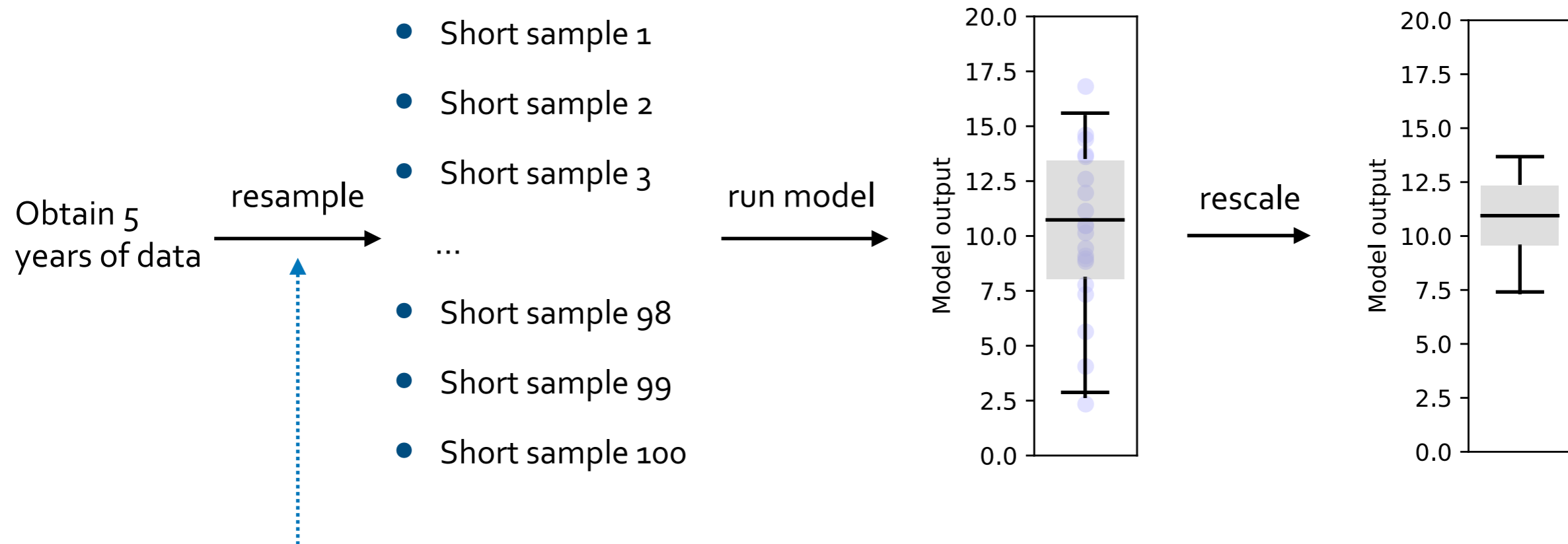
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



Resample weeks from seasons

e.g. one week from winter,
spring, summer, autumn

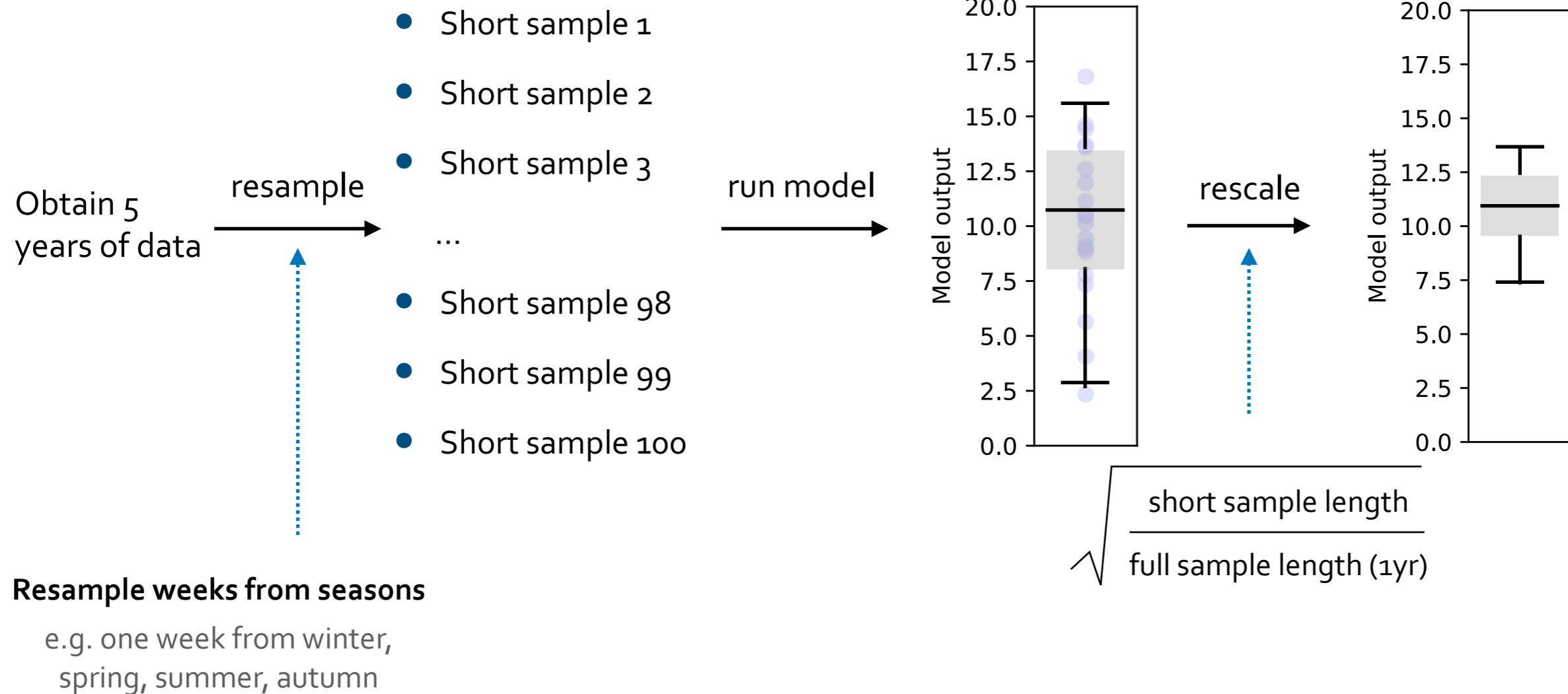
New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



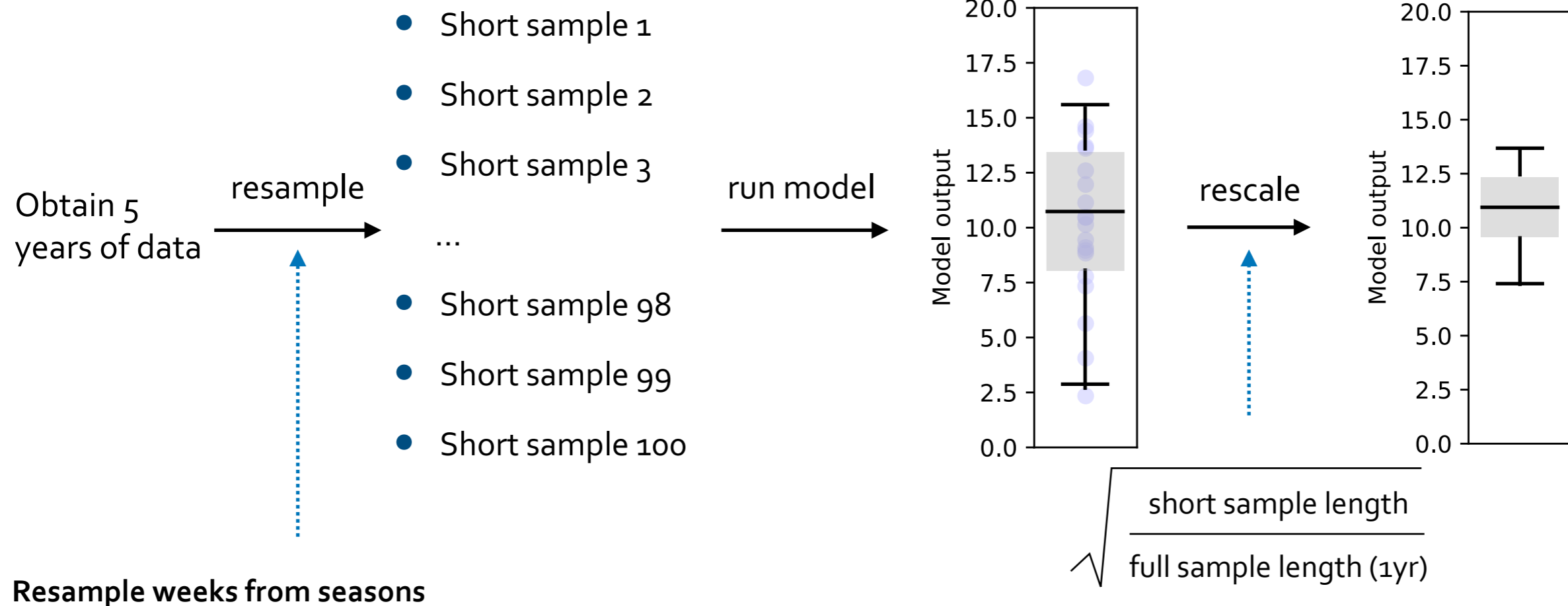
Resample weeks from seasons

e.g. one week from winter,
spring, summer, autumn

New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



New method resamples data into shorter subsamples to calculate uncertainty intervals more efficiently



Resample weeks from seasons

e.g. one week from winter, spring, summer, autumn

Efficient in

- data: ~~100~~ 5 years of demand and weather data
- computation: 100 ~~1-year~~ short simulations

Summary

Summary

- Impact of demand and weather uncertainty on energy system model outputs can be significant.

Summary

- Impact of demand and weather uncertainty on energy system model outputs can be significant.
- Existing uncertainty quantification techniques inefficient in data and computation, often unfeasible.

Summary

- Impact of demand and weather uncertainty on energy system model outputs can be significant.
- Existing uncertainty quantification techniques inefficient in data and computation, often unfeasible.
- Approach, based on m out of n bootstrap, resamples shorter datasets, reducing computing cost and removes need for any additional data.

Summary

- Impact of demand and weather uncertainty on energy system model outputs can be significant.
- Existing uncertainty quantification techniques inefficient in data and computation, often unfeasible.
- Approach, based on m out of n bootstrap, resamples shorter datasets, reducing computing cost and removes need for any additional data.
- Details: AP Hilbers, DJ Brayshaw, A Gandy (2020). Efficient quantification of the impact of demand and weather uncertainty in power system models. *IEEE Transactions on Power Systems*.