Regional wind resource distributions: mesoscale results and importance of microscale modeling

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Background and Outline

- Last Snowmass conference raised questions whether resolution of the wind resource matter or not within the Climate mitigation models.
- No quantitative results were shown only an illustrative example
- A new method based on terrain and roughness will be presented
- Outline of how upscale the wind resource in different steps will be presented.

Case studies

Nine cases studies using WAsP now performed:

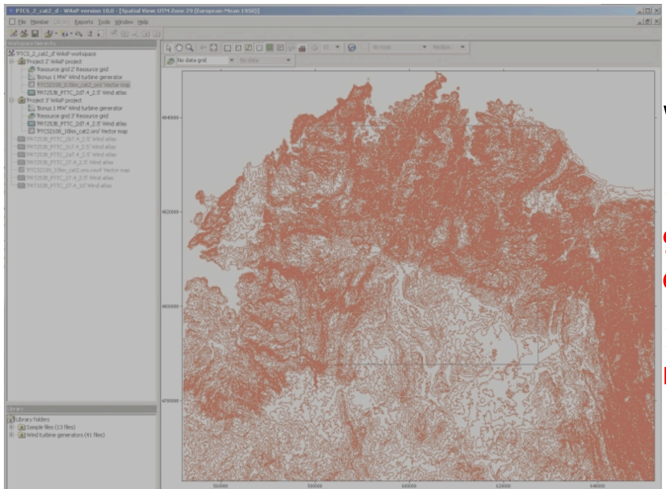
DENMK - Denmark
PRSP1 - Portugal / Spain border
PRSP2 - Northern Spain

NECH1 – Northeast China
NECH2 – Northeast China
NECH3 – Northeast China

AEOM – United Arab Emirates / Oman border
EGYP – Central Egypt
INDI – Central India

Location of case study areas

WAsP resource grid calculation: example



WAsP terrain map

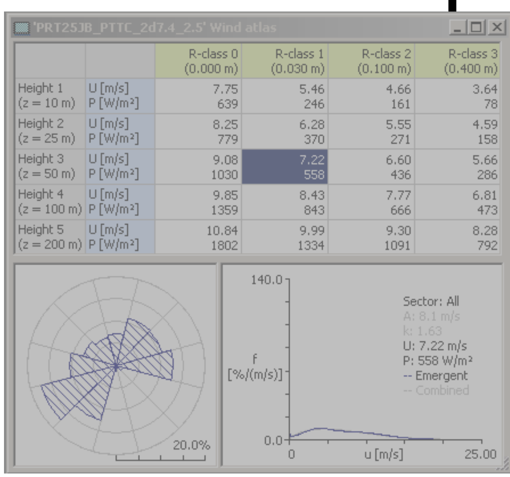
WAsP Map:

100x100 km

90m SRTM for elevation

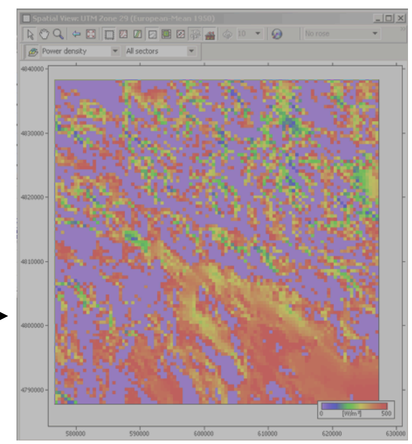
1km GLCC for roughness

location of case study area



Generalized wind climate

WAsP calculates the orographic and roughness change at microscale.

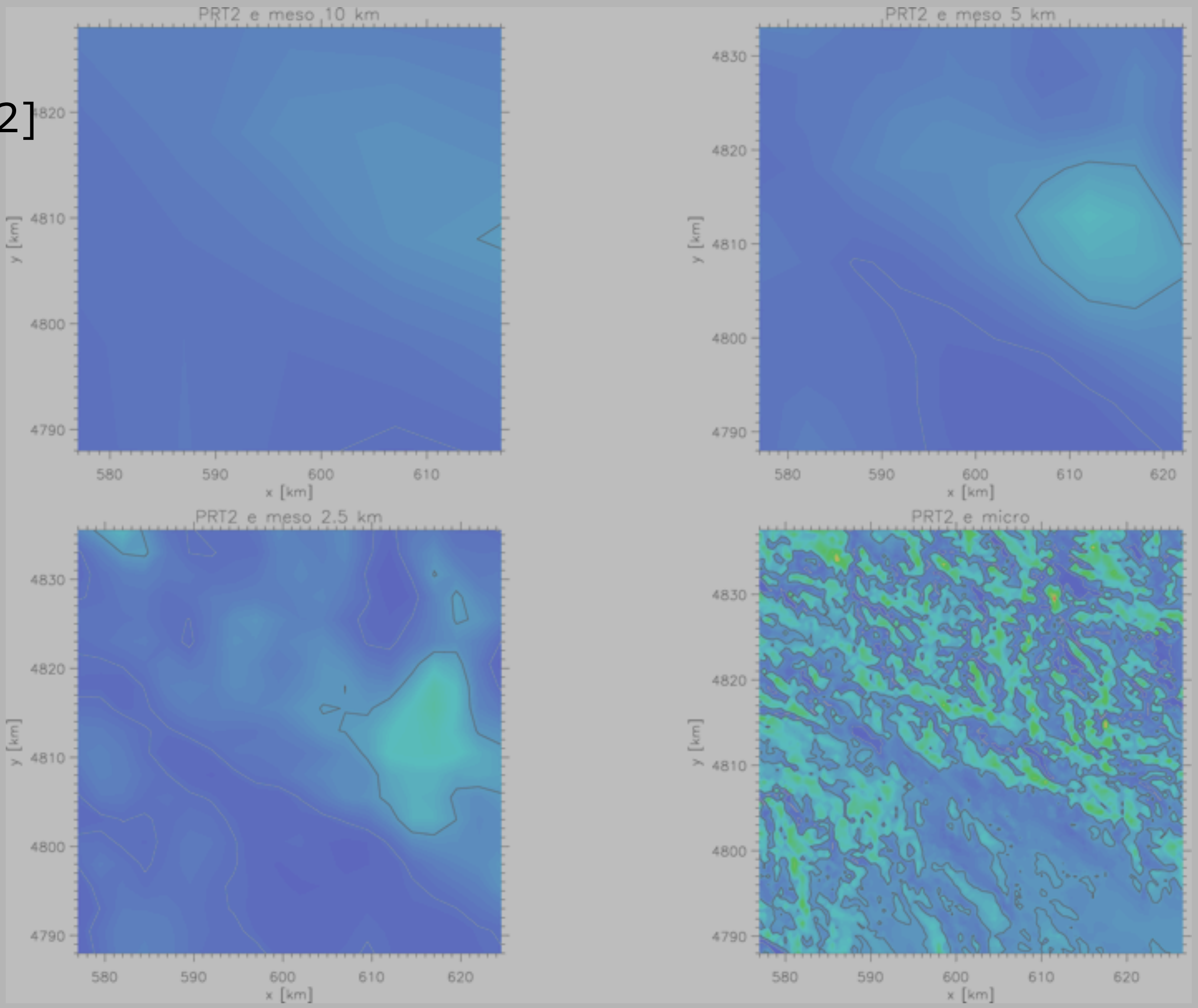


Wind resource grid

50x50km

Comparing area wind power density

- wind power density [W/m**2] at 50 m a.g.l.
- contours at 0.95 and 0.05 full range of 10 km results



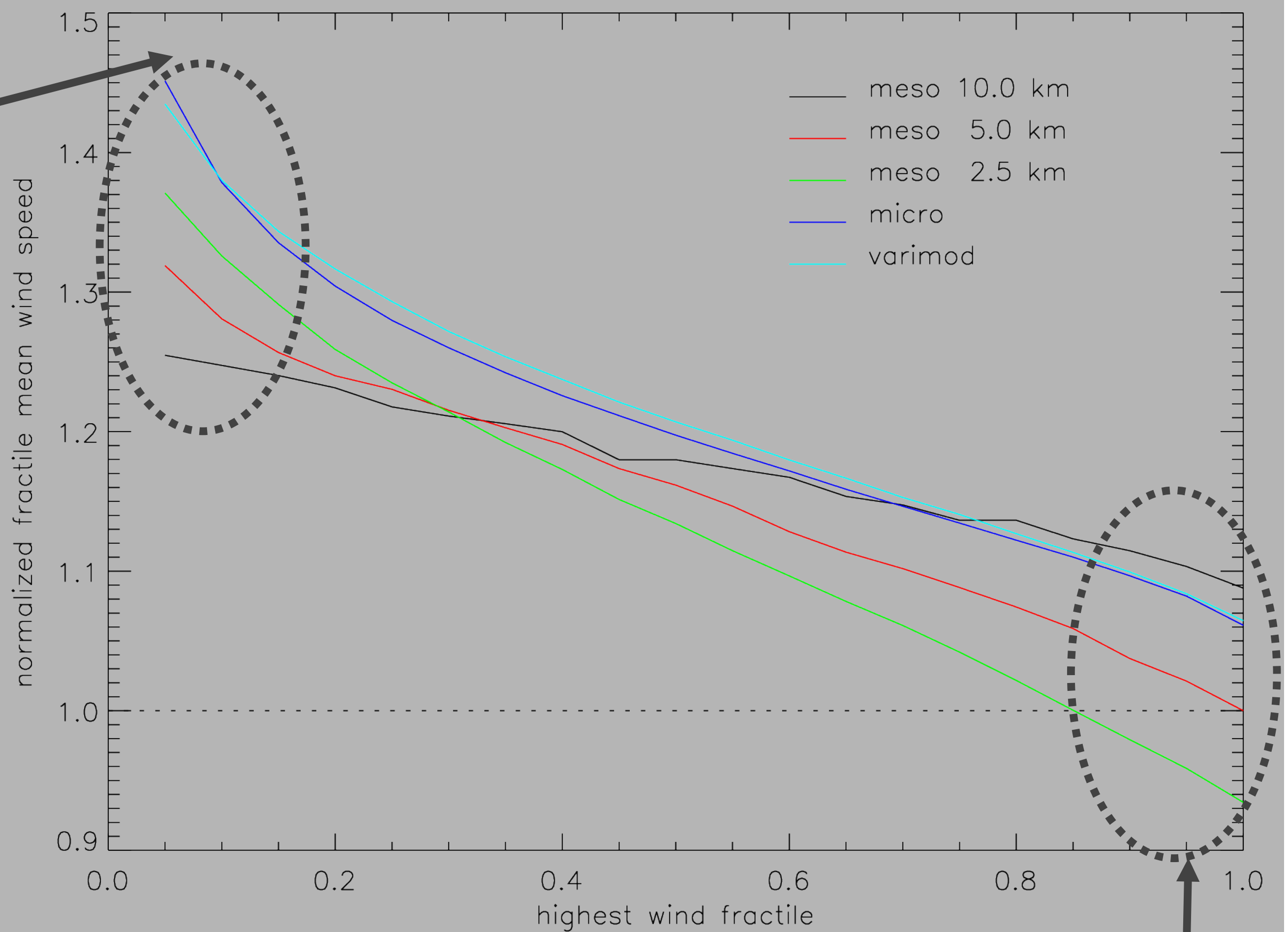
Wind speed fractile plot

Wind speed at 50 m a.g.l.

Enhancement larger for higher resolution modelling for windy fractile

Differences in whole area means, but microscale mean lies in range of mesoscale results.

Mesoscale winds drop with increased resolution; an orography drag effect.

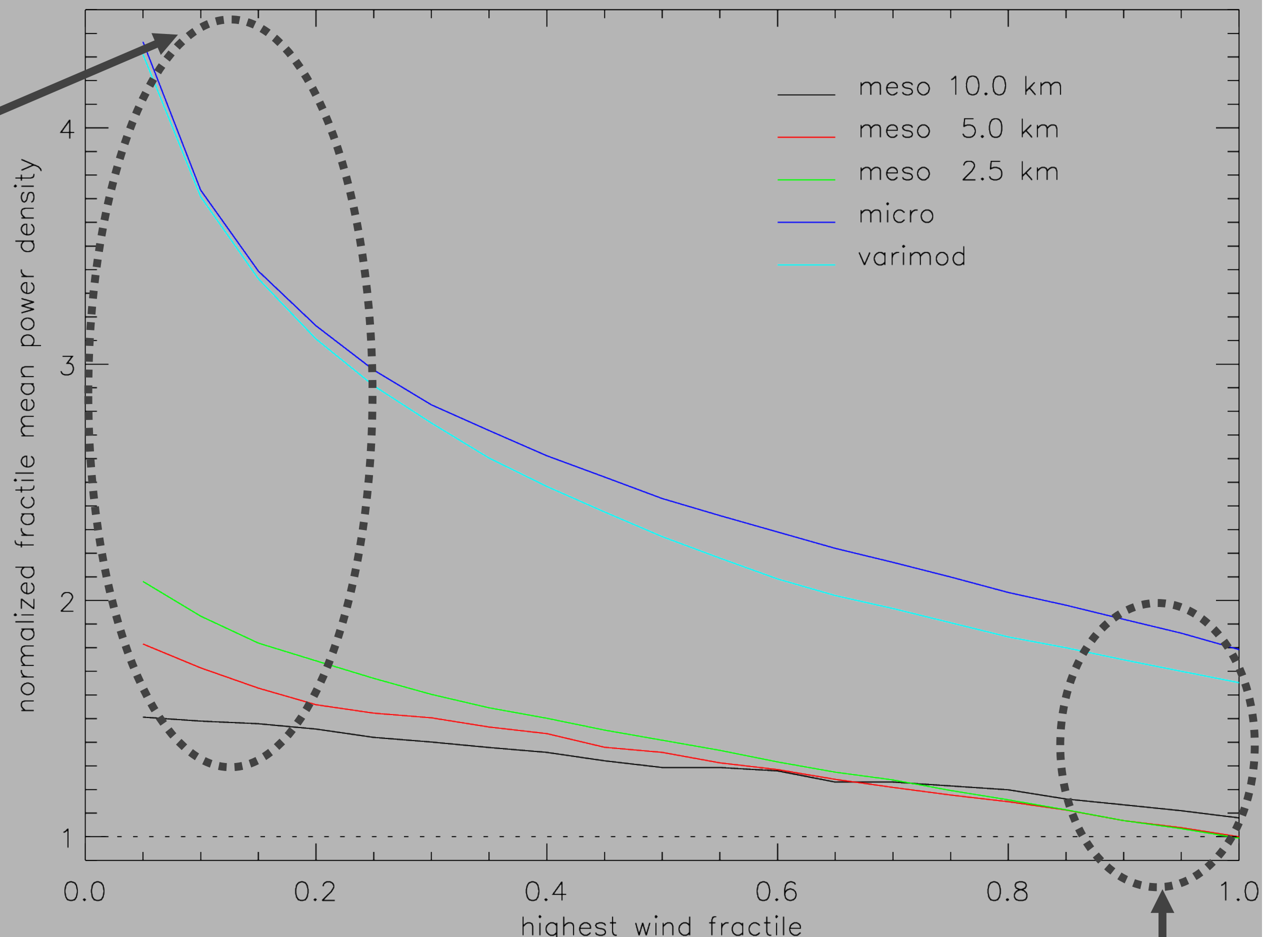


Power density fractile plot

Wind power density
at 50 m a.g.l.

Very large (~100%) enhancement for the microscale modelling for windy fractile

Big differences in whole area mean, related to the variance of the wind speed within the test area



Time averaging of wind power density

$$e = \frac{1}{2}\rho u^3$$

power density

$$u = \bar{u} + u'$$

Reynold's decomposition of wind speed into time mean and time perturbation part.

$$\bar{e} = \frac{1}{2}\rho(\bar{u}^3 + 3\sigma_T^2\bar{u})$$

wind speed variance in time

Time average wind power density contribution from time mean wind <u>and wind speed variance in time</u>.

Spatial (area) and time averaging of wind power density

[ ] = spatial average

$$\bar{u} = [\bar{u}] + \bar{u}^*$$

Reynold's decomposition of time mean wind speed into area mean and area perturbation part.

variance of time mean wind speed in space

$$[\overline{u^3}] = [\bar{u}]^3 + 3\sigma_A^2[\bar{u}]$$

Area average of time mean wind speed cubed has contribution from area averaged time mean wind and variance of time mean wind speed variance in space.

$$[\bar{e}] = \frac{1}{2}\rho([\bar{u}]^3 + 3(\sigma_A^2[\bar{u}] + [\sigma_T^2][\bar{u}] + [\sigma_T^{2\,*}\bar{u}^*]))$$

Putting area and time averaging parts together.

$$\frac{\overline{u'^2}}{\bar{u}^2} = \frac{\sigma_T^2}{\bar{u}^2} = \frac{\Gamma(1+\frac{2}{k})}{\Gamma^2(1+\frac{1}{k})} - 1$$

Weibull distribution for time varying part can give time variance.

Variance Model

A simple model to recreate the microscale results seen in the wind speed and wind power density fractile plots has been developed.

The basis for the model is that wind speed data is synthesised using the mean wind speed and spatial variance given by microscale modelling, i.e. the WAsP resource grid. A Gaussian distribution of wind speed is assumed.

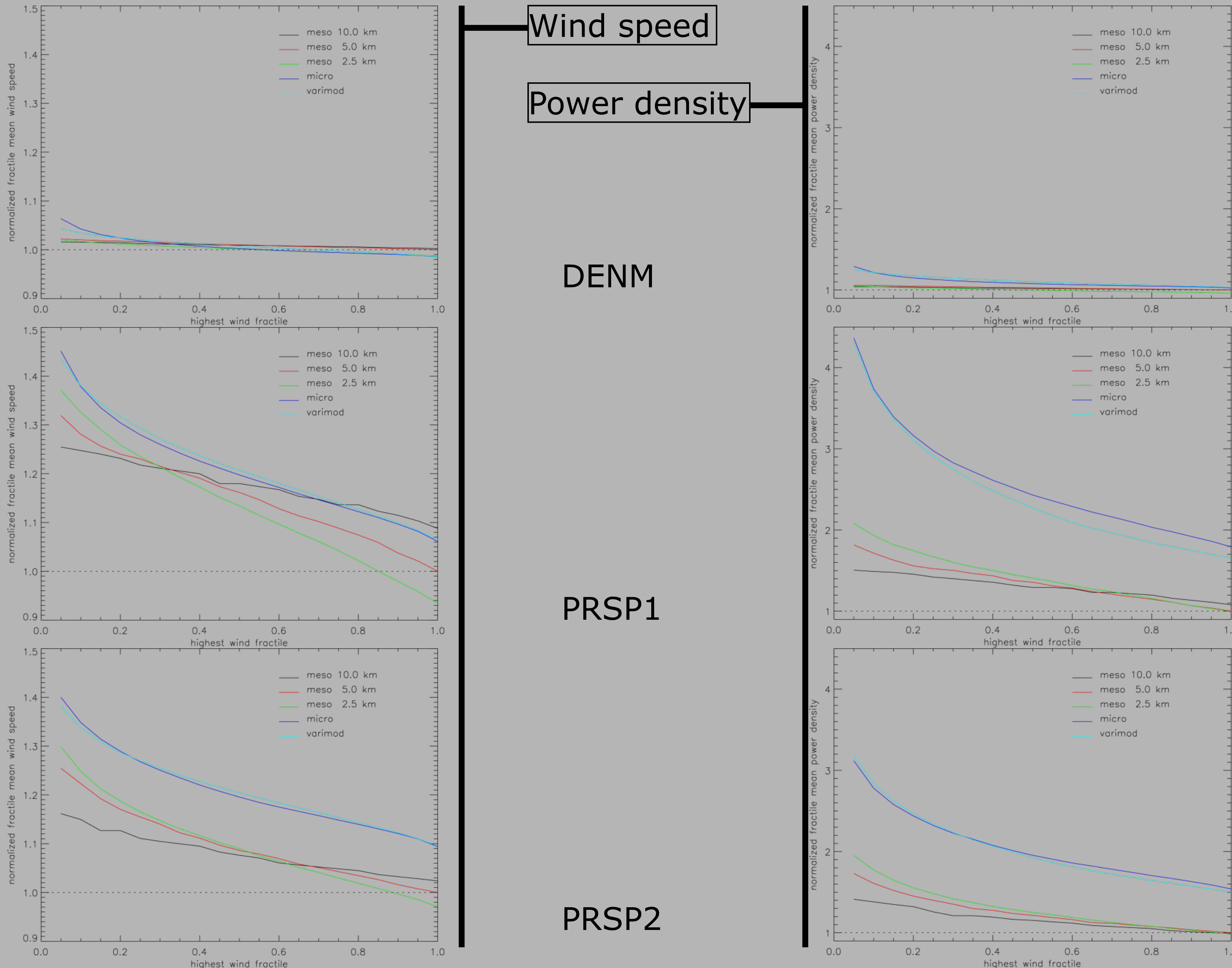
In the wind speed fractile plots the synthesised data is shown by the line labelled 'varimod'.

In order to calculate the wind power density using the synthesised data the wind speed variance in time is modelled according to

$$\sigma_T = \frac{\sigma_T^{GEN}}{\bar{u}}(u + |\bar{u} - u|)$$

where σ_T^{GEN} is the variance in time derived from the generalized wind climate Weibull distribution.

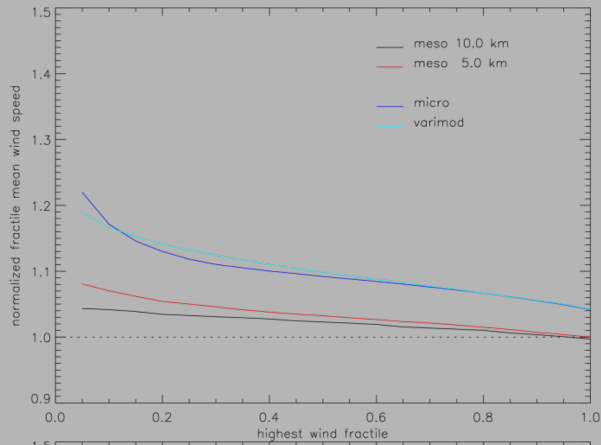
In the wind power density fractile plots the synthesised data (labelled 'varimod') tends to lie close to curve for the WAsP calculate microscale winds. The largest deviations occurring for the windiest fractiles.

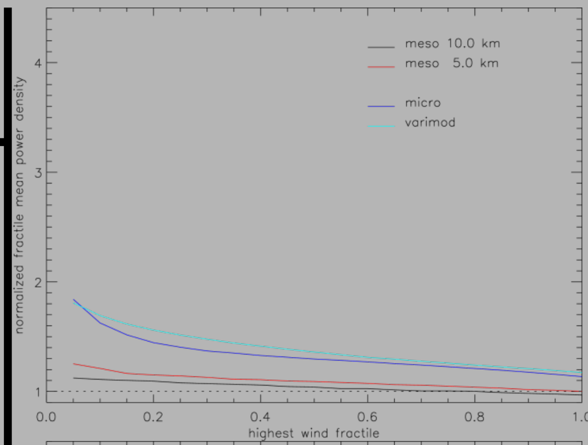

Wind speed
Power density
DENM
PRSP1
PRSP2
meso 10.0 km
meso 5.0 km
meso 2.5 km
micro
varimod
normalized fractile mean wind speed
normalized fractile mean power density
highest wind fractile

Wind speed

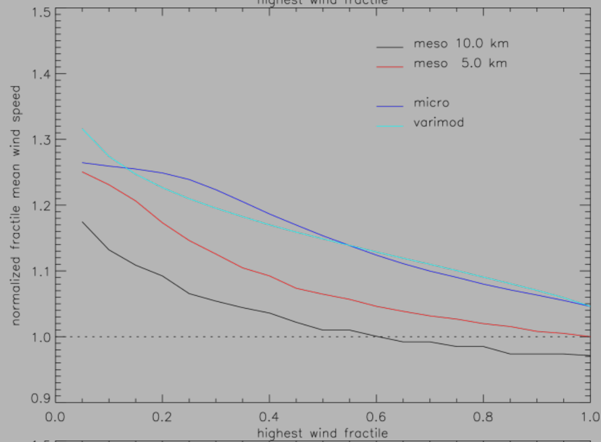
Power density

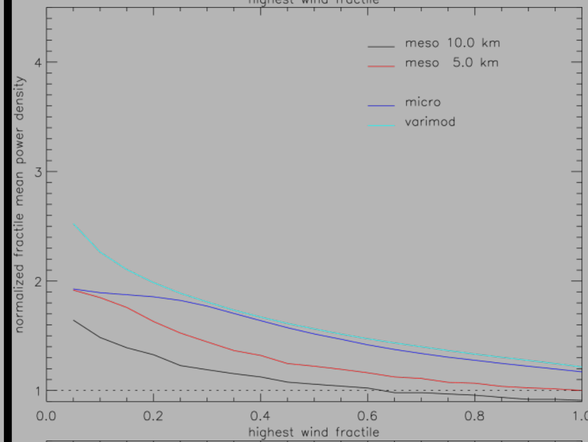
NECH1



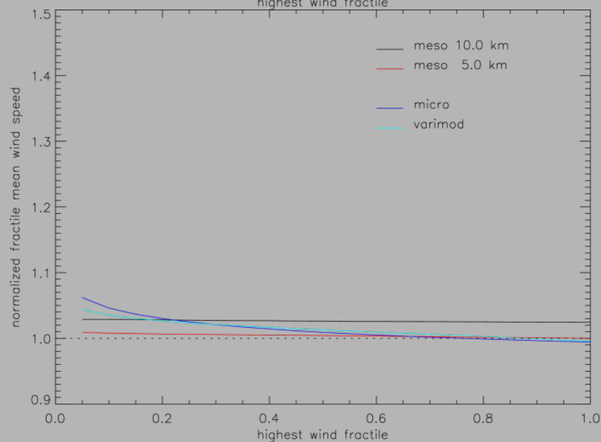


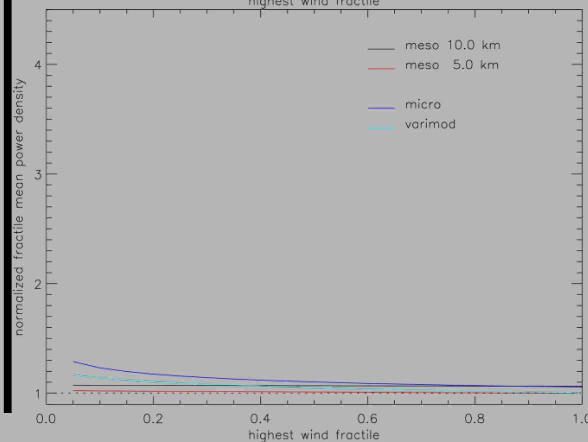
NECH2

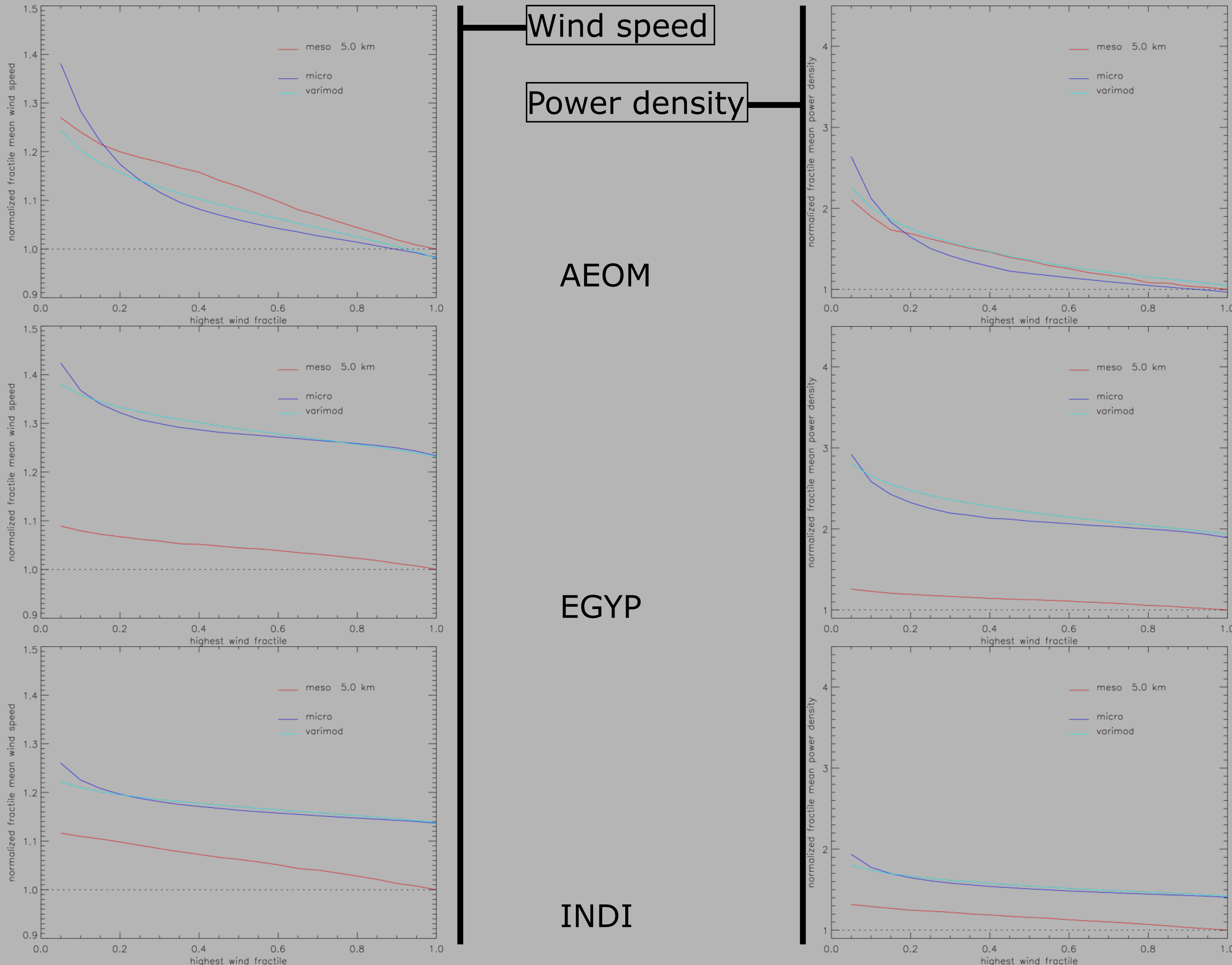




NECH3







Wind speed
Power density
AEOM
EGYP
INDI
normalized fractile mean wind speed
normalized fractile mean power density
highest wind fractile
meso 5.0 km
micro
varimod

Simple models to evaluate spatial variance

Simple spectral orography model (SSOM)

$$h' = H_k \sin(kx + \phi_k)$$

Orography Fourier decomposed, single wavenumber given.

$$u'_k = \frac{S_k k H_k}{2\pi}[u]\sin(kx + \phi_k)$$

Velocity perturbation due to orography, single wavenumber given.

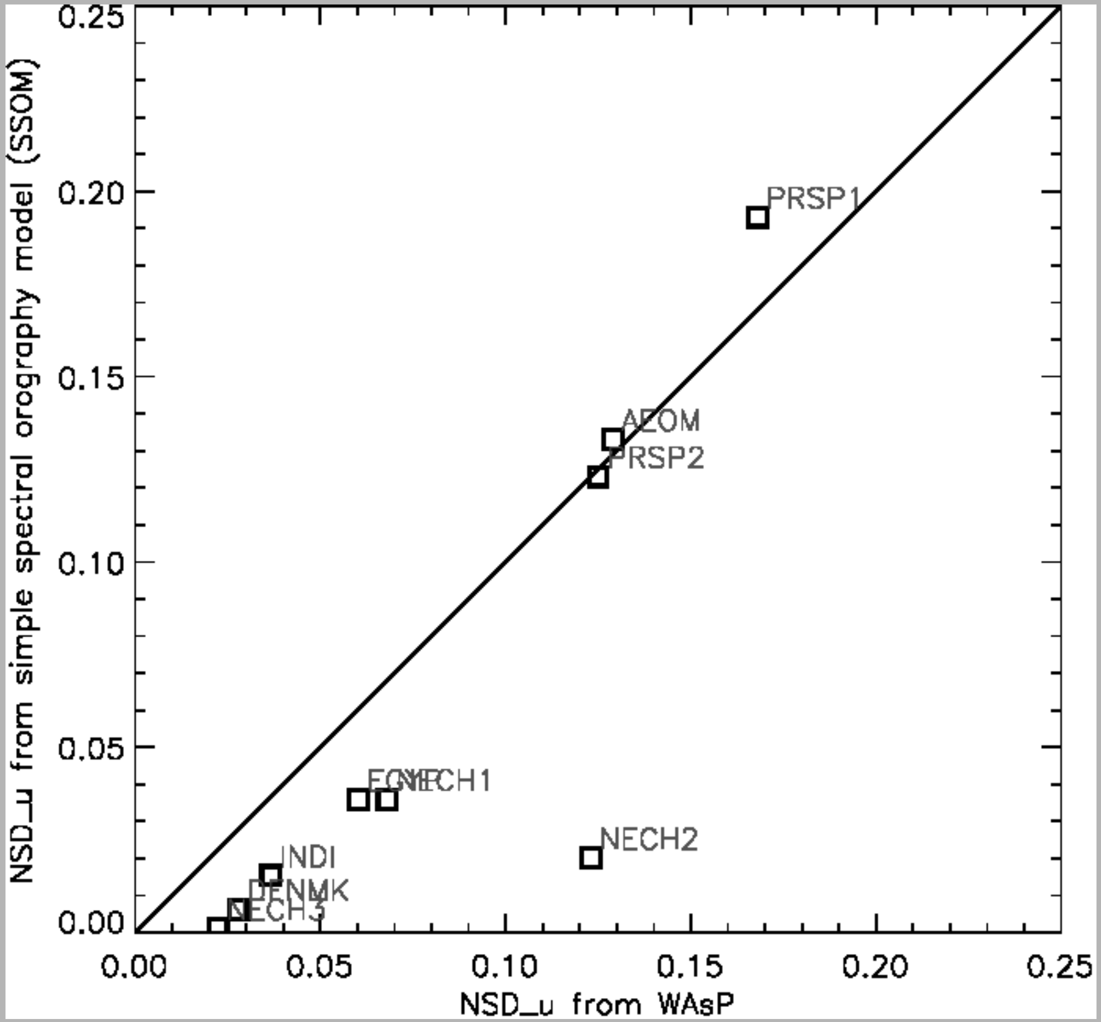
$$[u'^2]_{oro} = \frac{[u]^2}{8\pi^2}\sum_{k=1}^{k=N}(S_k k H_k)^2$$

Wind speed variance in space due to resolvable orography. Standard deviation normalized by division by area mean of u. Model extended to 2-dimensions by calculated ring spectra.

Orography contribution to normalized standard deviation of wind speed (NSD_u)

Orography contribution to standard deviation of wind speed against standard deviation given by WAsP.

Note: NECH2 study area well below unity line.



Simple models to evaluate spatial variance

Simple geostrophic drag model (SGDM)

$$G = \frac{u_*}{\kappa}\sqrt{(\ln\frac{u_*}{f z_0} - A)^2 + B^2}$$

Geostrophic drag law, relates the geostrophic wind to surface layer friction velocity, u_*.

$$u = \frac{u_*}{\kappa}\ln\frac{z}{z_o}$$

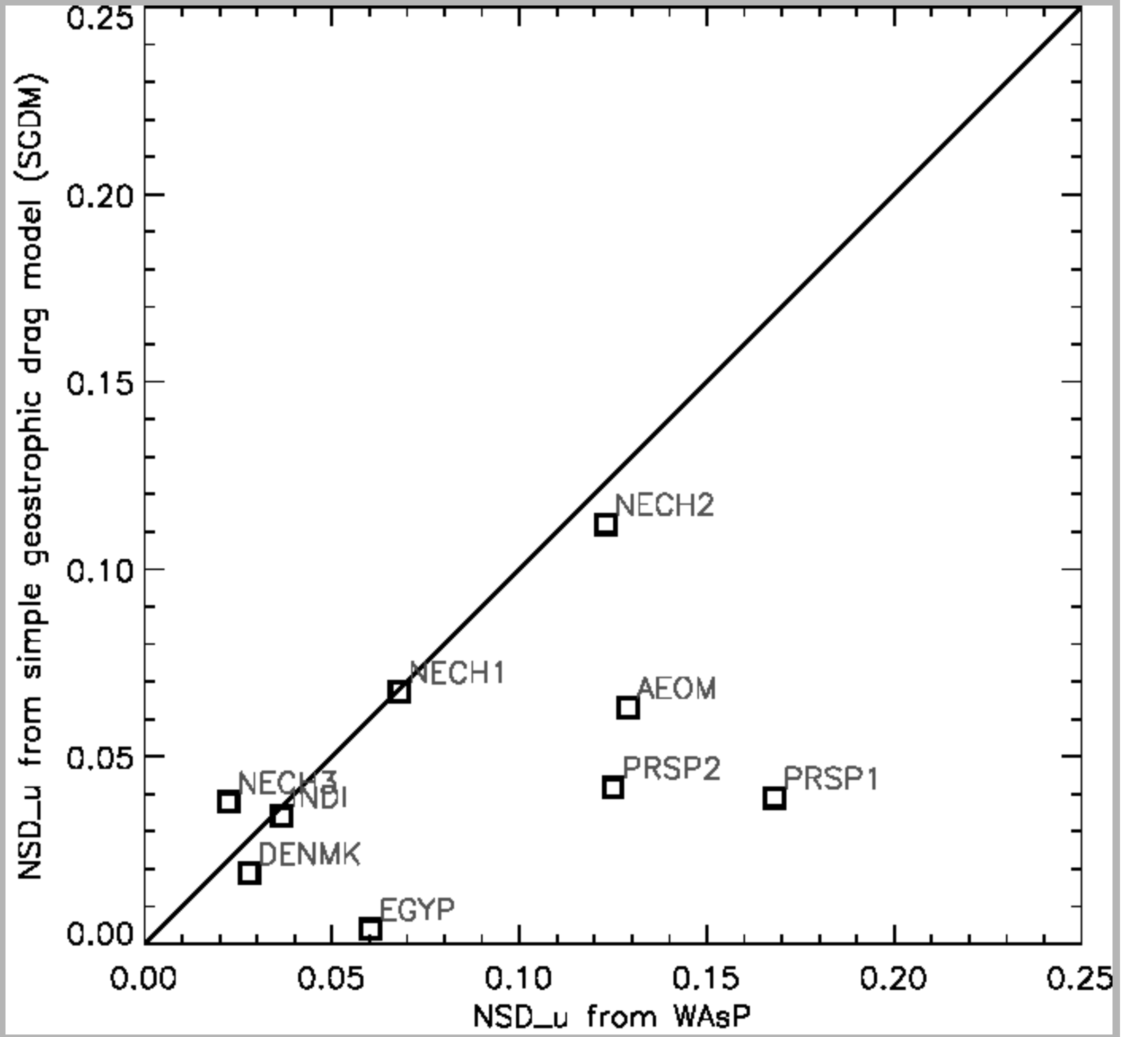
Logarithmic profile relates surface layer friction velocity, u_*, to wind speed at height z.

- assume G is 10 m/s everywhere for the case study area.
- use the values of z_0 at the microscale (WAsP map) and the geostrophic drag law to give u_*.
- use the logarithmic profile to give u at height z.
- evaluate standard deviation of u normalized by area mean of u.

Orography contribution to normalized standard deviation of wind speed (NSD_u)

Roughness contribution to standard deviation of wind speed against standard deviation given by WAsP.

Note: NECH2 study area well close to unity line.

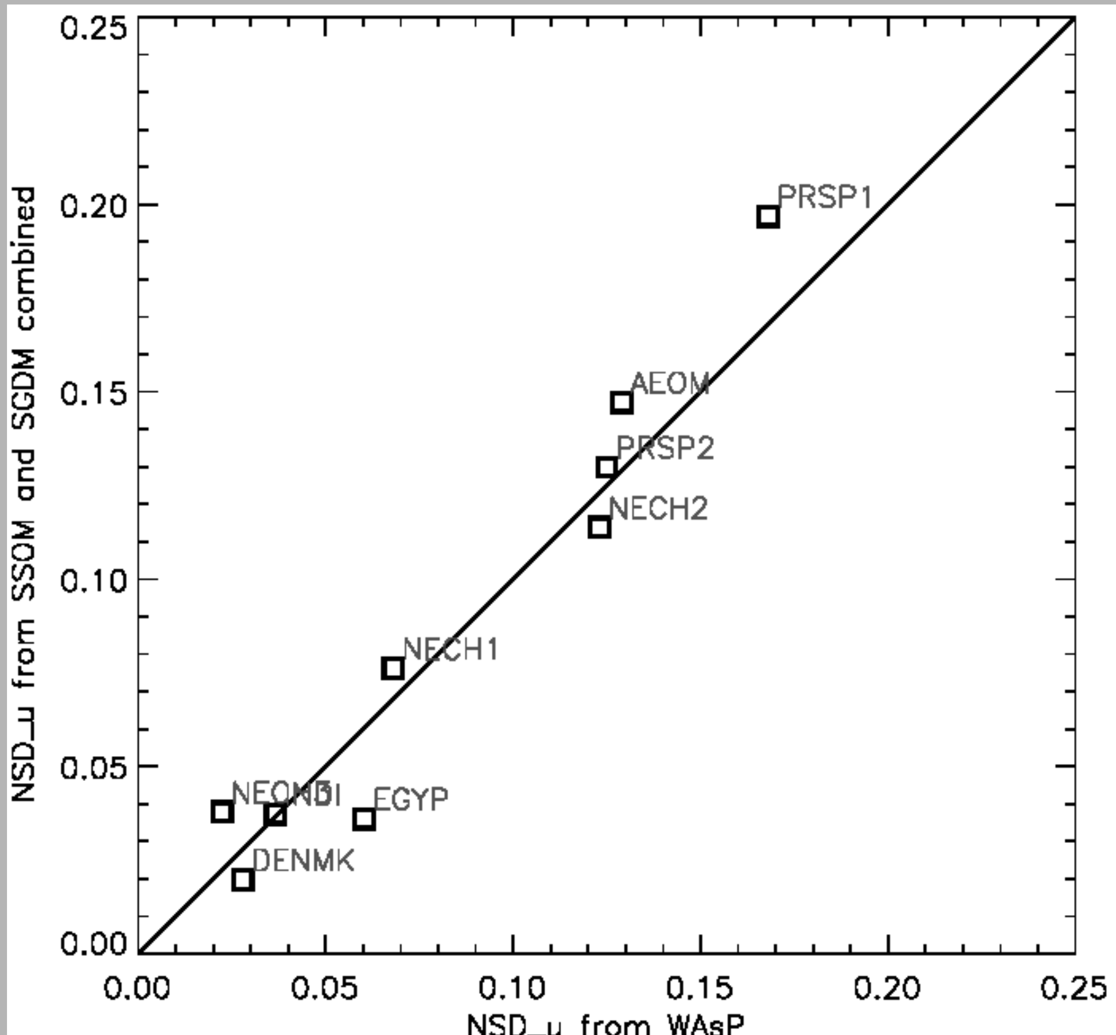


Orography and roughness contribution to normalized standard deviation of wind speed (NSD_u)

The orography and roughness standard contributions deviations are simply combine by the following:

$$\sigma_A = \sqrt{\sigma_{oro}^2 + \sigma_{rou}^2}$$

The result of the combination plotted against the standard deviation from WAsP shows reasonable aggreement.



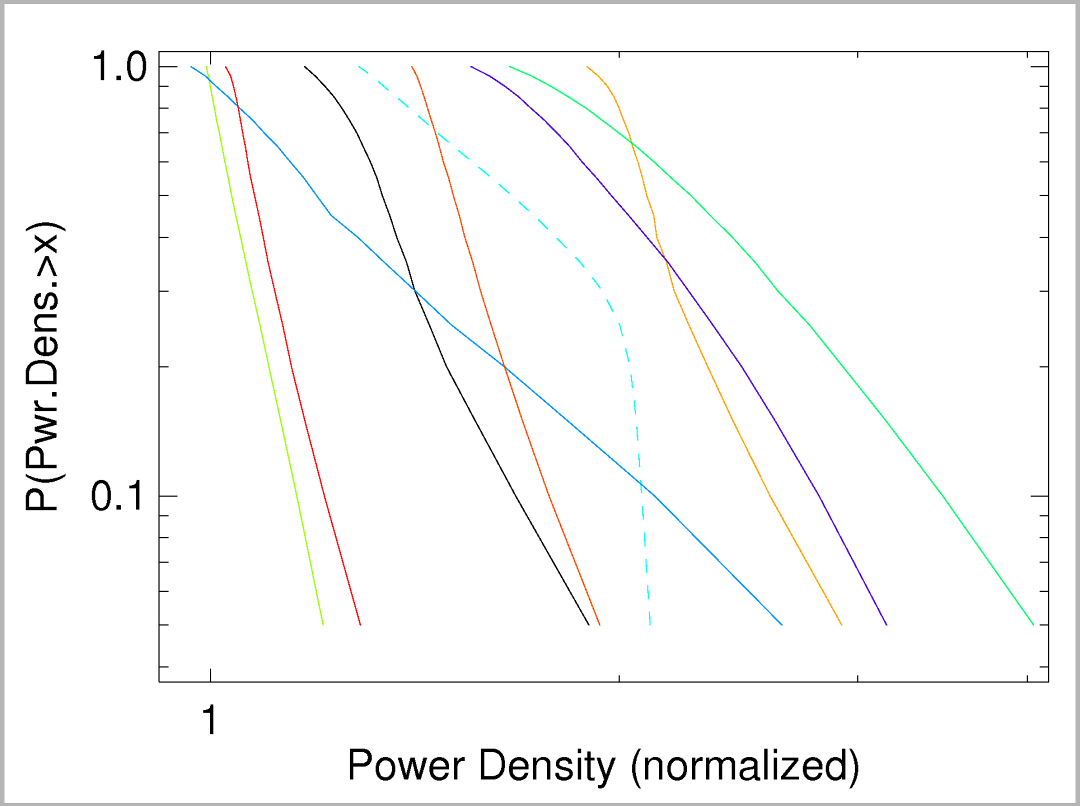
From terrain spectra to estimates of rank-distributions of wind power density:

in support of (linearized) micro-scale flow models

Statistical connection between
terrain elevation map and expected *distributions of wind power*,
over large domains (>~ 20 km)

- relate *spectra of terrain slope* to *distribution of power density*
- provides first estimate of spatial variation of relative potential wind power in a region
- underlines the need for microscale modeling
(mesoscale models alone are not enough!)

Ranked wind power densities from the 9 case study



‘, ordinahighest power areas: ~ constant slopes

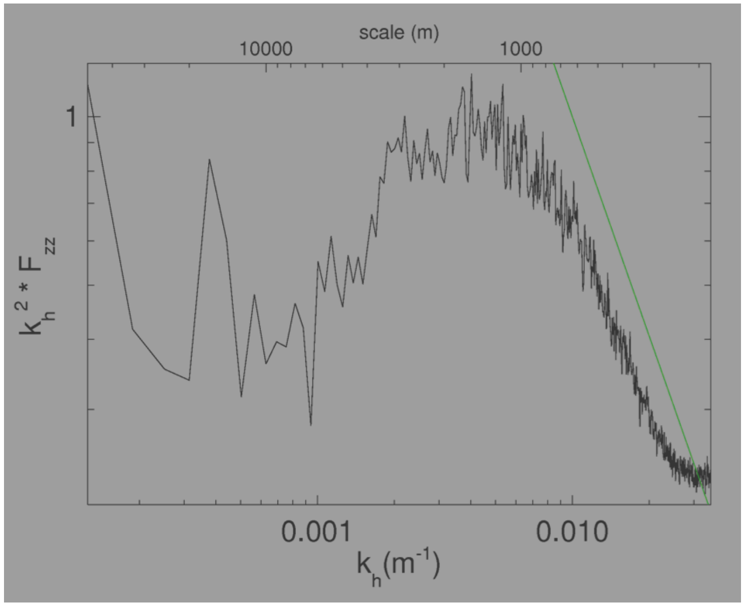
Terrain elevation spectra

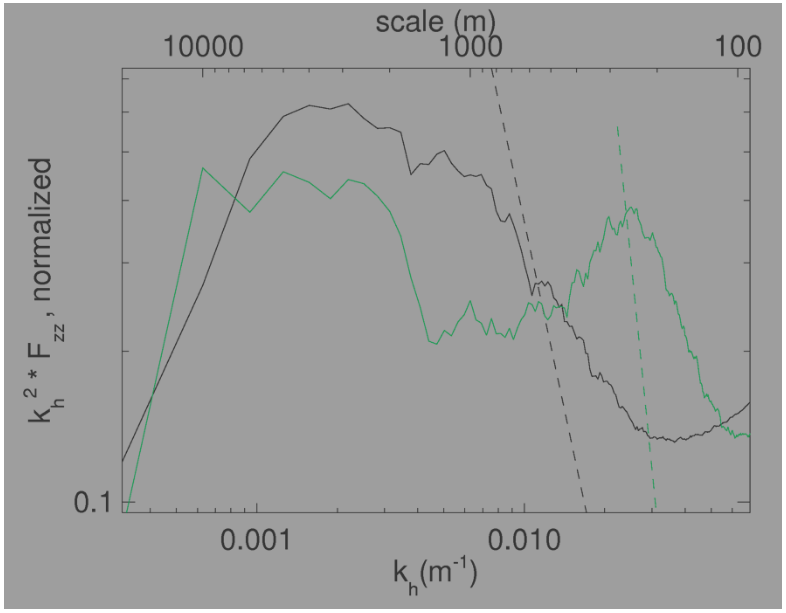
Statistical connection between *terrain elevation map*

and expected *distributions of wind power*,

over large domains (>~ 20 km)

— relate *spectra of terrain slope* to *distribution of power density*





ring-averaged 2-D spectra: UAE (left), NE.China 1&3 (right)

Estimating the spatial wind power CDF's:

Linearized flow models (e.g. WAsP)

directly relate terrain slope to speed-up of wind speed U

→ relate characteristic slope (α) of *terrain slope spectrum*

$$k_h^2 F^r(k_h) \propto k_h^{-\alpha}$$

(where F=scalar 2-D power spectrum of height)

to *cumulative distribution function of power density* $C(U^3)$

Assume power spectral density ~ probability density

[assume effectively monofractal process (Selvam, 2010)],

$$\left[k_h^2 F^r(k_h)\right]^3 \sim P(\text{power density}) \sim k^{-3\alpha}$$

Now since $P(x) = dC/dx$, For CDF $C(x) \propto x^{-\beta}$ of wind power density,

the slope of a power-law CDF is equivalent to

$$\beta = 3\alpha - 1$$

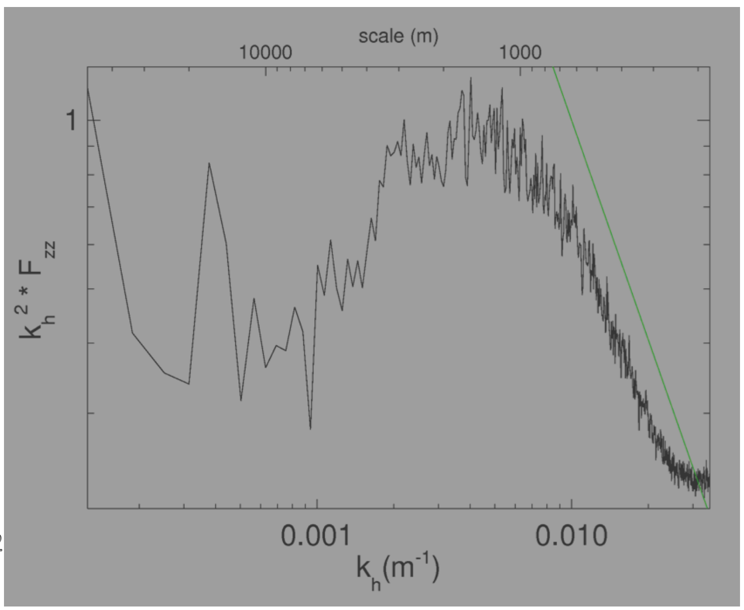
Using "terrain-slope" spectra

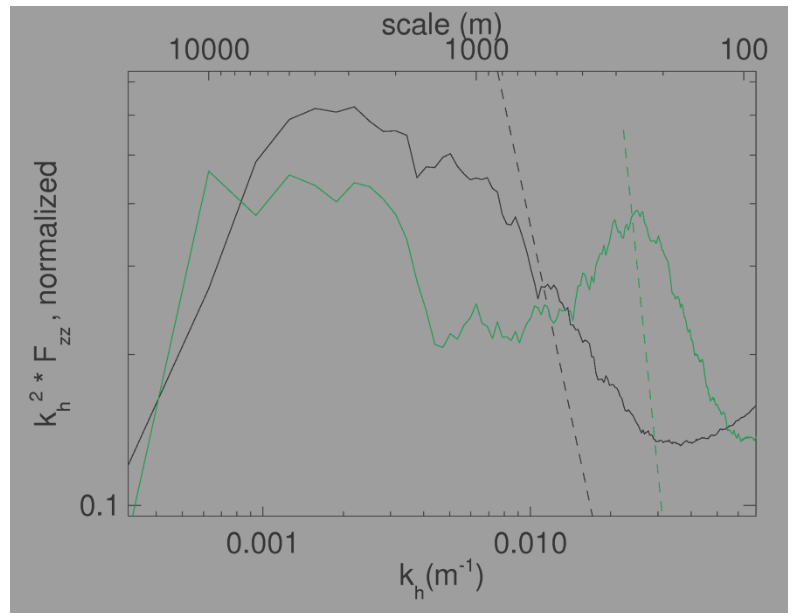
First estimate/method: use scalar (ring-averaged) 2-D spectra

Characteristic slope: average the steepest definitive features

- present study: 'engineering-like' rules to do this; conservative
- Future/better: use *sector transects*, prevailing winds / rose
- likely have stretched exponential $C(x)=e^{-(x/x_0)^{\gamma}}$ [or log-normal]

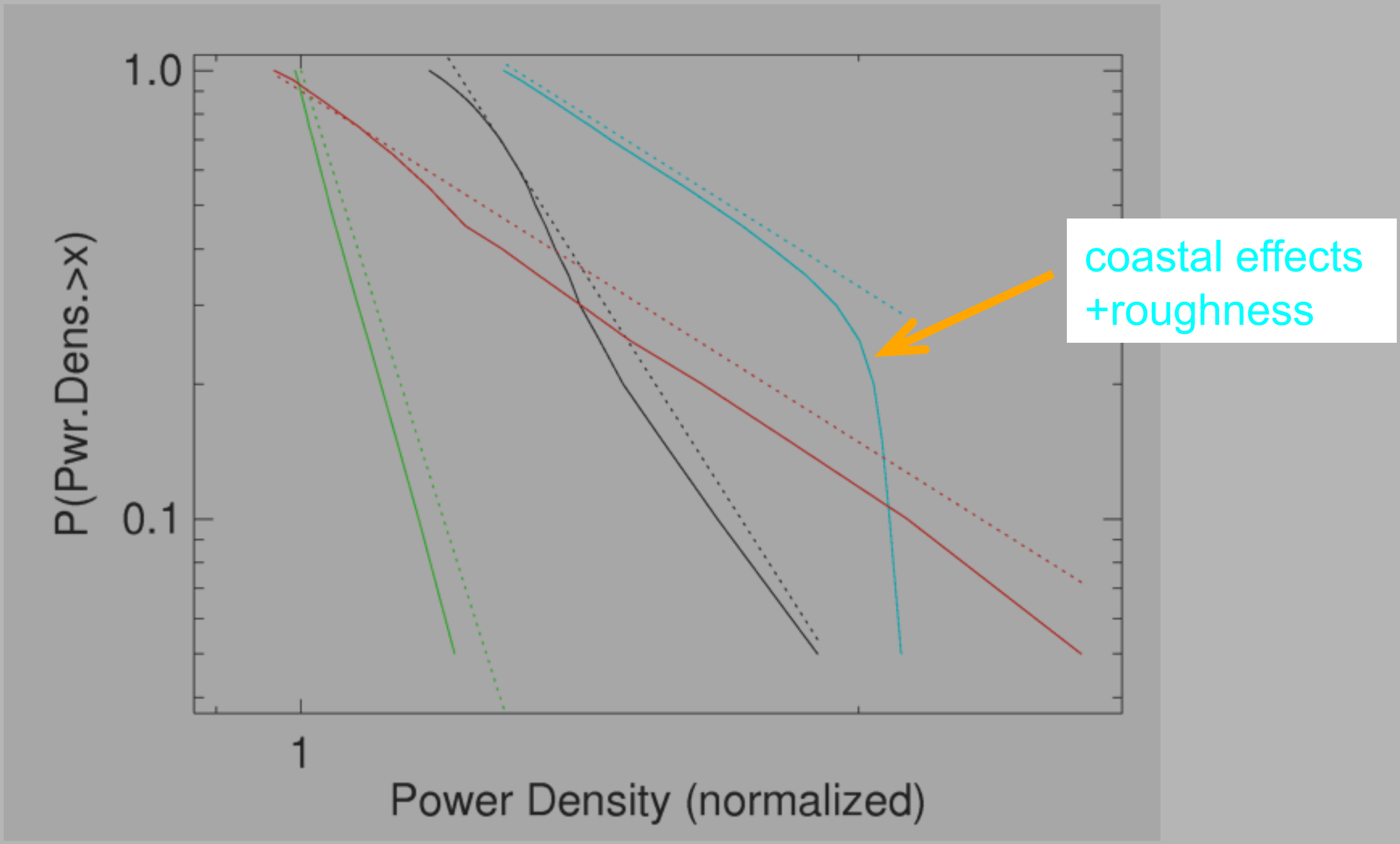
  but are interested in power-law tails (slope → γ)





Spatial CDF of wind power from terrain spectra

scalar (ring-averaged) 2-D spectra; slope from steepest definitive features



cases: N.E.China (black, green, blue); ArabEmirates (red)

putting it all together

- Spectral exponent gives spatial distribution function of wind power
  i.e., only the shape of ranked normalized power densities

- Can use more information (normalization vs. offset):
  - integrated terrain-slope variance information
  - Wind-climate variation, e.g. (spatial) distribution of Weibull stats

- Account for roughness in estimate (Not done so- far)
  - Adaptation of geostrophic drag law (reduced)
    - Spectral-based perturbations

$$\tilde{u}_* / u_{*0} = \ln\left(\frac{\widetilde{z_0}}{z_{00}}\right) \times \frac{0.3 g(\theta) z_{00}^{1/3} k_h^{-1/3} \left[(k_x U + k_y V)^2 k_h^{-4} + K^2 \right]^{1/4}}{1 -`g(\theta) z_{00}^{1/3} k_h^{-1/3} \left[(k_x U + k_y V)^2 k_h^{-4} + K^2 \right]^{1/4} \left(\tfrac{2}{3} \ln(k_h z_{00}) + 0.8 \right)}$$

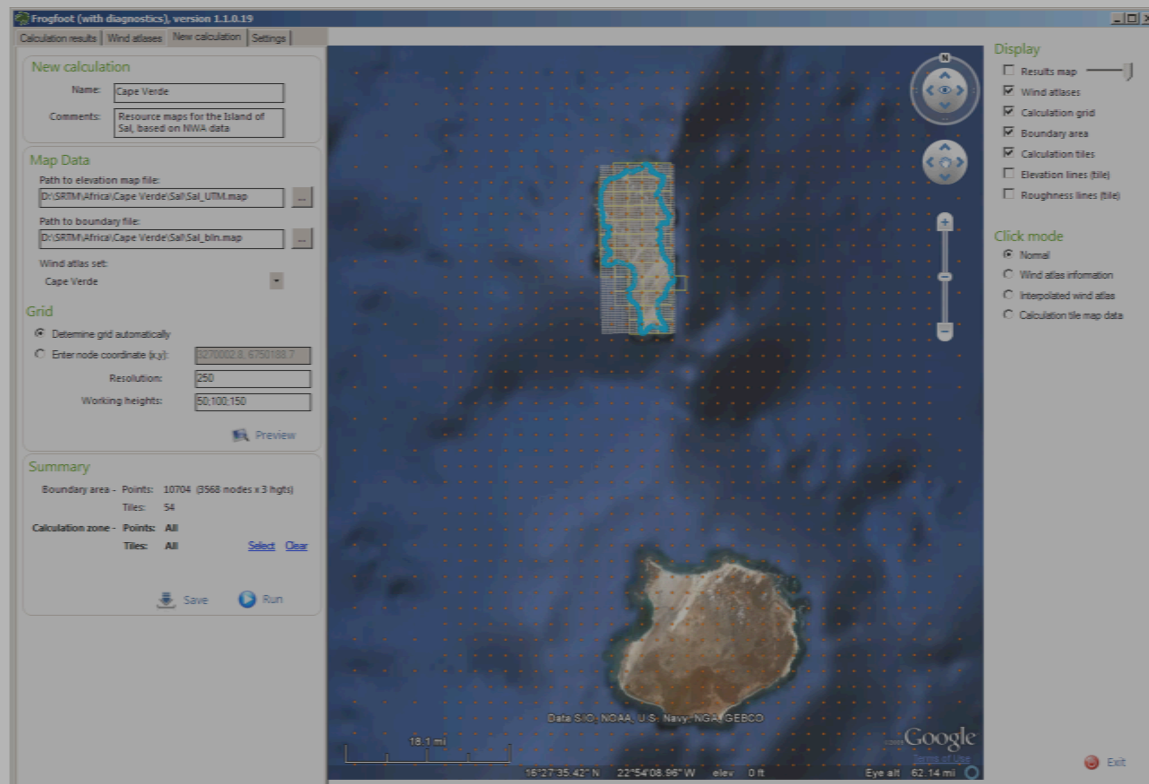
Advanced microscale modelling (frogfood)

So far, each study area microscale modelling used a single generalized wind climate

However, a new WAsP tool called Frogfood allows for several generalized wind climates to be used.

The 50x50km study areas are covered by 100 generalized wind climates (5 km grid spacing).

It is very interesting to see how this may introduce more variance to the wind speed, and thus greater mean wind power density.



Frogfoot: dots represent generalized wind climates from mesoscale modelling. WAsP resource grid microscale modelling can make use the nearest generalized wind climate files.

How to procced : Developing implementation/use-heirarchy

Method	Inputs	Result type	Time scale
Correction factor to low resolution data spectral / 'varimod'	High-res maps +Hadley	statistical; domain-scale resolution	0.5- 1 year
spectral / 'varimod' + meso-scale	+ mesoscale-derived generalized wind climates +climate/NCAR 50 km x 50 km (new)	Improved statistical; domain-scale resolution	1 year
'FrogFoot' / WAsP	High resolution maps + mesoscale-derived generalized wind climates	High-resolution spatially varying;	2 years

Summary (1)

- Aggregate microscale modeling gives good indication of potential peak wind resource: fractile (area-rank) plots of power density
- Can estimate rank-order (fractile) distributions of power based on terrain elevation and roughness maps, with 'varmod' method via WAsP results, or map-estimated variance (latter pending)
- Can also use spectra to estimate spatially-based distribution function for normalized wind power densities (=fractile plots)
- Both estimation methods:
  - work for many sites, even with little/no roughness information
  - give regional "prospecting" information
  - are statistical tools, giving no detailed information
  - be careful with terrain map; quality: ~100m or better (SRTM ok)
- Again: need microscale models to estimate specific energy resource or to get useful info <~10km (mesoscale alone is not enough)

Summary

- Avoiding the high resolution modeling creates nearly always an biased underestimate if the wind resource in the order of 20 -80 % onshore
- Offset in the means unlikely to be investigated without comparisons to measurements.
- A relative simple method is developed to upscale wind power estimates based on high resolution terrain and roughness maps combined with large scale made probability functions of the wind speeds
- Pure offshore grid cell values does not need to be upscaled. The issue here is the offset. Here meso-models can be verified with satellite images of wind (SAR data). *Merete Badger et al 2010* in JAMC