Operational Numerical Weather Prediction (NWP) of Hub-height Winds for Mountainous British Columbia

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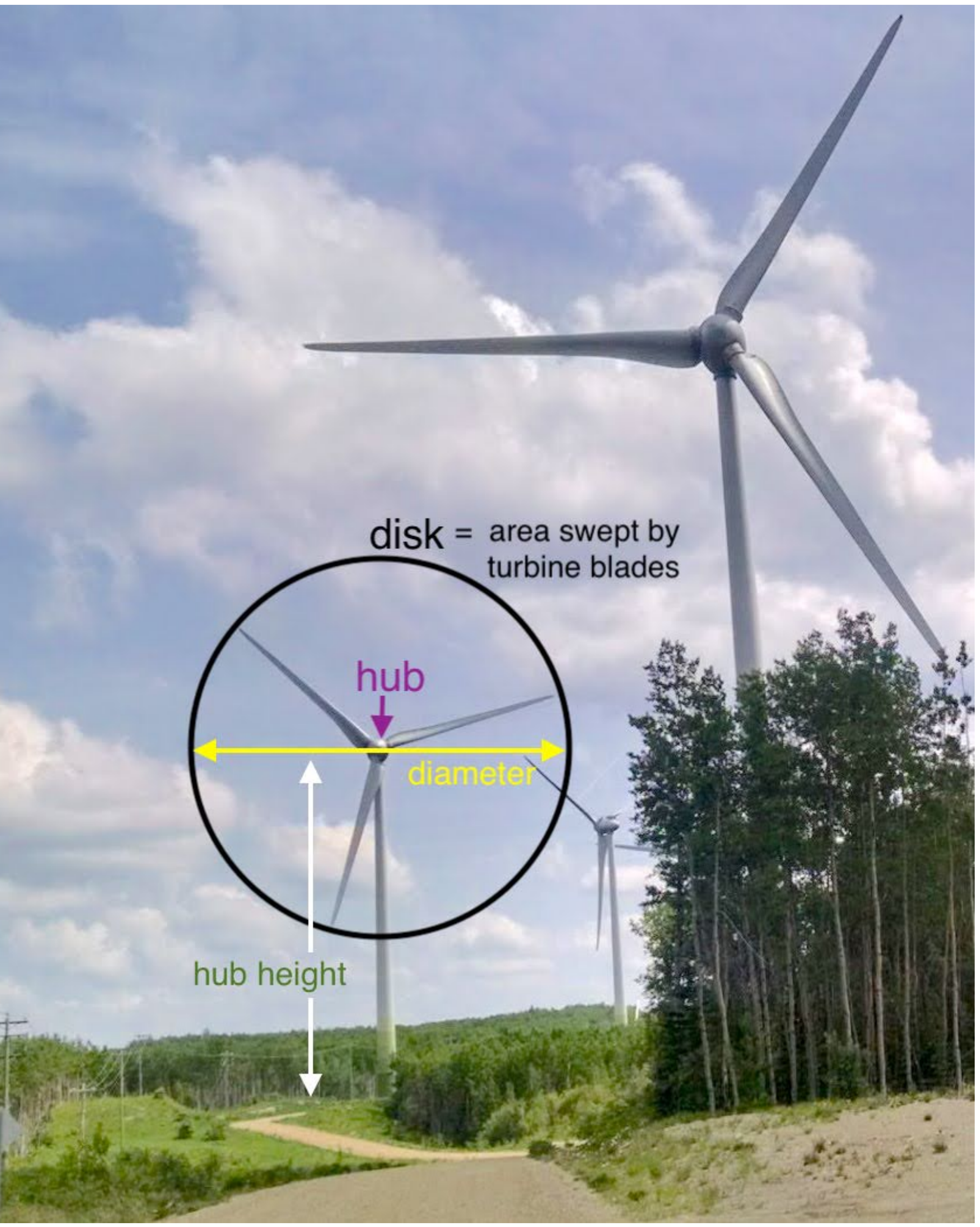
Topics:

1. Terrain Issues
2. Power curves, heterogeneity, convolution, farm-average power
3. Need for extensive upwind modeling
4. Sensitivities, partially addressed via ensemble NWP
5. Operational hub-height forecasts made by UBC
6. Current research and a renewable-energy meteorology course

Background: Wind farms in BC



WFRT member Bryan Jansens provides hub-height wind forecasts for all wind farms in BC except Grouse Mtn.

Figure 4. Map of wind-farm regions in British Columbia.

Source: Google Map, annotated by R. Stull.

Wind Farm	Brand/Model	Year Built	Hub Height (m) agl	Rotor Diam. (m)	# of turb.	Power (MW)	Map Location	Latitude (°)	Longitude (°)	Terrain elevation (m)
Bear Mtn.	Enercon E82	2009	78	82	34	102	A	55.6986	-120.4306	961
Dokie Ridge	Vestas V90	2011	80	90	48	144	A	55.8167	-122.2586	1366
Cape Scott	Vestas V100	2013	80	100	55	99	B	50.7655	-127.9954	405
Quality 1	Vestas V90	2011	95	90	35	63	A	55.1887	-120.8682	1225
Quality 2	Vestas V100	2012	95	100	44	79.2	A	55.1887	-120.8682	1225
Meikle 1	GE Energy 103	2016	100	103	35	112	A	55.2750	-121.4761	1251
Meikle 2	GE Energy 120	2017	110	120	26	71.5	A	55.2750	-121.4761	1251
Pennask	Senvion M114	2017	100	114	5	15	C	49.9200	-120.1070	1670
Shinish Creek	Senvion M114	2017	100	114	5	15	C	49.6580	-120.1230	1970
Moose Lake	Enercon E141	2019	99	141	4	16.8	A	55.2883	-121.2715	1433
Sukunka	Enercon	2020	116-135	140	4	15	A	55.5569	-121.5600	980
Zonnebeke	Enercon	2020	116-135	140	4	15	A	55.5569	-121.5600	980
Not operating:										
Grouse Mtn.	Leitwind 77	2010	65	77	1	1.5	N.Vanc.	49.3874	-123.0740	1220

Utility of Accurate Hub-height Wind Forecasts

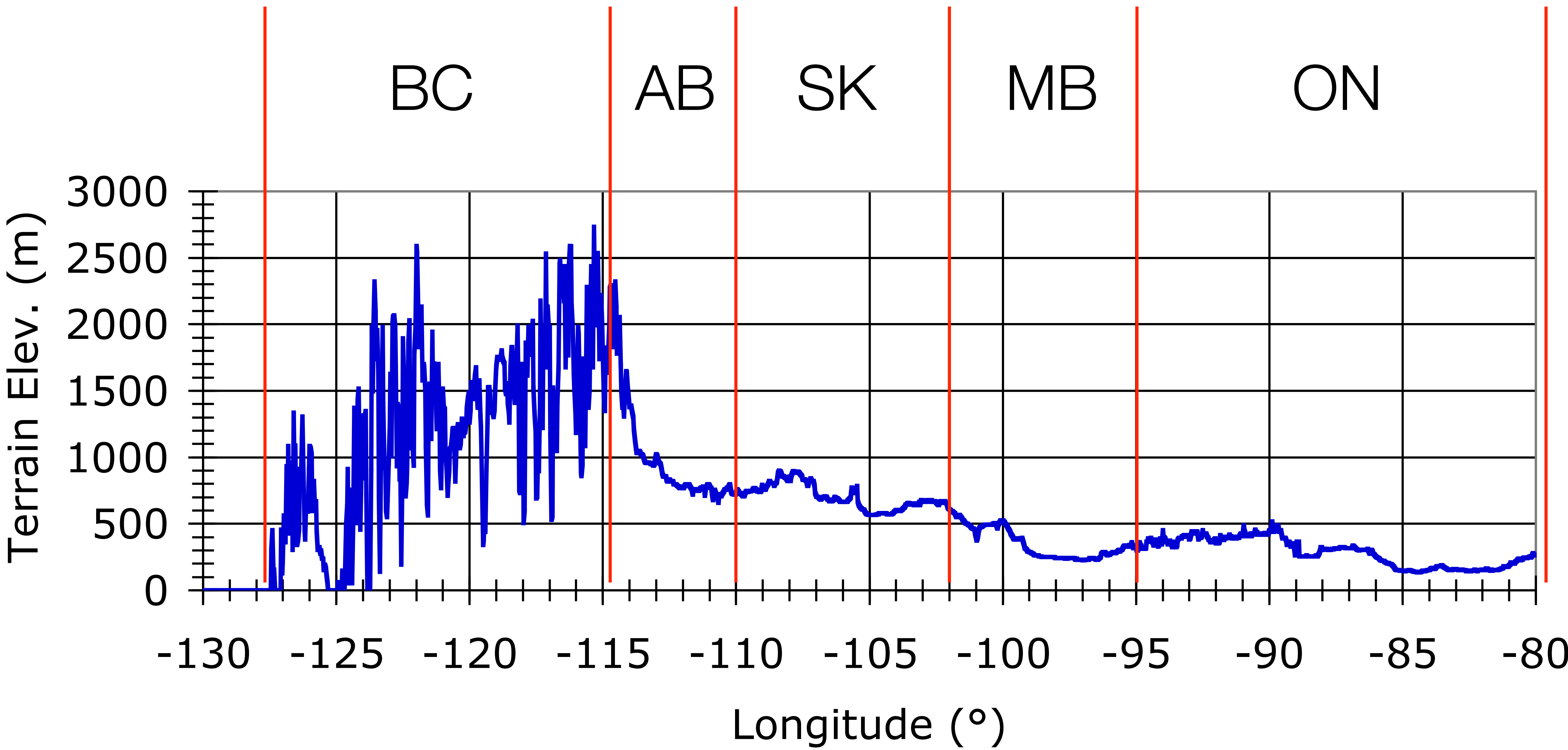
- utility companies (e.g., BC Hydro) can better manage the mix of non-dispatchable wind power with dispatchable hydro power to provide reliable service to their customers

- energy traders (e.g., PowerEx) can optimize the buying and selling of power cross-border to reduce overall electric cost to customers

- independent power producers (e.g., wind-farm operators) can better anticipate and mitigate extreme events, and can plan for routine maintenance when conditions will be favorable

https://sustainabilitymag.com/net-zero/top-10-energy-sources-what-are-they-and-who-has-the-most-emissions-net-zero-oil-coal-wind-solar-nuclear
https://www.windpowerengineering.com/awea-new-type-wind-power-customer-factor-transmission-planning/

1. Canadian Terrain Cross Section



- West-East terrain cross section through Whistler (50.12°N)

Turbines at a Wind Farm have a Variety of Locations relative to Terrain

What is the relationship between power curves for individual turbines and the whole wind farm?

Credits: Quality Wind Farm. screen capture from: https://www.youtube.com/watch?v=Fq6iVMwPJhI .

2. Power curves, heterogeneity, farm-average output

a. Idealized Power Curves

- Let:
  - M_{in} = cut-in speed
  - M_R = rated-power wind speed
  - M_{out} = cut-out speed

- Power (P) is:
  - for $M_{in} \le M \le M_R$:

$$P = P_R \left(\frac{M - M_{in}}{M_R - M_{in}} \right)^b$$

  - for $M_R \le M \le M_{out}$:
    $P = P_R$

  - $P = 0$ elsewhere

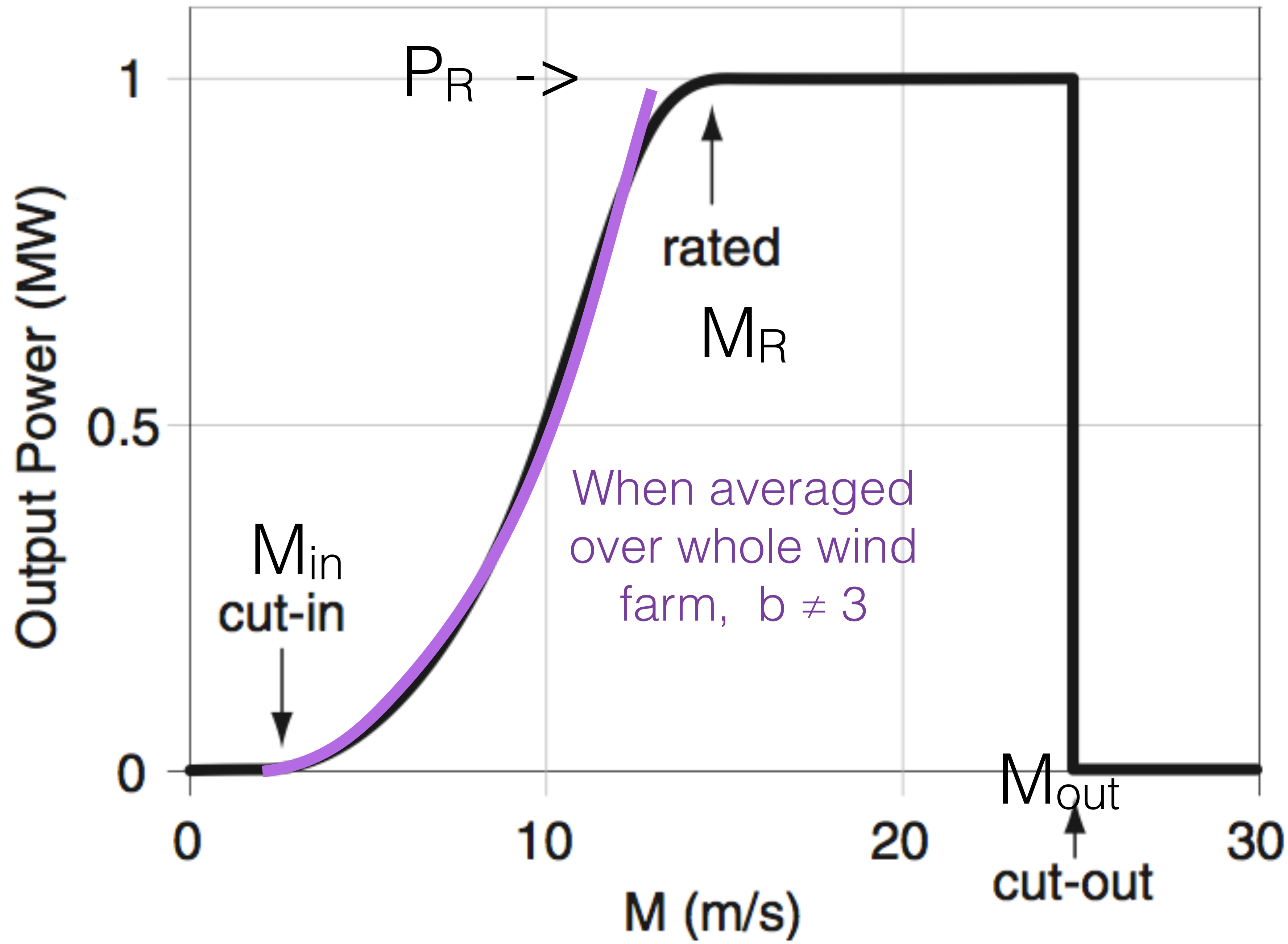


Fig. 1.1. *Idealized curve of output power P vs. wind speed M for a single hypothetical wind turbine with maximum rated power of 1 MW.*

b. Variability

- Let M_S be a specified wind, forecasted to be representative of whole farm.
- Let M be the actual wind speed at any one turbine.

M can vary from M_S because of:

- turbines at different locations in wind farm
  - topographic effects
  - synoptic & mesoscale variability
  - interference from upstream turbines
- turbines with different models or efficiencies
- different turbulence gusts at different turbines

M_S can vary because NWP forecasts have spread

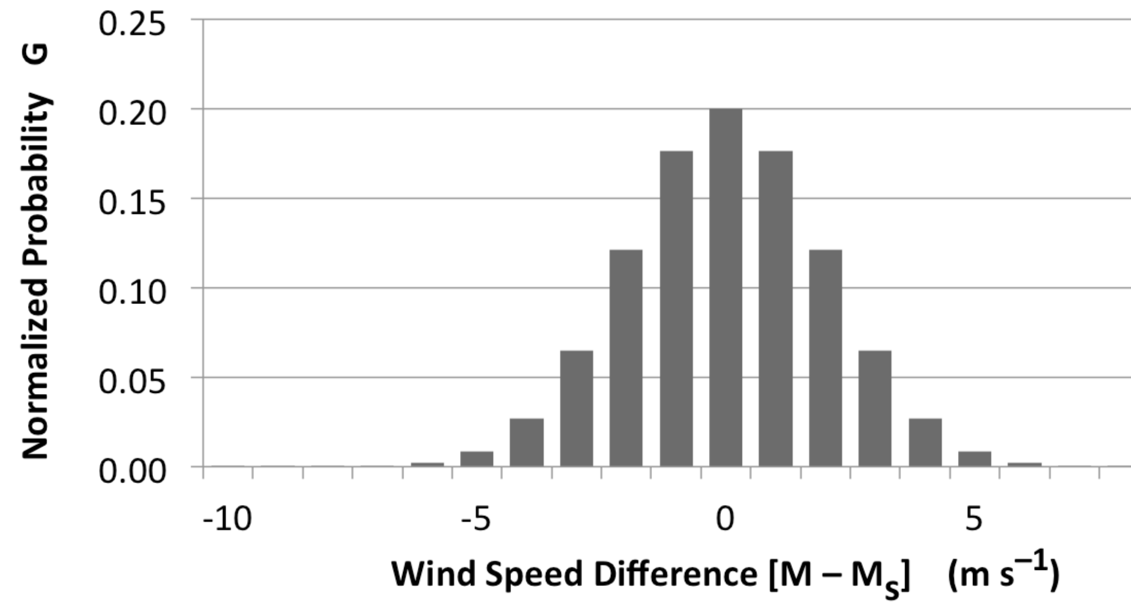


Fig. 1.2. *Example of Gaussian variability (illustrated with σ = 2 m/s) of wind speed M about the specified wind-farm average M_S.*

b. Variability

Sort the winds anomalies into discrete bins.

Assume the wind variability is Gaussian:

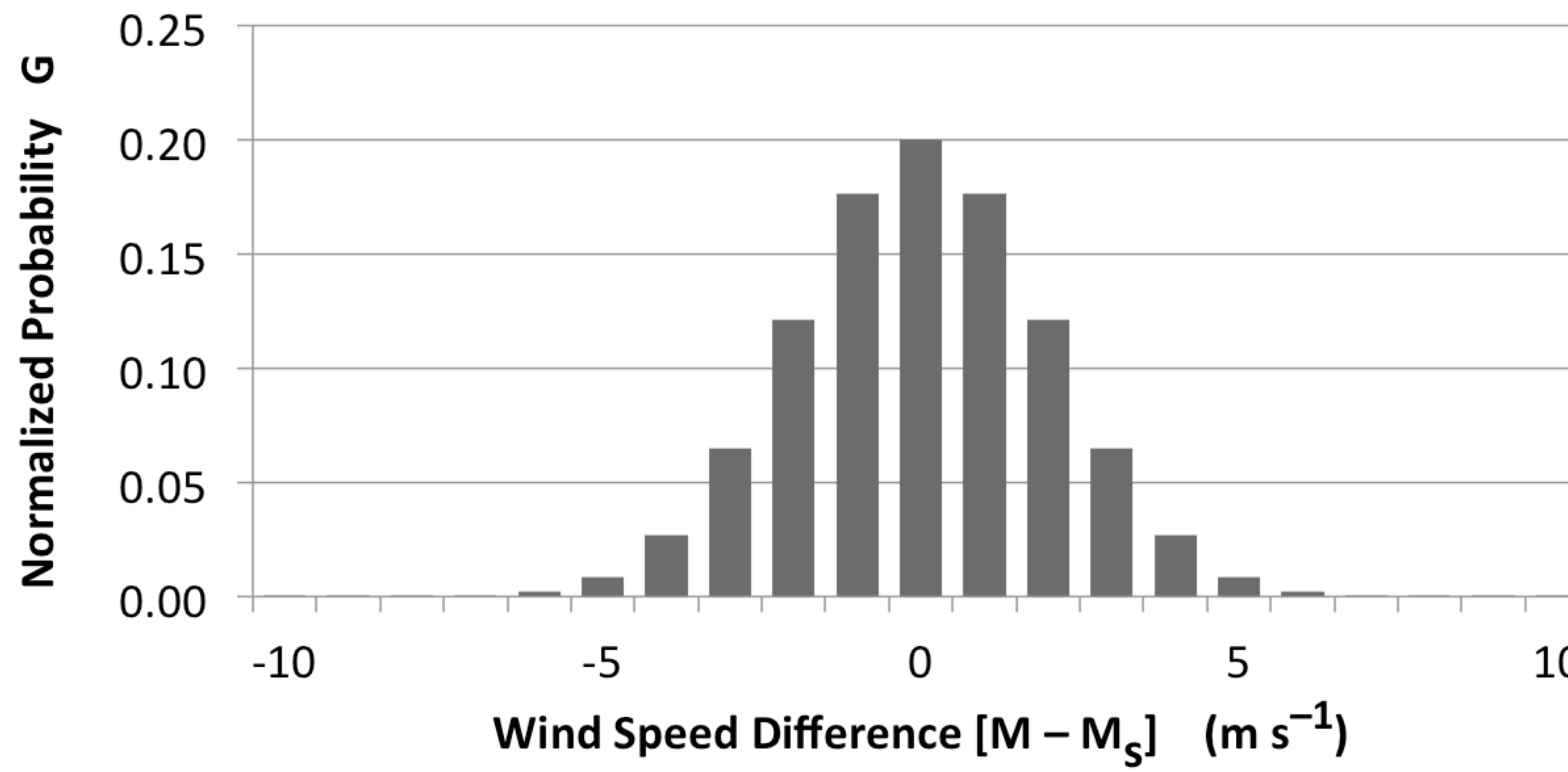


Fig. 1.2. *Example of Gaussian variability (illustrated with σ = 2 m/s) of wind speed M about the specified wind-farm average M$_S$.*

Let the discrete farm-average speed be M_i , on which the Gaussian curve is centered.

Let j be a bin-offset index (relative to i) for the actual winds M_j , for $-J \le j \le J$.
J is finite but large, such as J = 30 bins.

Let $\widetilde{G}_{i,j}$ be the un-normalized Gaussian shape.

$$\widetilde{G}_{i,j} = \exp\left[-0.5\left(\frac{M_{i+j} - M_i}{\sigma_i}\right)^2\right]$$

Let $G_{i,j}$ be the normalized Gaussian shape.

$$G_{i,j} = \widetilde{G_{i,j}} \,/ \sum_{j=-J}^{J} \widetilde{G_{i,j}}$$

c. Convolution

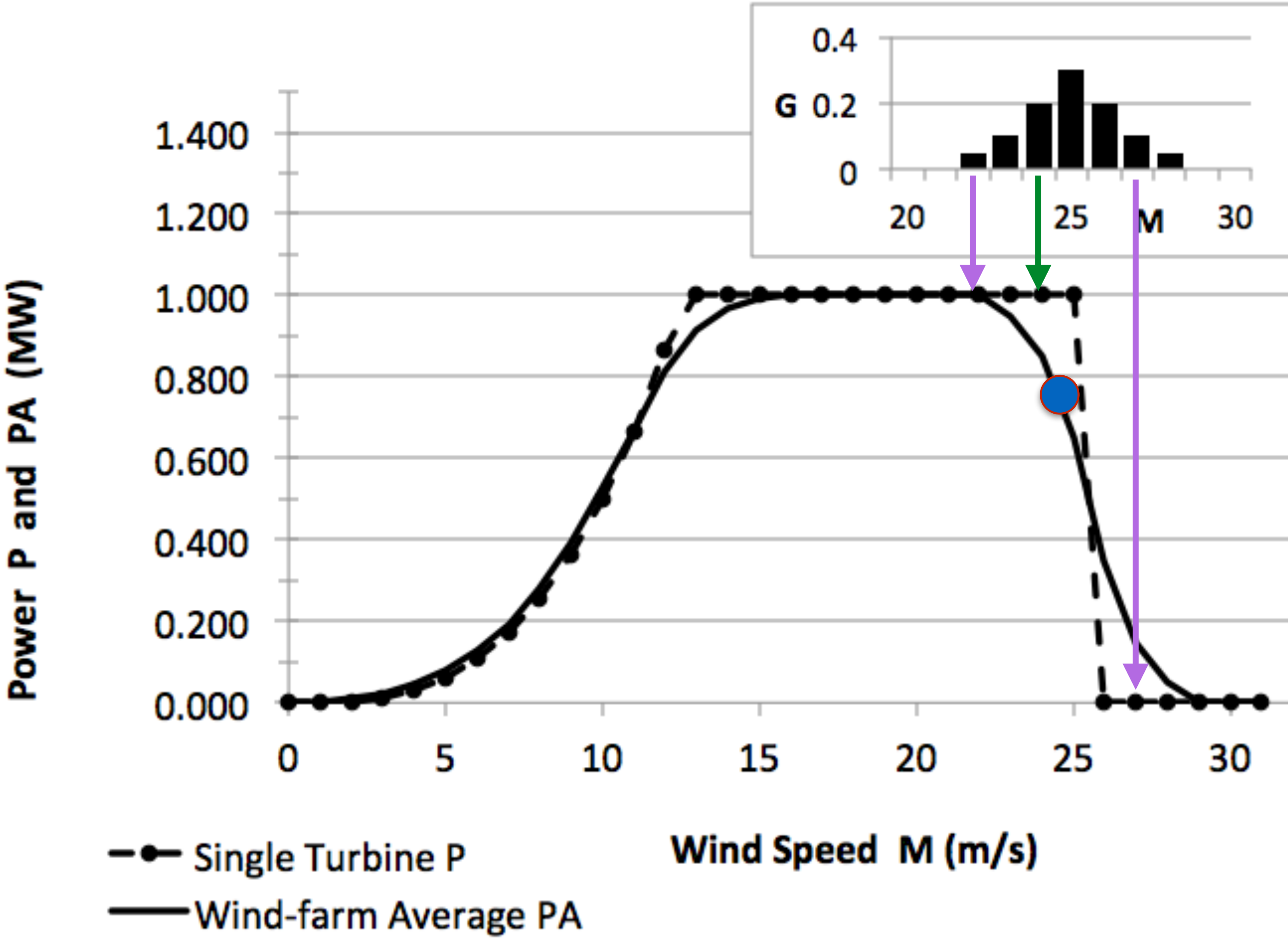


***Fig. 1.3**. Slide the insert figure left or right to be centered on any wind speed M_i of interest (25 m/s in this illustration). Then multiply the weights G by the single-turbine power values P from the dashed curve to give the average power PA value (a point on the solid line) for that one M_i. Repeat at other values of M_s to generate the whole solid curve.*

For any one turbine, its wind speed determines its power output (using the idealized power curve).

But different turbines with different speeds are at different locations on the power curve.

Thus, the farm-average power is the sum of all points on the power curve, weighted by the number of turbines producing that power.

Mathematically, this weighted average is a **convolution**.

d. Application

<u>We know:</u>

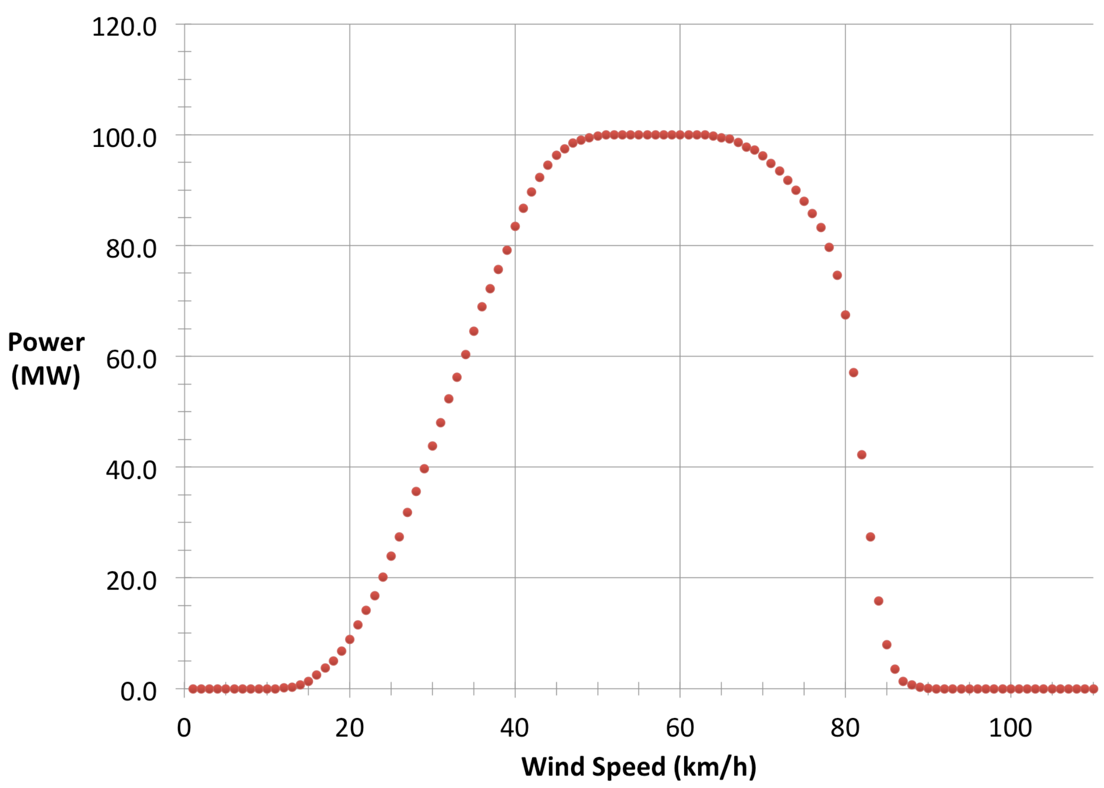
- The theoretical (design) power curve for individual turbines

<u>We don't know:</u>

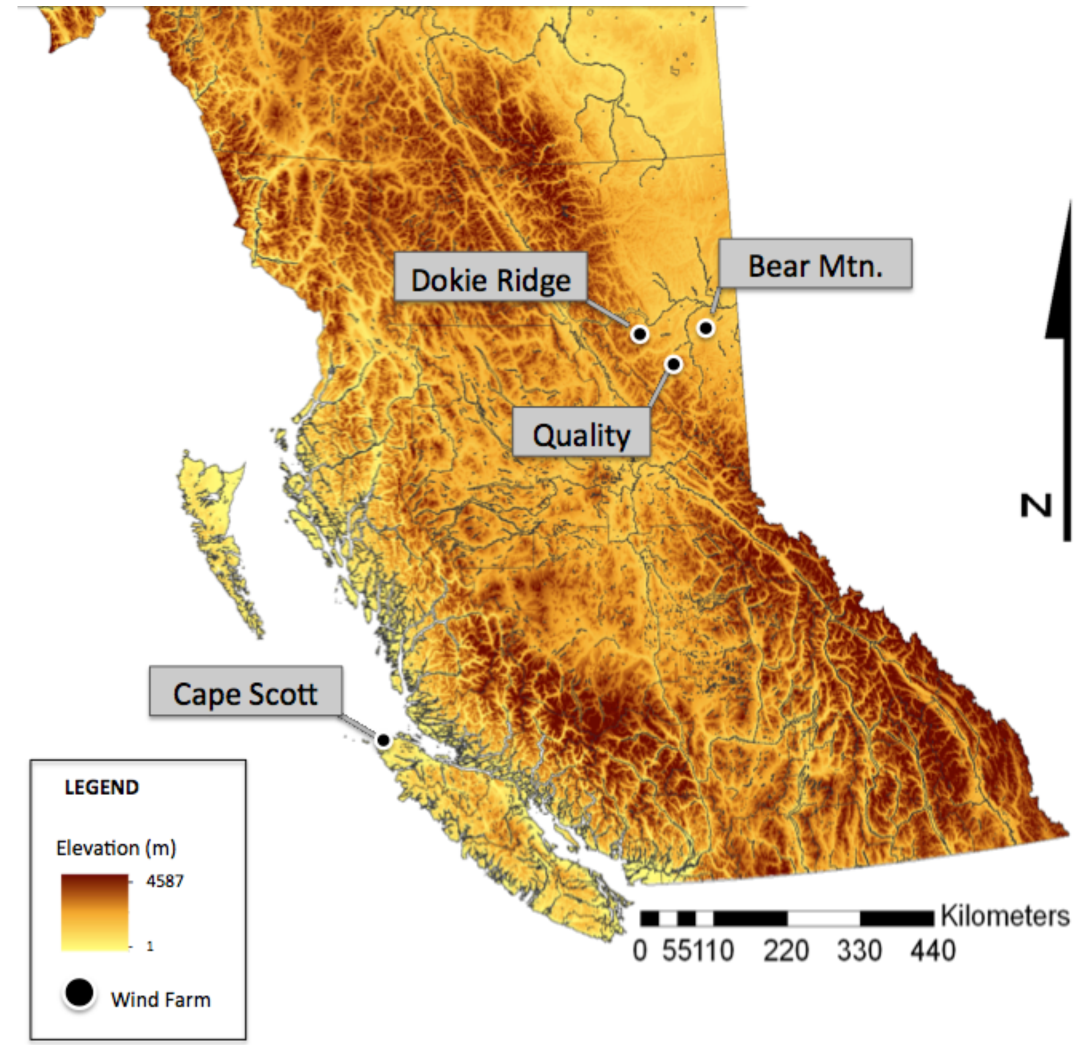
- Any inefficiencies that have developed in the turbines
- Which turbines are down for maintenance
- What is the measured wind speed at each turbine
- How the empirical power curve varies with season, synoptic regime, location in the farm, etc.
- Whether the distribution is Gaussian
- How sigma varies with wind speed

<u>We DO know:</u>

- The empirical wind-farm total power curve for past times, for each wind farm.



d. Application



Approach:

- Use power curve from past, with NWP forecast winds, to make power forecasts.
- Find a model to empirically fit the past power curve.

Advantages of the Convolution Model (over curve fitting):

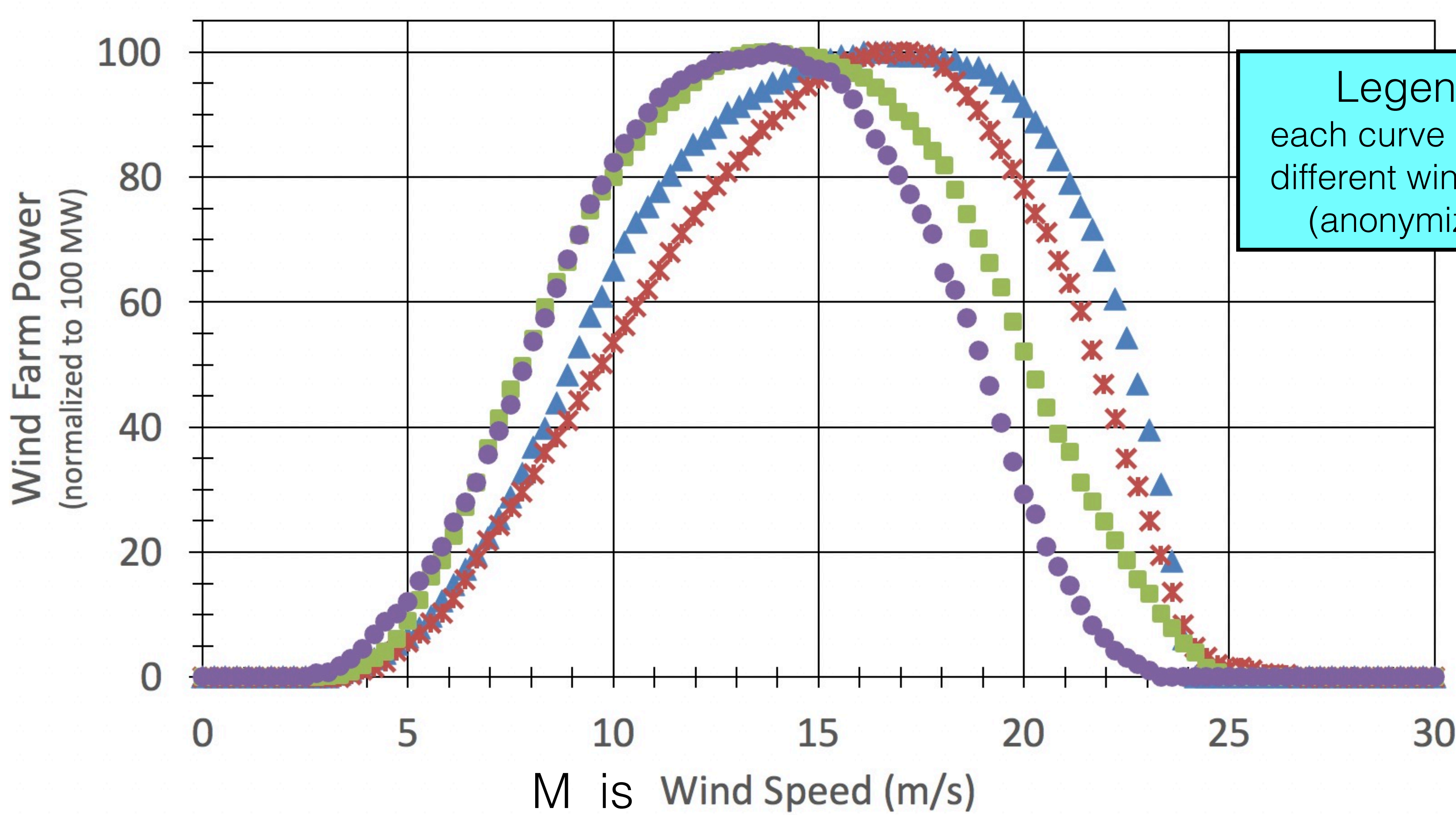
- Based on (simplified) physical attributes
- Best-fit parameters fit the physically anticipated signal and not the noise.
- Physical changes (adding/removing turbines) can be incorporated by modifying the single-turbine curve.

Dis-Advantages of the Convolution Model:

- Curve fitting (polynomial or spline) is easier, and works just as well.

e. The empirical power curves

for 4 wind farms in BC, all normalized to 100 MW.



Legend:
each curve is for a different wind farm (anonymized)

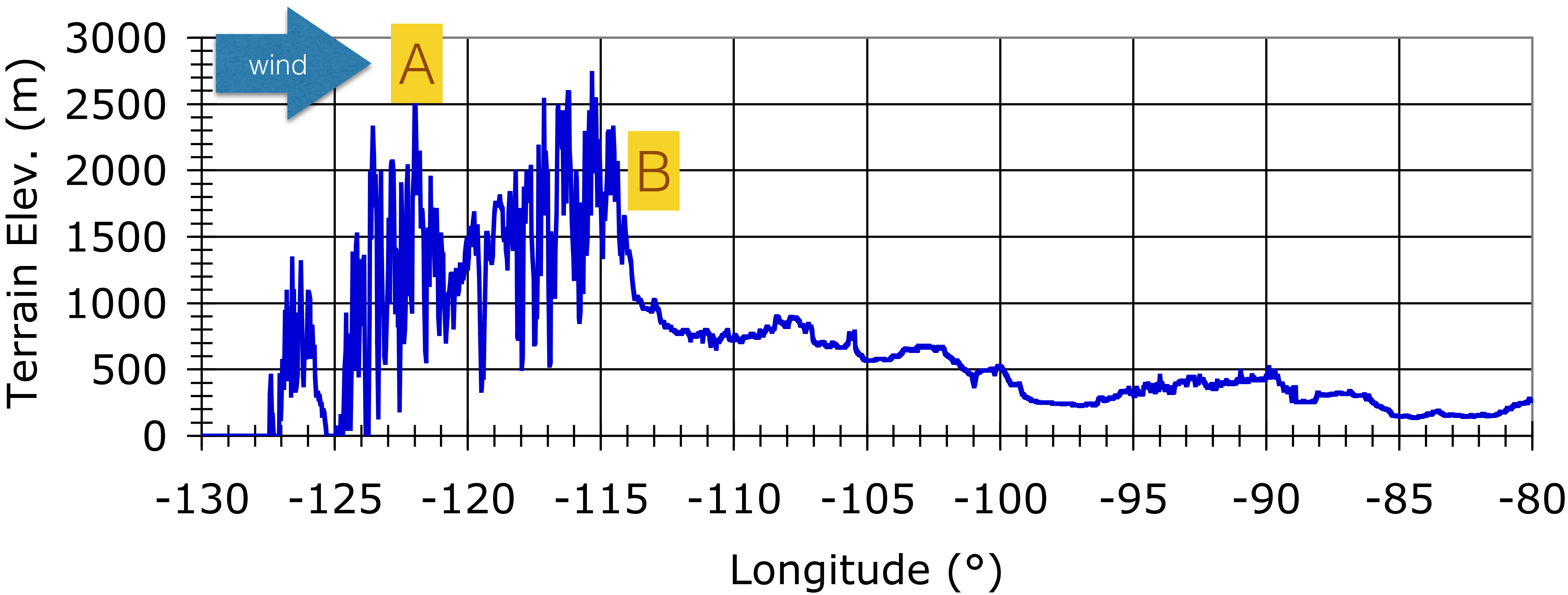
$$P = P_R\left(\frac{M - M_{in}}{M_R - M_{in}}\right)^b$$

None of the curves exhibit a cubic power-law !
Instead, powers are: b = 1.0, 1.6, 1.6, 1.8

3. Need for forecast domain to extend upwind

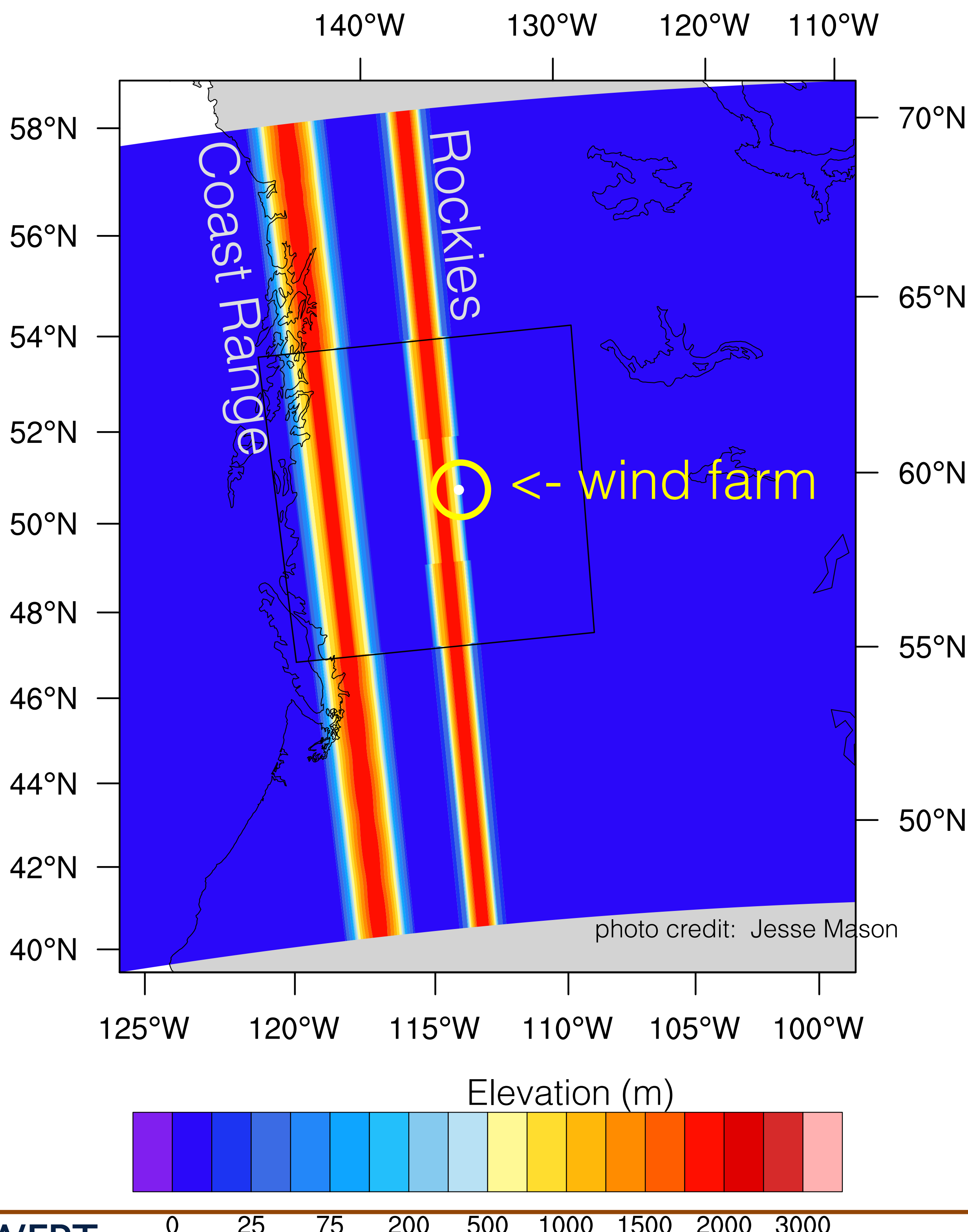
Not appropriate to use Local Models of Terrain near the Wind Farm, because Upwind Terrain has a Significant Influence

Namely, the flow at A affects the hub-height winds at B.



Nonlocal Flow Effects

Simulations by Jesse Mason



Numerical Simulations of Idealized Terrain

for a wind-ramp event at a wind farm**:**

- Rocky Mountains (add / remove)
- Coast Range (add / remove)

Enables discovery of alternative / better forecast methods

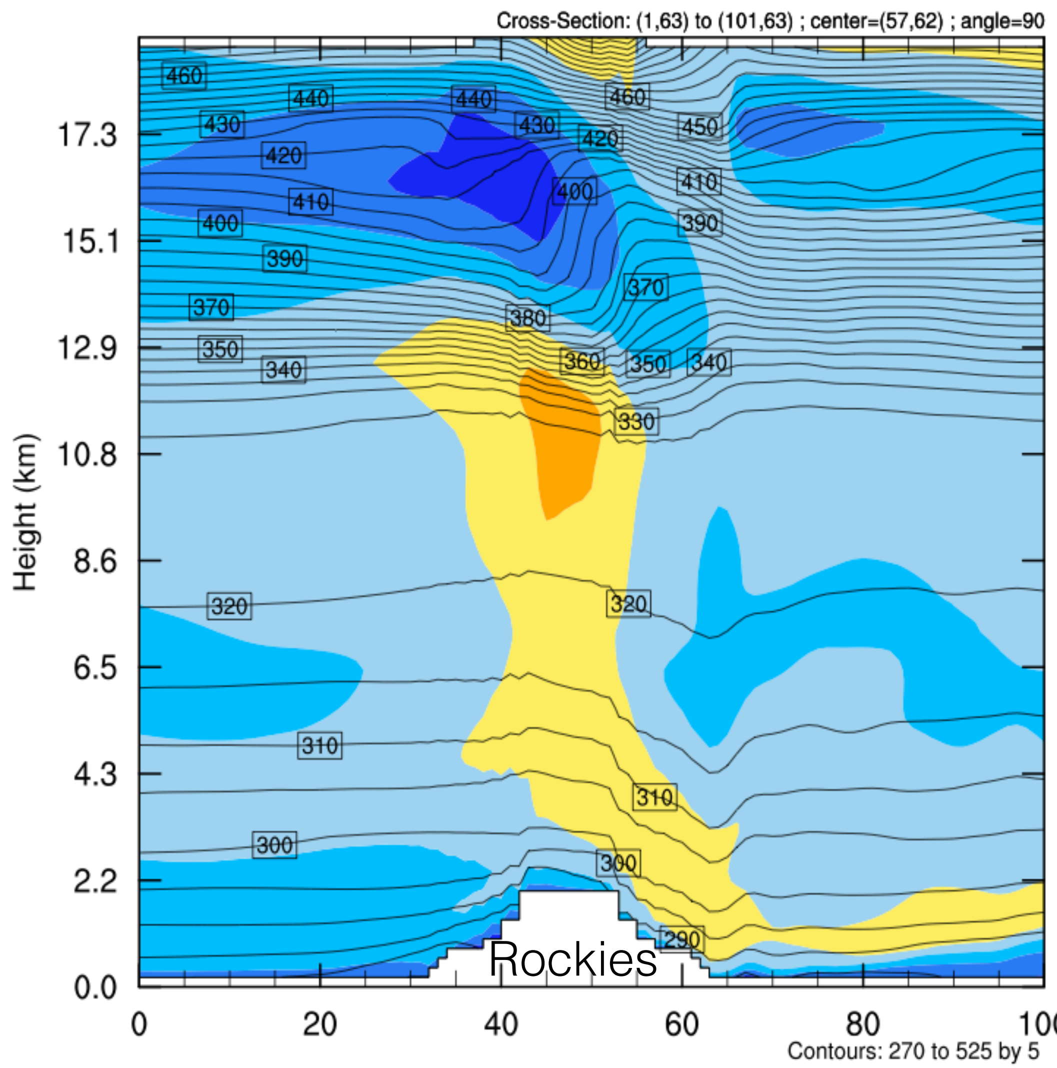
WFRT
WEATHER FORECAST RESEARCH TEAM

Nonlocal Flow Effects

Simulations by Jesse Mason

Enables discovery of alternative / better forecast methods

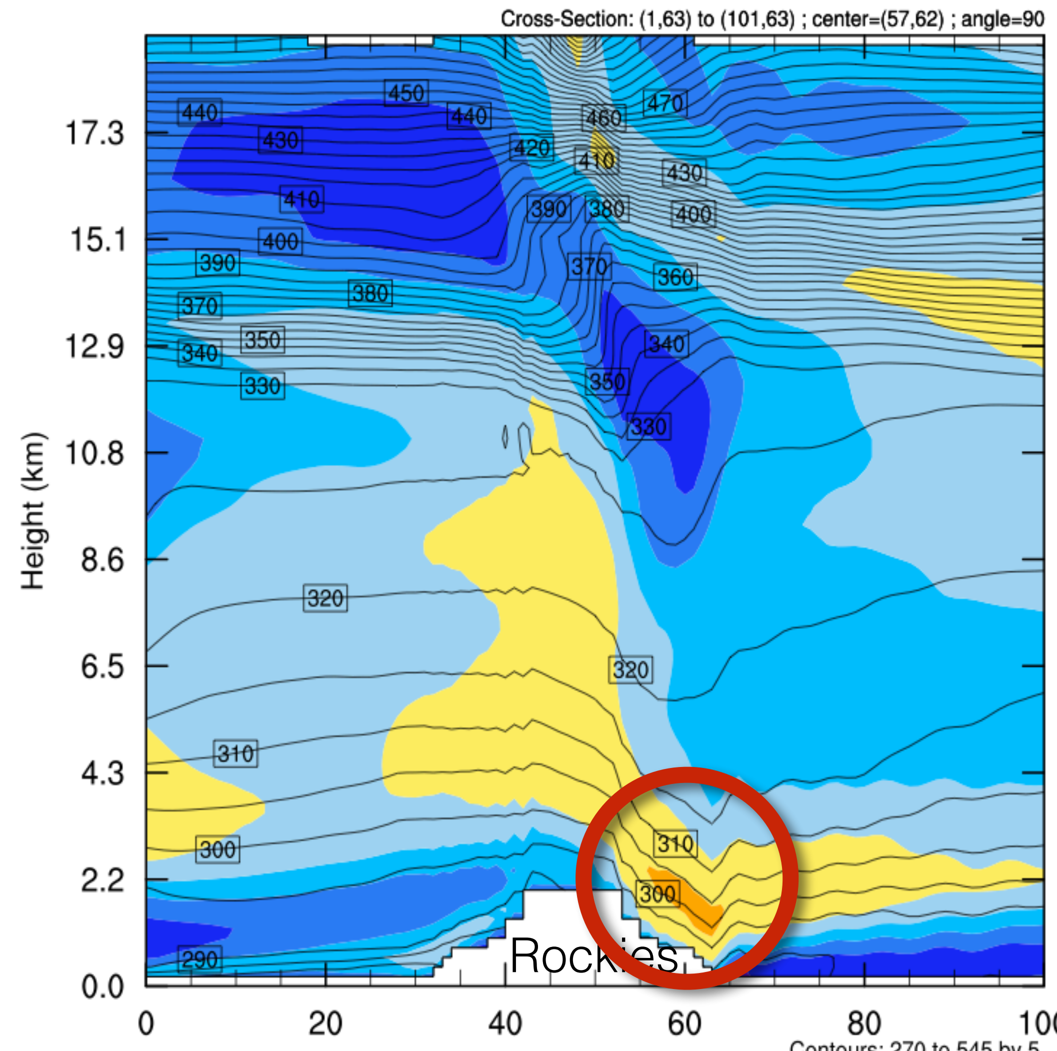
Idealized Rockies Only



colours indicate wind speed (m/s)

10 20 30 40 50 60 70 80 90

Both Coast & Rocky Mtns.



Is more accurate for this wind-ramp event

photo credit: Jesse Mason

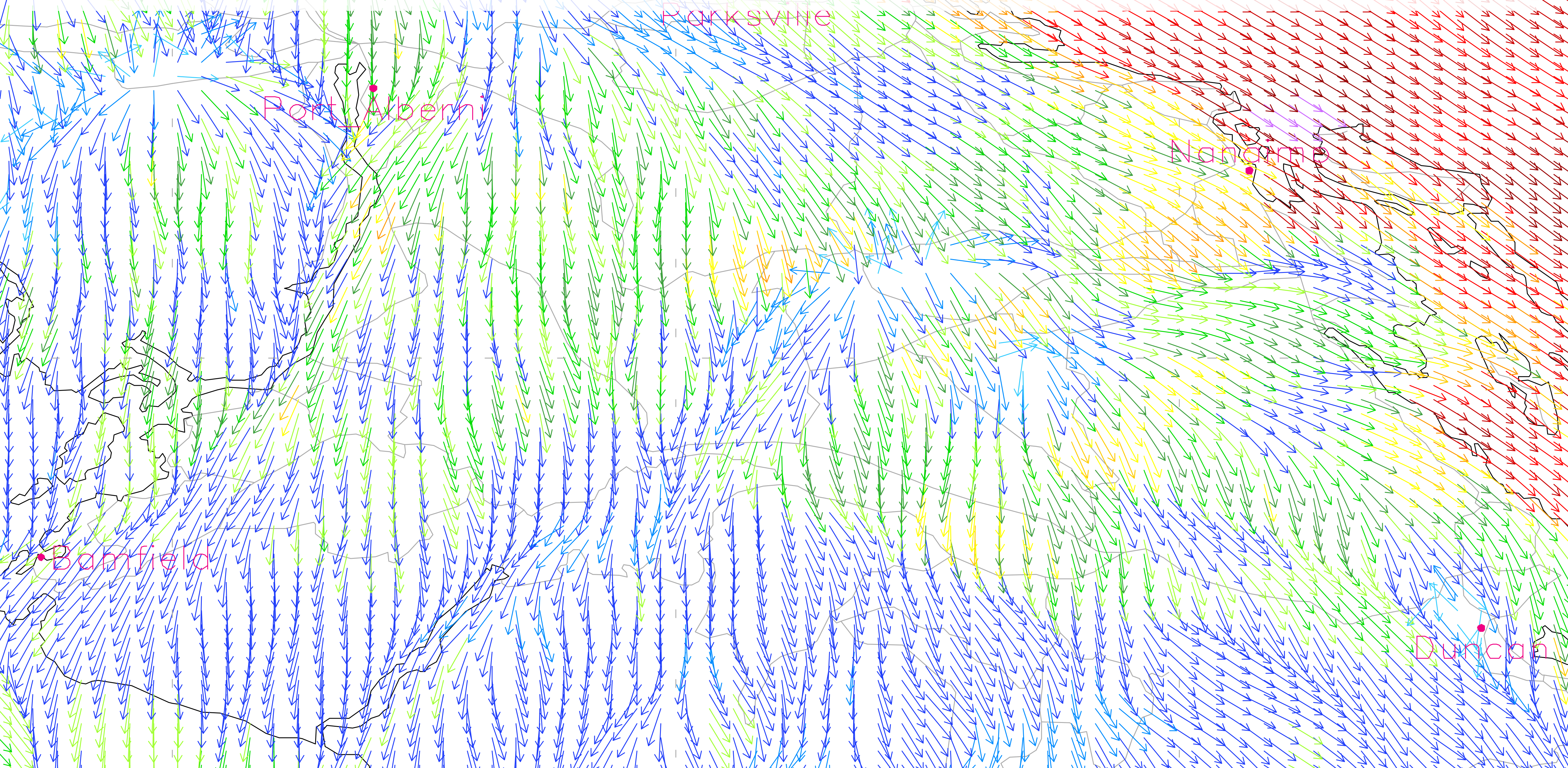
colours indicate wind speed (m/s)

10 20 30 40 50 60 70 80 90

Inference: need sufficiently <u>large</u> NWP forecast domain to capture upwind effects.

4. Numerical Weather Prediction

- NWP is a physics-based approach. The atmosphere is divided into a 3-D grid of cells, and the approximate equations of dynamics and thermodynamics are solved at each grid cell. The cells interact with neighboring cells as the solution takes many small time steps to reach the desired forecast horizon.
- The winds are just one portion of the total weather that is forecast.
- Output of the NWP is not perfect, and can be improved with statistical / AI approaches, in a step called “post-processing”.



4. Sensitivities and how to mitigate them with ensemble NWP forecasts

1) Local flows that affect any individual wind turbine are sensitive to the wind direction relative to the terrain.

2) Wind directions from Numerical Weather Prediction (NWP) are sensitively dependent on initial conditions (which for BC, is the poorly observed air over the Pacific Ocean).

One way to compensate is to make an ensemble of many NWP forecasts for each wind farm for each hour, each with slight different wind forecasts.

google.earth view
of Cape Scott
wind farm

5. UBC Operational NWP for BC Wind Farms

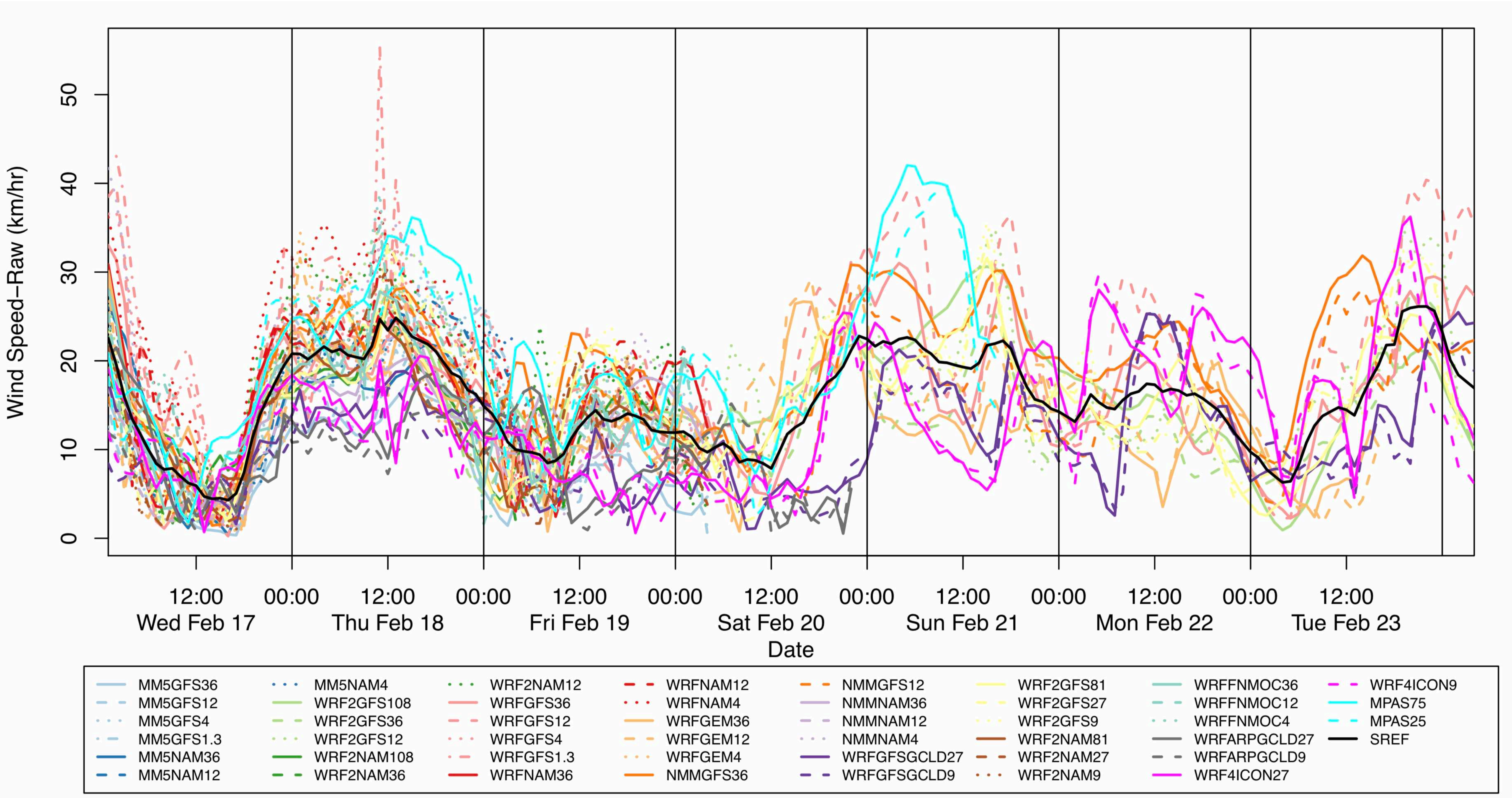
The Weather Forecast Research Team at UBC runs and **ensemble** of 51 NWP forecasts every day initialized from 00 UTC. These are:

- multi model (WRF-ARW, WRF-NMM, MM5, MPAS)
- multi Initial Condition (from gov't centers in Canada, USA, France, Germany)
- multi-physics parameterizations
- multi-grid spacings

Model:	MM5	MM5	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW) GC01	WRF (ARW) ARPEGE	WRF (ARW) ICON	WRF (NMM)	WRF (NMM)	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW)	MPAS25
Init. Cond.:	NAM	GFS	GEM	NAM	GFS	FNMOC	GFS	ARPEGE	ICON	NAM	GFS	NAM	GFS	NAM	GFS	GFS
Init. Time (UTC):	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00
Extra Large	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3.5 days [108 km]	7.5 days [108 km]	3.5 days [81 km]	7.5 days [81 km]	5.0 days [92 km]
Large	2.5 days [36 km]	3.5 days [36 km]	7 days [36 km]	3.5 days [36 km]	7.5 days [36 km]	5.0 days [36 km]	7.5 days [27 km]	4.25 days [27 km]	7.5 days [27 km]	3.5 days [36 km]	7.5 days [36 km]	3.5 days [36 km]	7.5 days [36 km]	3.5 days [27 km]	7.5 days [27 km]	5.0 days [25 km]
Medium	2.5 days [12 km]	3.5 days [12 km]	7 days [12 km]	3.5 days [12 km]	7.5 days [12 km]	5.0 days [12 km]	7.5 days [9 km]	4.25 days [9 km]	7.5 days [9 km]	3.5 days [12 km]	7.5 days [12 km]	3.5 days [12 km]	7.5 days [12 km]	3.5 days [9 km]	7.5 days [9 km]	N/A
Small	2.5 days [4 km]	3.5 days [4 km]	3.5 days [4 km]	2.5 days [4 km]	3.5 days [4 km]	3.5 days [4 km]	N/A	N/A	N/A	3.5 days [4 km]	N/A	N/A	N/A	N/A	N/A	N/A
Extra Small	N/A	3.5 days [1.3 km]	N/A	N/A	3.5 days [1.3 km]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

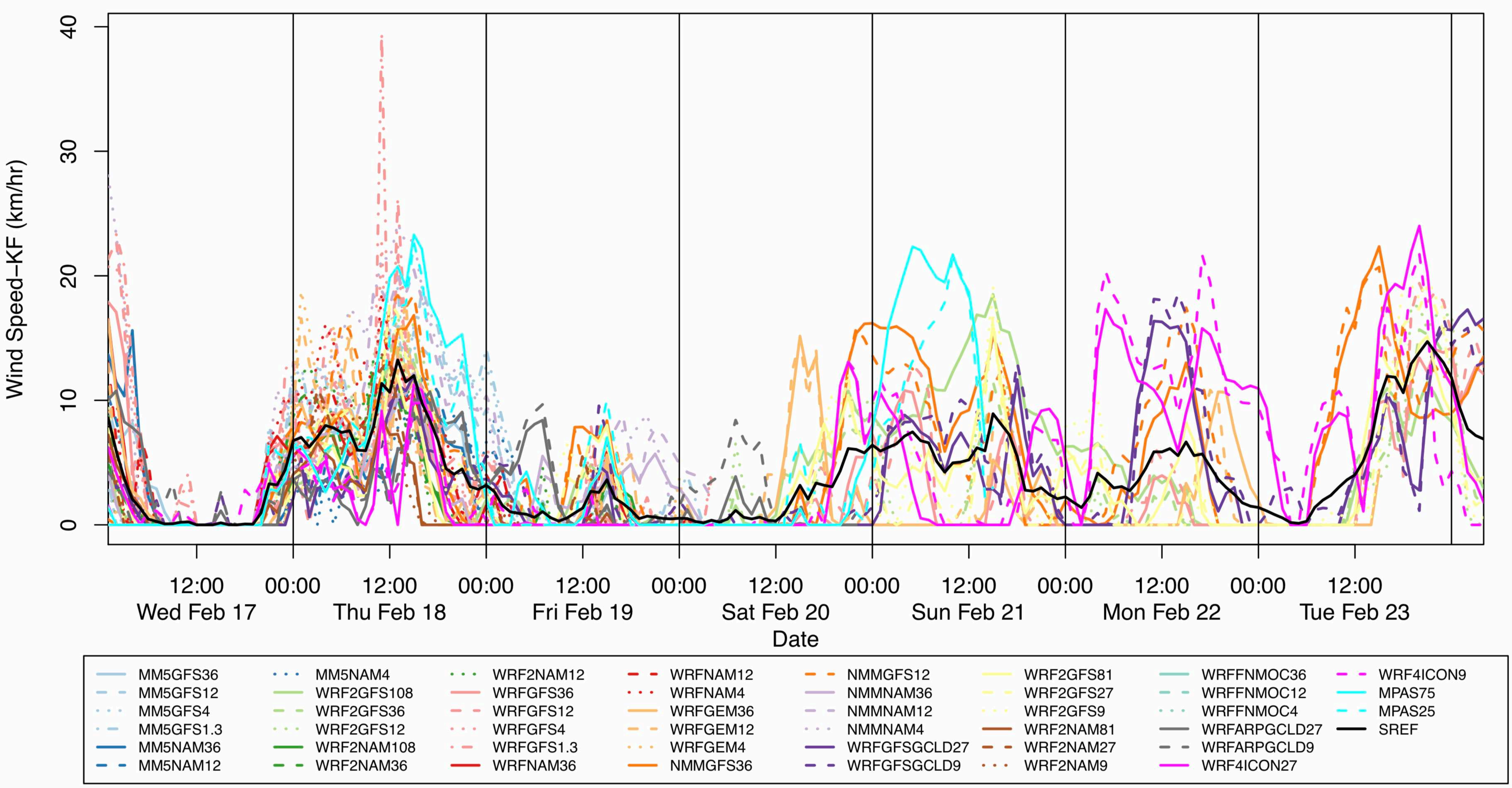
Example spaghetti diagram of ensemble of wind forecasts

Raw forecasts for a wind farm.

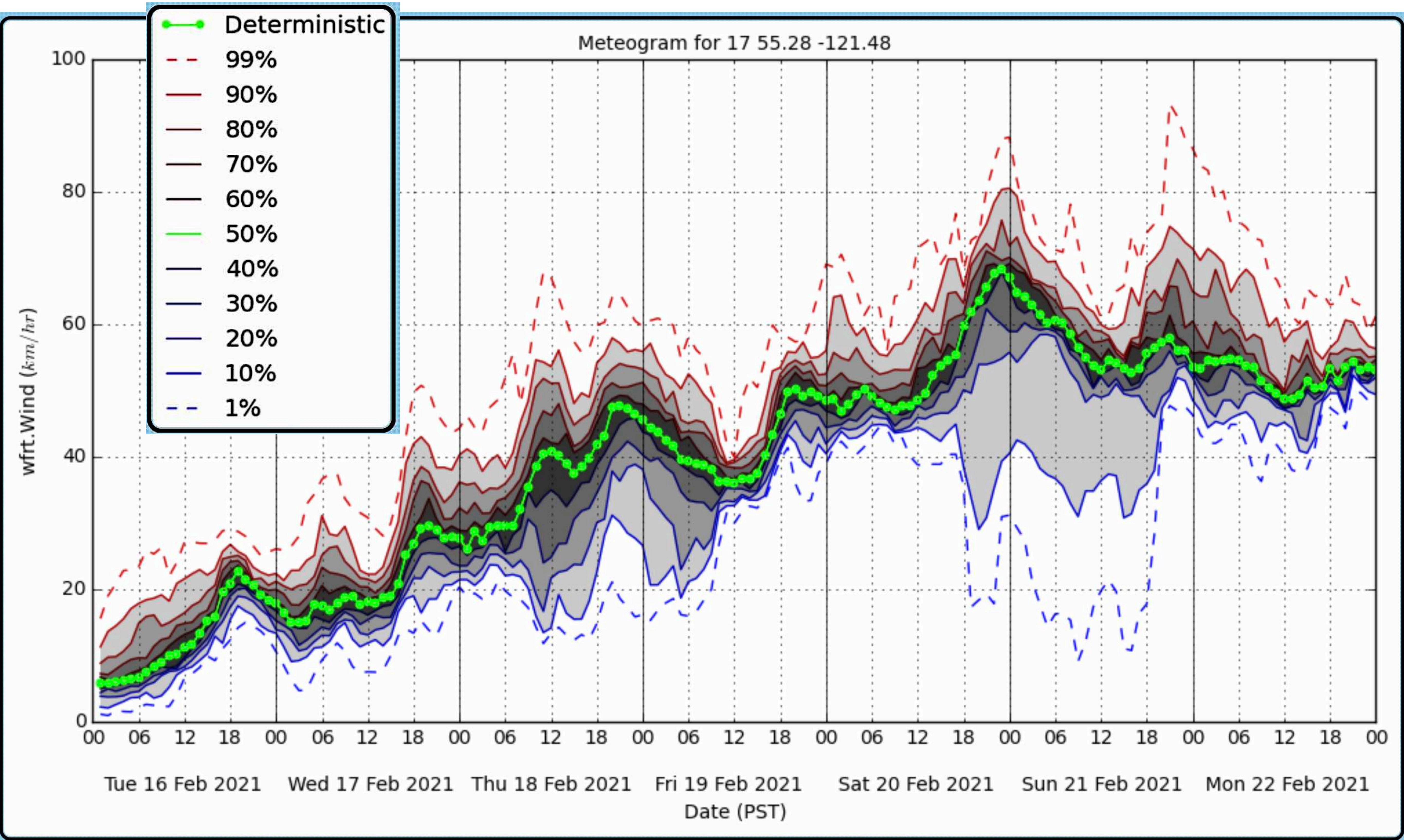


Example spaghetti diagram of ensemble of wind forecasts

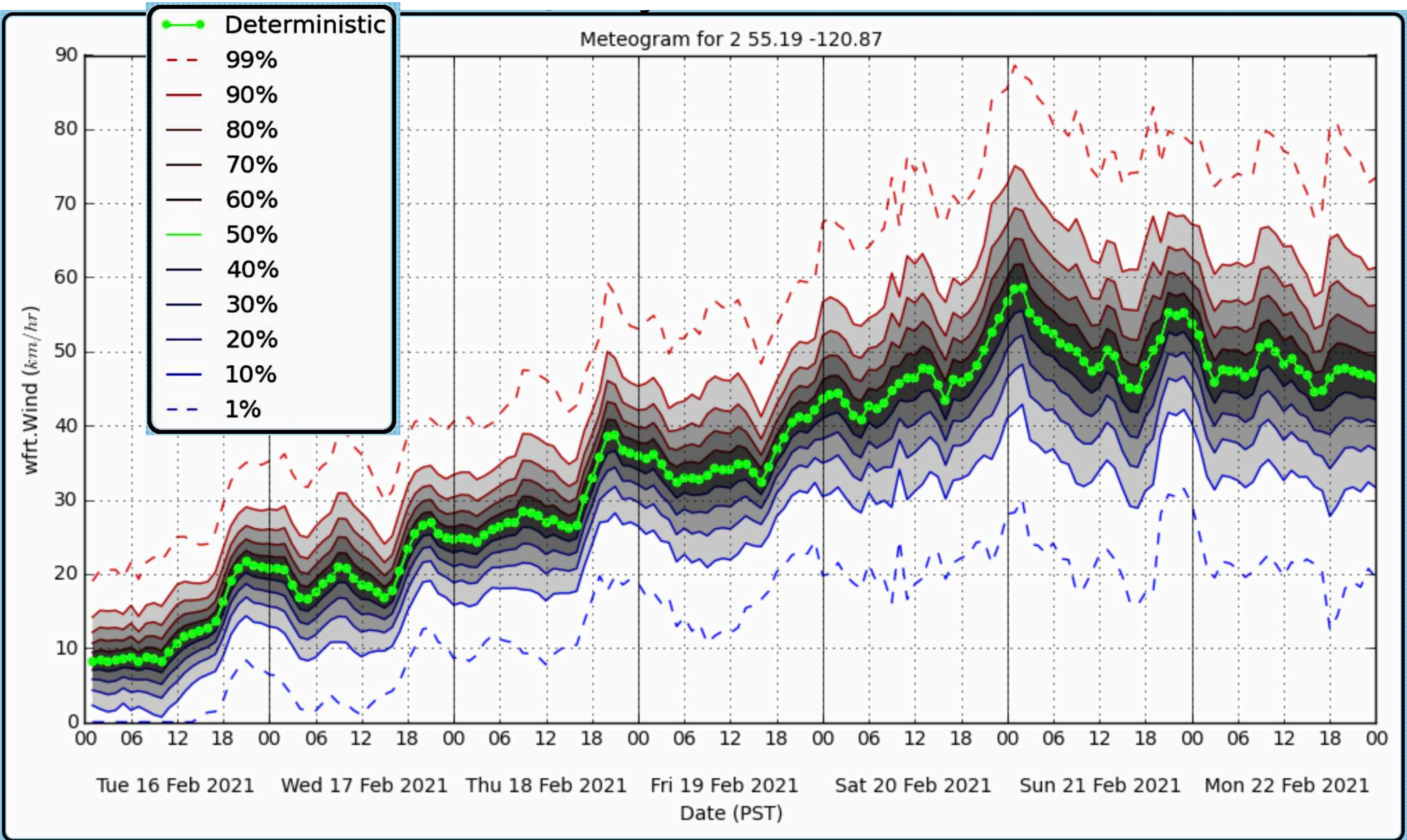
Bias-corrected forecasts for a wind farm.



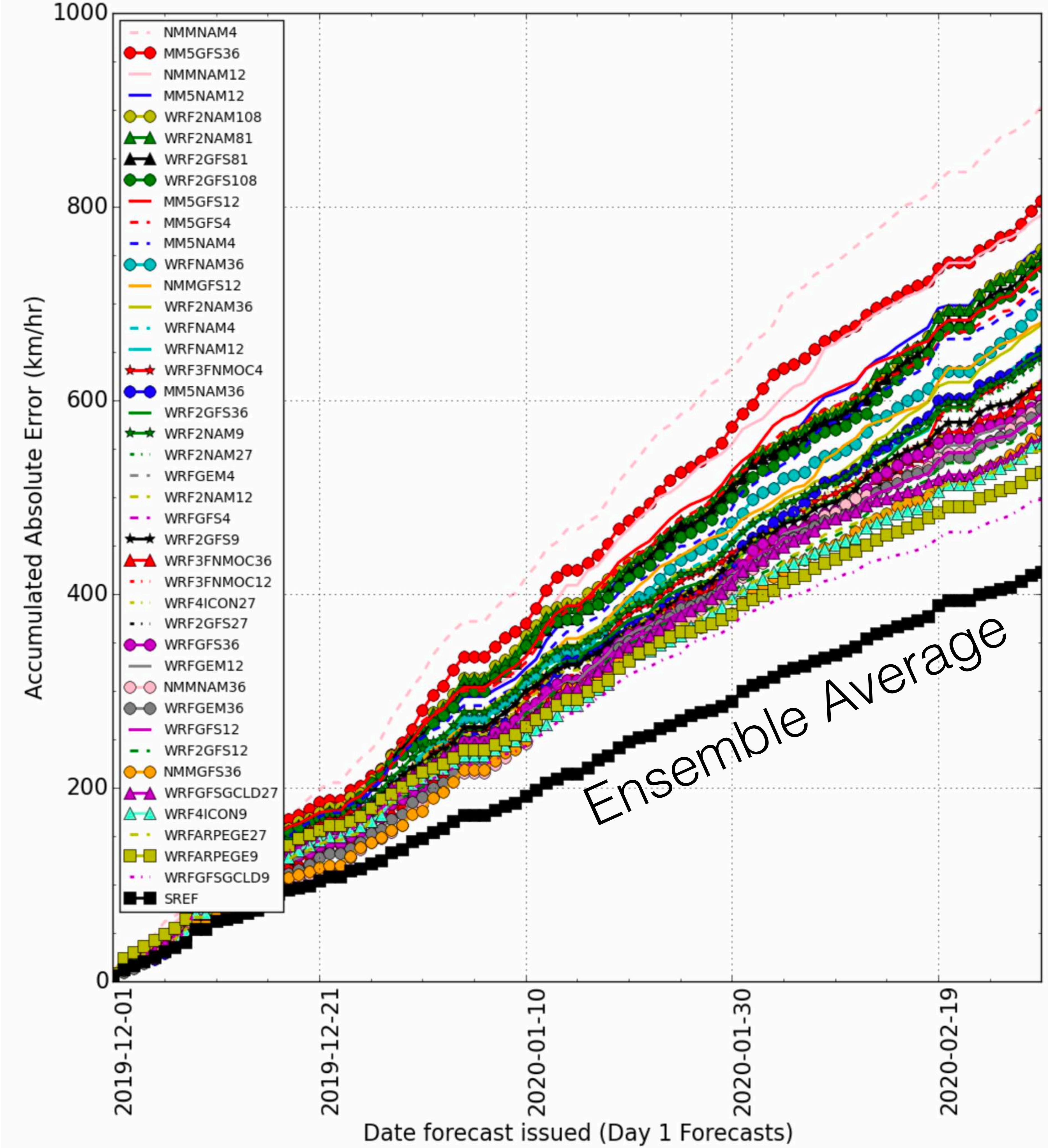
Create a best-guess:
Deterministic forecast (= ensemble average), &
Probabilistic forecast (based on spread)



Calibrate the Probabilistic Forecast based on past Observations from the wind farm, to improve statistical reliability



Verify over Seasons



Absolute error from each model is accumulated over every hour for 3 months.

Smaller error is better.

6. Current Research

- more ensemble members (Tim Chui, Henryk Modzelewski, & Roland Schigas)
- weighted ensembles (Reagan McKinney)
- longer-range (out to 2 weeks) forecasts (Jill Psotka)
- post-processing with machine learning (Bryan Jansens)
- improved forecasts with AI (Nina Effenberger)

Course: ATSC 313: Renewable Energy Meteorology (3 cr. online)

www.eoas.ubc.ca/courses/atsc313/

Taught by Doug McCollor

UBC ATSC 313 Renewable Energy Meteorology

| Home | Basics | Hydro | Wind | Solar | Synthesis | Tools |

ATSC 313 Renewable Energy Meteorology

Weather for Hydro, Wind, and Solar Power. (3 credits)

Welcome to this online course.

Syllabus:

For New & Prospective Students:

Welcome - Glad you are interested. (dm)

Course Info - Whom this course is for. (dm)

Syllabus Overview - Main topics in this course. (dm)

Course Goals - What you will be able to do. (dm)

Sample (pdf) - Showing all 9 steps within a learning module.

Conclusions

- Complex terrain compounds NWP forecast errors
- Wind distribution among multiple turbines can be accounted for via convolution
- Need for NWP models to extend extensively upwind
- Sensitivities can be partially addressed via ensemble NWP in operational forecasts
- Research plans and a renewable-energy meteorology course

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WFRT
WEATHER FORECAST RESEARCH TEAM

Thanks to our sponsors:
BC Hydro, MITACS, NSERC,
and several wind farms in BC

Any Questions?

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