STATISTICAL PREDICTION OF SURFACE WIND COMPONENTS

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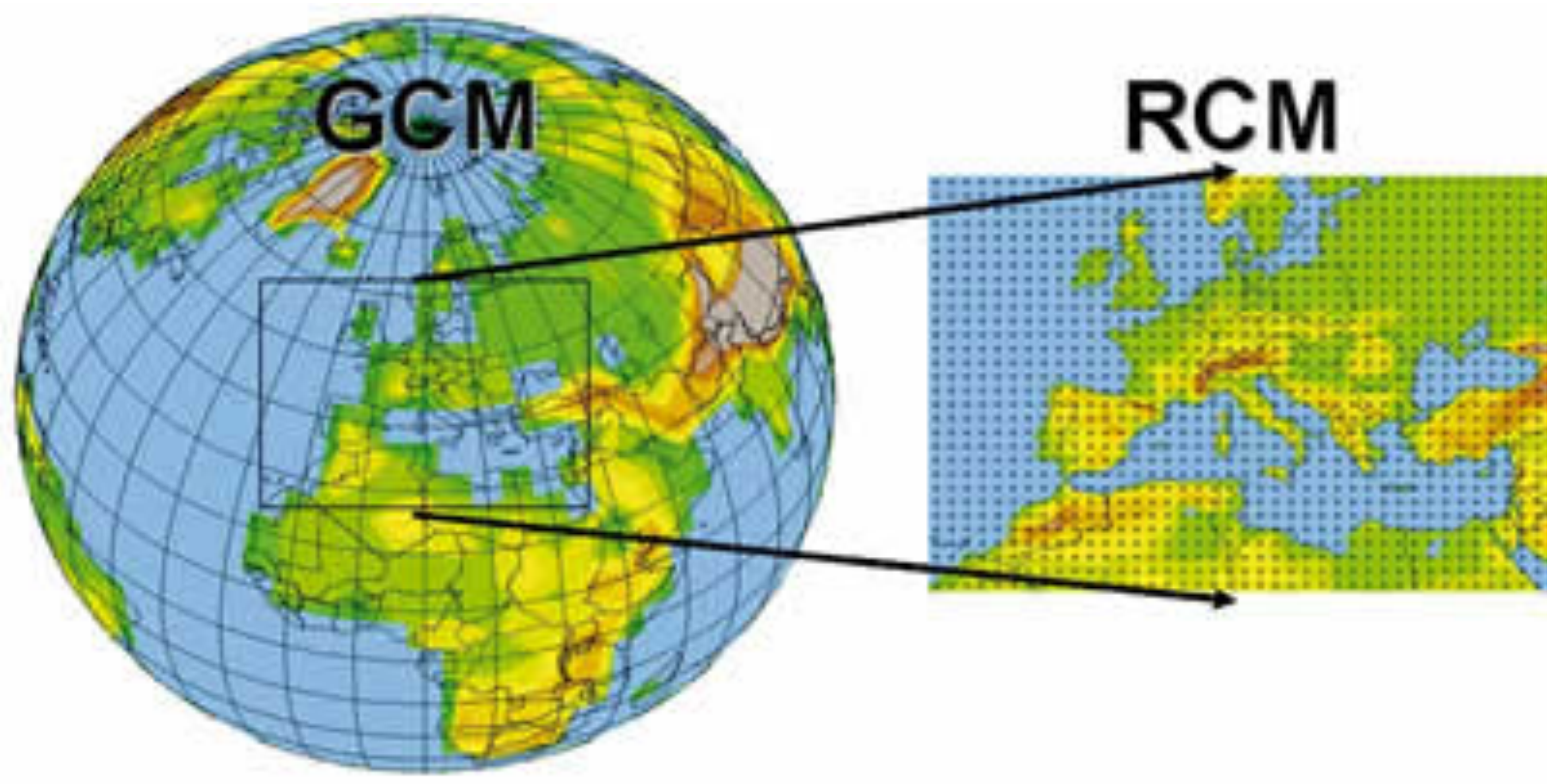
Introduction

- High-resolution, site-specific **surfaces winds** (e.g. transport of airborne particles, wind energy production)
- Global Climate Models (GCMs): coarse resolution (>100km) → **Cannot model surface winds**
- Downscaling:
  - **Methods** used to infer local-scale climate information (**predictands**) from coarsely resolved climate models (**predictors**)
  - **Dynamical** vs **Statistical** downscaling

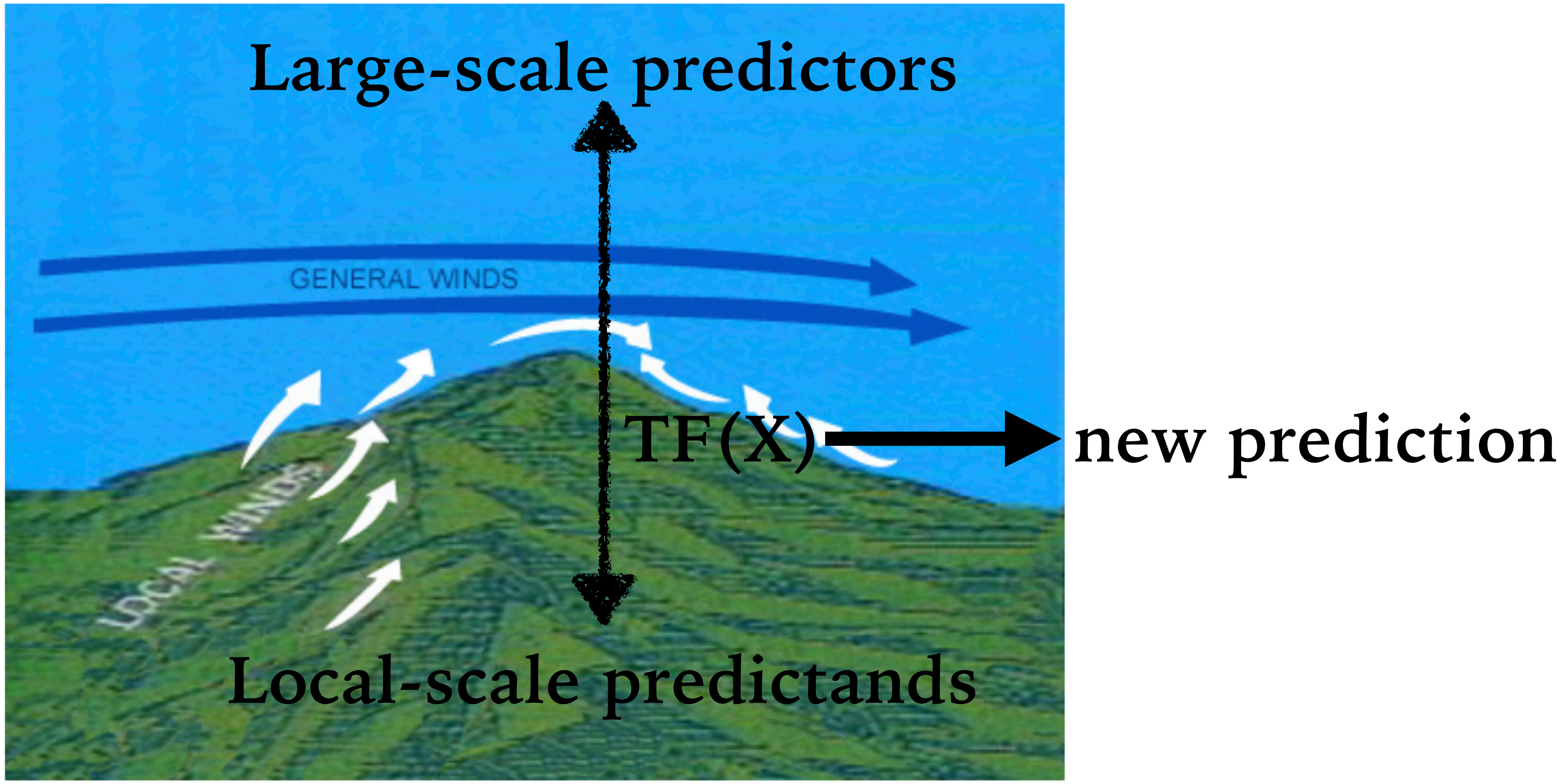
Dynamical downscaling (DD)

- Nest Regional climate models (RCMs) in the grids of GCMs
- Physically based ✓
- Computationally **expensive**



Statistical downscaling (SD)

- Derive a transfer function (TF) from empirical relationships between predictors and predictands
- **Flexible** functional form of TFs (**linear, nonlinear**)
- **Cheap** computational cost ✓



- DD and SD: Comparative skills in predicting historical data

- SD: cheap computational cost ★

SD: most commonly applied in predicting scalar variables (Temperature, Precipitation)

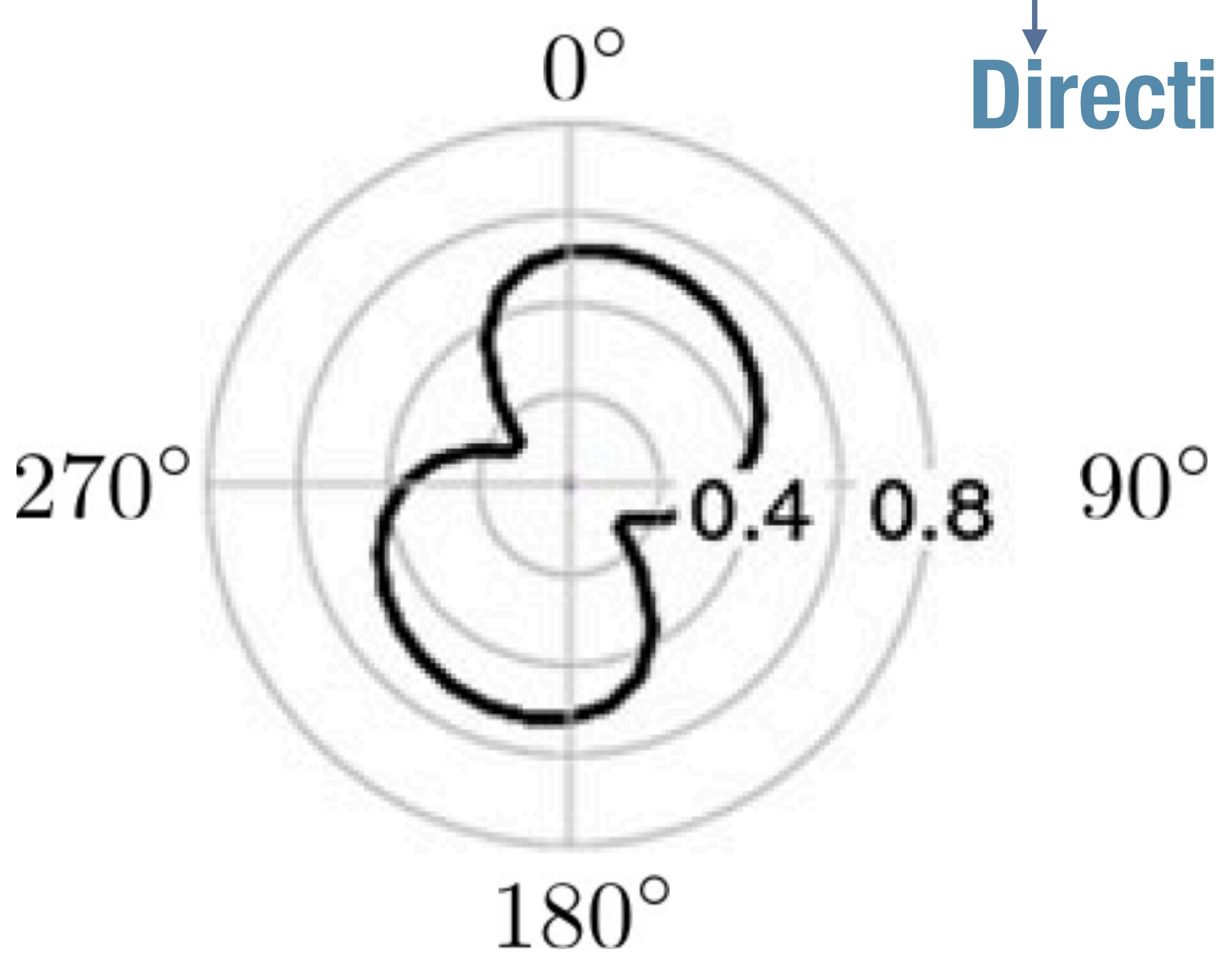
Research Focus

- Assess how well SD can do in predicting surface wind components (**vector**) → Directional Characteristics

- **Predictive anisotropy:** predictability of surface wind components varies with the direction of projection.

Predictability of $U(\theta)$

Direction of projection



Research Objectives

1. to provide a ***global characterization*** of statistical predictability of surface wind components

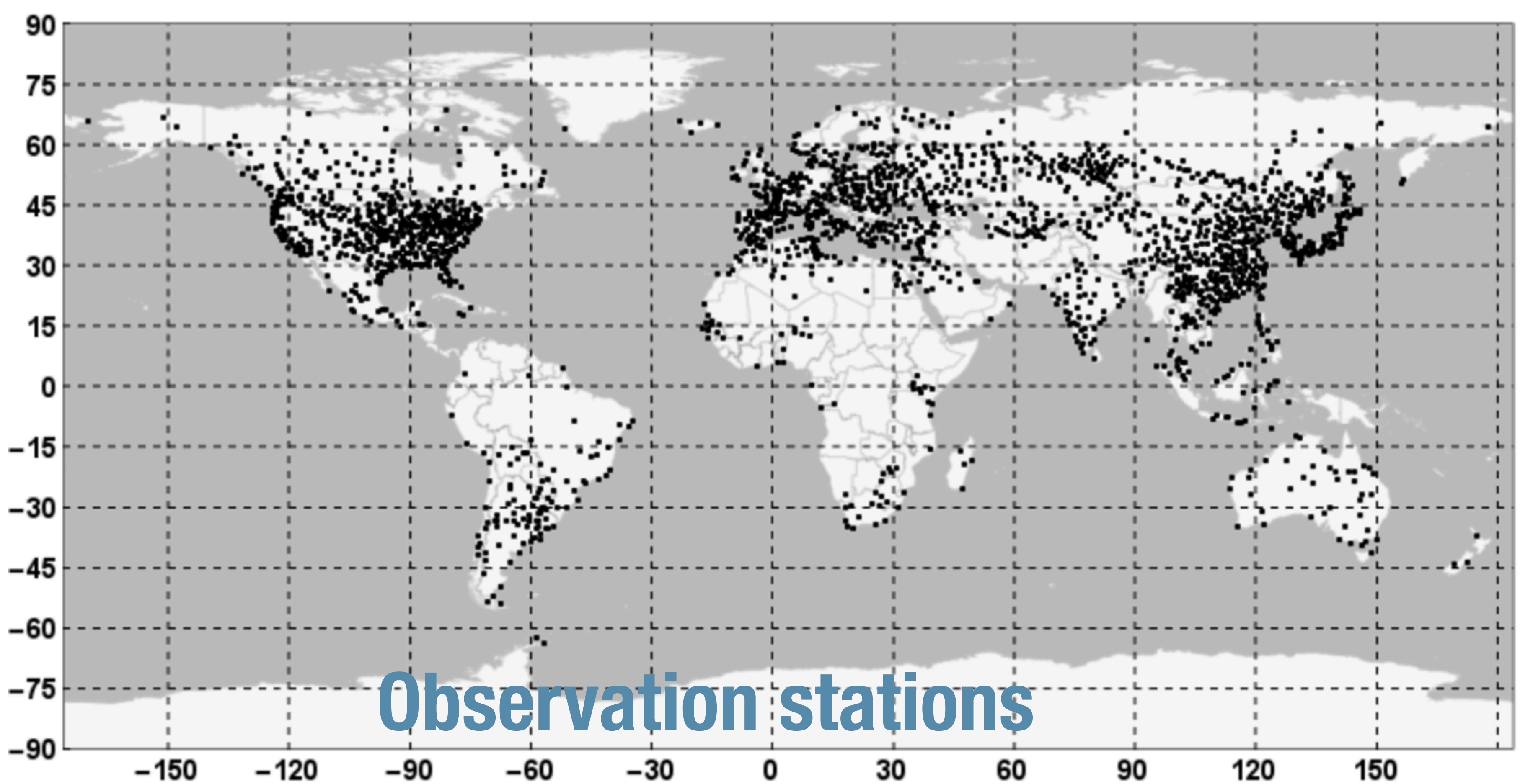
2. to compare the ***efficiency*** of ***linear*** and ***nonlinear*** TFs

3. to build ***a general framework*** to explain characteristics of statistical predictability with an emphasis on ***predictive anisotropy*** (***contributing factors***)

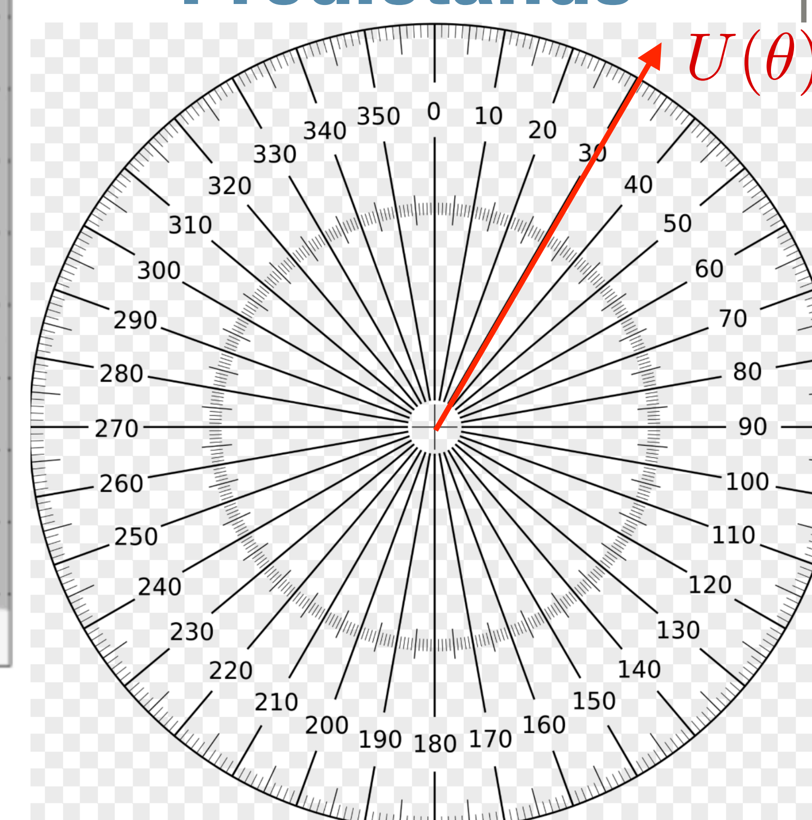
- wrong functional form of TFs (i.e. linear)?
- physical factors?

Methodology

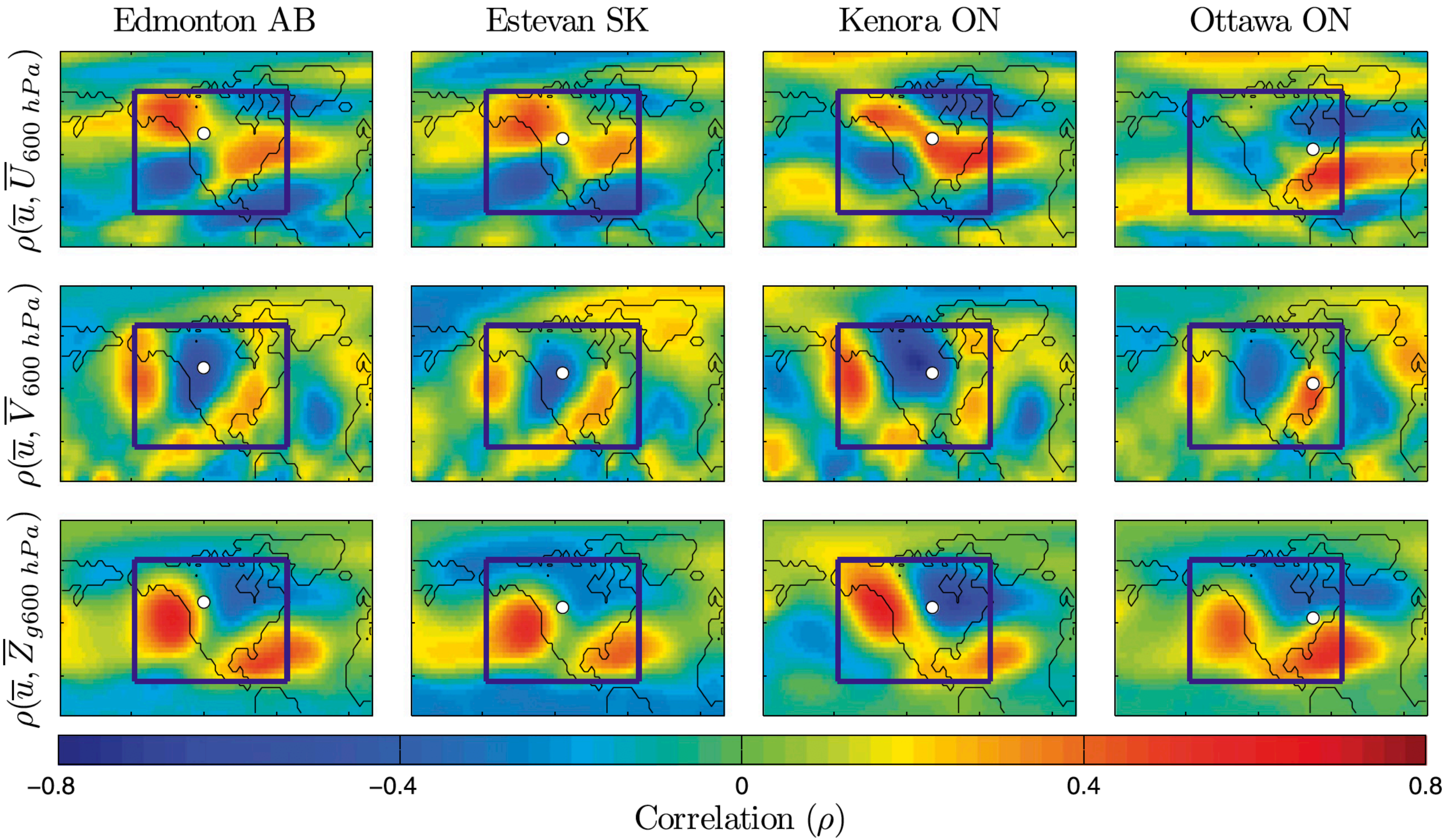
- **Predictands:** surface wind components projected onto 0, 10, 20,…360 deg at 2109 land stations
- **Predictors:** Temperature (T), Geopotential height (Z), zonal (U), meridional (V) wind components at 500 mb from NECP2 reanalysis
- **Prediction period:** 1980-2012, Summer/Winter, Daily/Monthly
- **Predictability:** R^2 = corr^2(Obs, Pred)



Predictands



Predictive Information



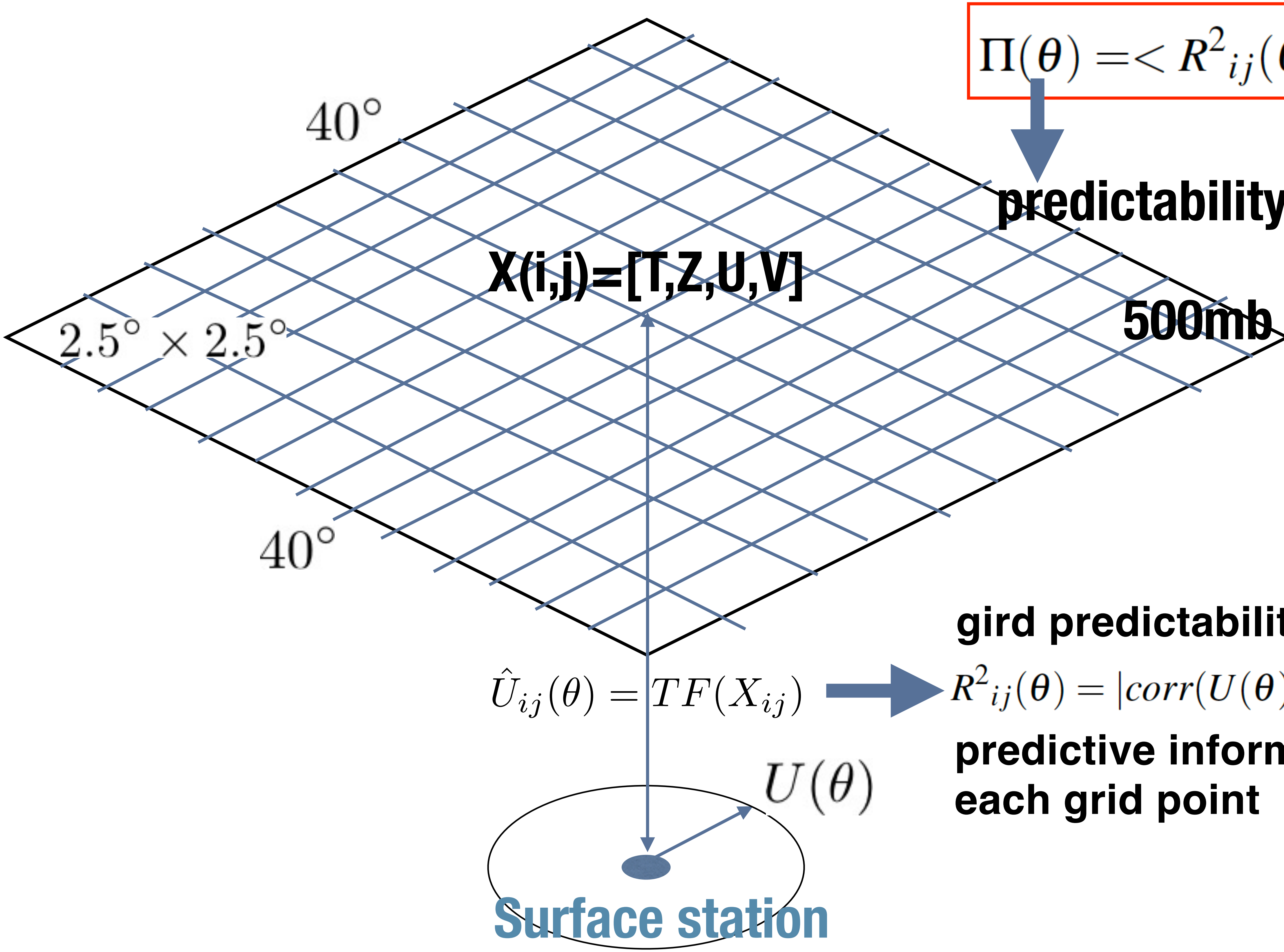
Culver AM, Monahan AH. The statistical predictability of surface winds over western and central Canada. Journal of Climate. 2013 Nov;26(21):8305-22.

Prediction at each station

average of top 2% gird predictability

$$\boxed{\Pi(\theta) = < R^2{}_{ij}(\theta) >}$$

predictability of $U(\theta)$



gird predictability

$$R^2{}_{ij}(\theta) = |corr(U(\theta), \widehat{U}_{ij}(\theta))|^2$$

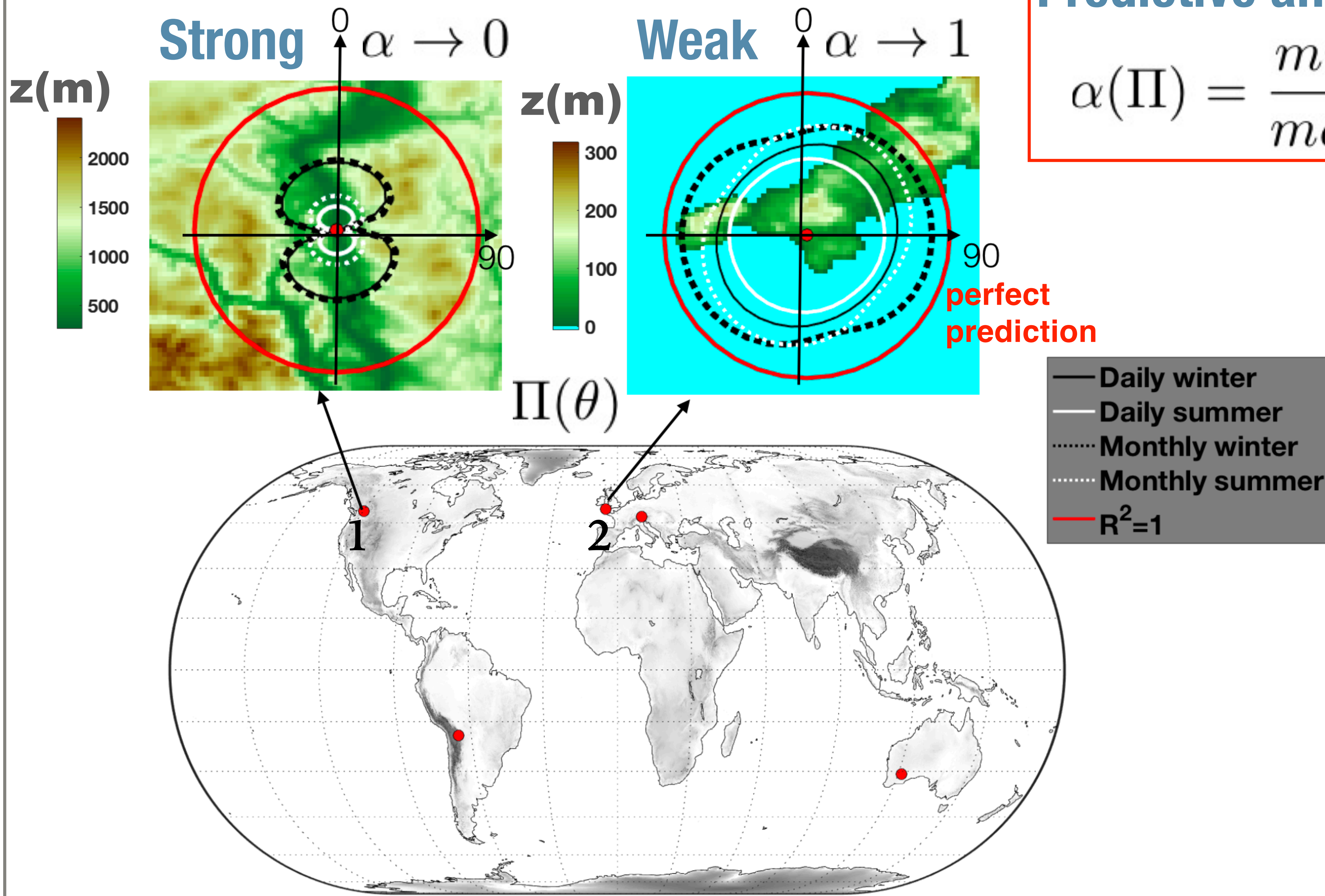
predictive information at each grid point

TF: linear regression

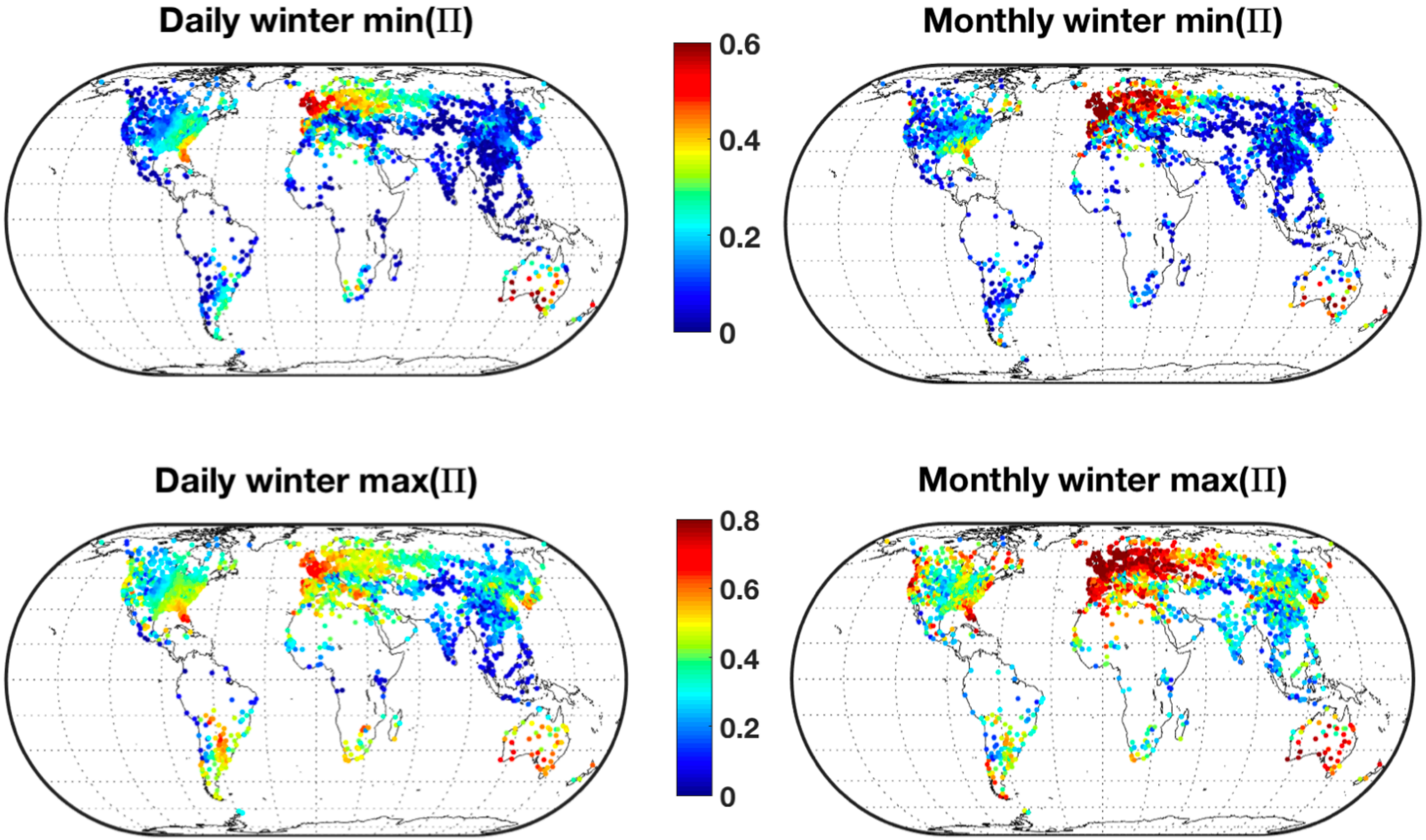
Metrics of Predictability: $min(\Pi), max(\Pi), \alpha(\Pi)$

Predictive anisotropy

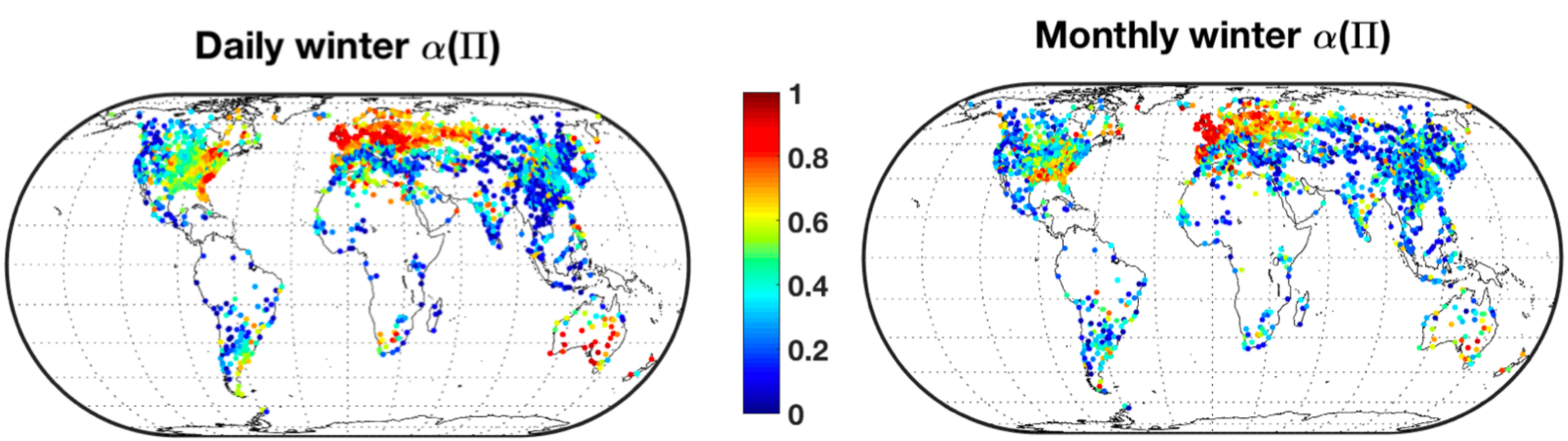
$$\alpha(\Pi) = \frac{min(\Pi)}{max(\Pi)}$$



Predictability

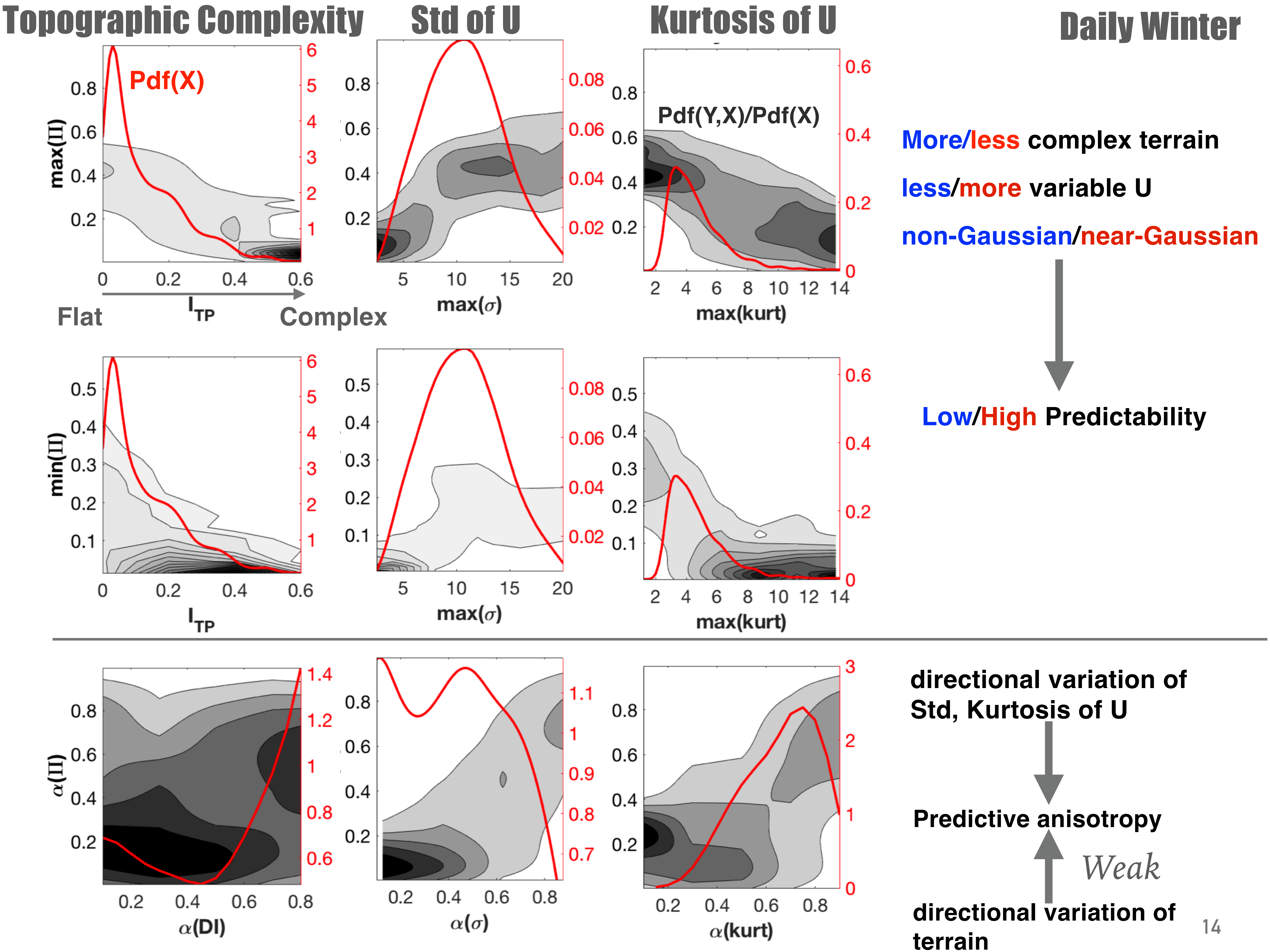


Predictive anisotropy



Potential factors that can influence predictability

- Topographic complexity
- Variability and shape of fluctuations of surface wind components



Topographic Complexity
Std of U
Kurtosis of U
Daily Winter
Pdf(X)
Pdf(Y,X)/Pdf(X)
max(II)
min(II)
α(II)
I_{TP}
Flat
Complex
max(σ)
max(kurt)
α(DI)
α(σ)
α(kurt)
More/less complex terrain
less/more variable U
non-Gaussian/near-Gaussian
Low/High Predictability
directional variation of Std, Kurtosis of U
Predictive anisotropy
Weak
directional variation of terrain

$\rho(\Pi(\theta), DI(\theta))$

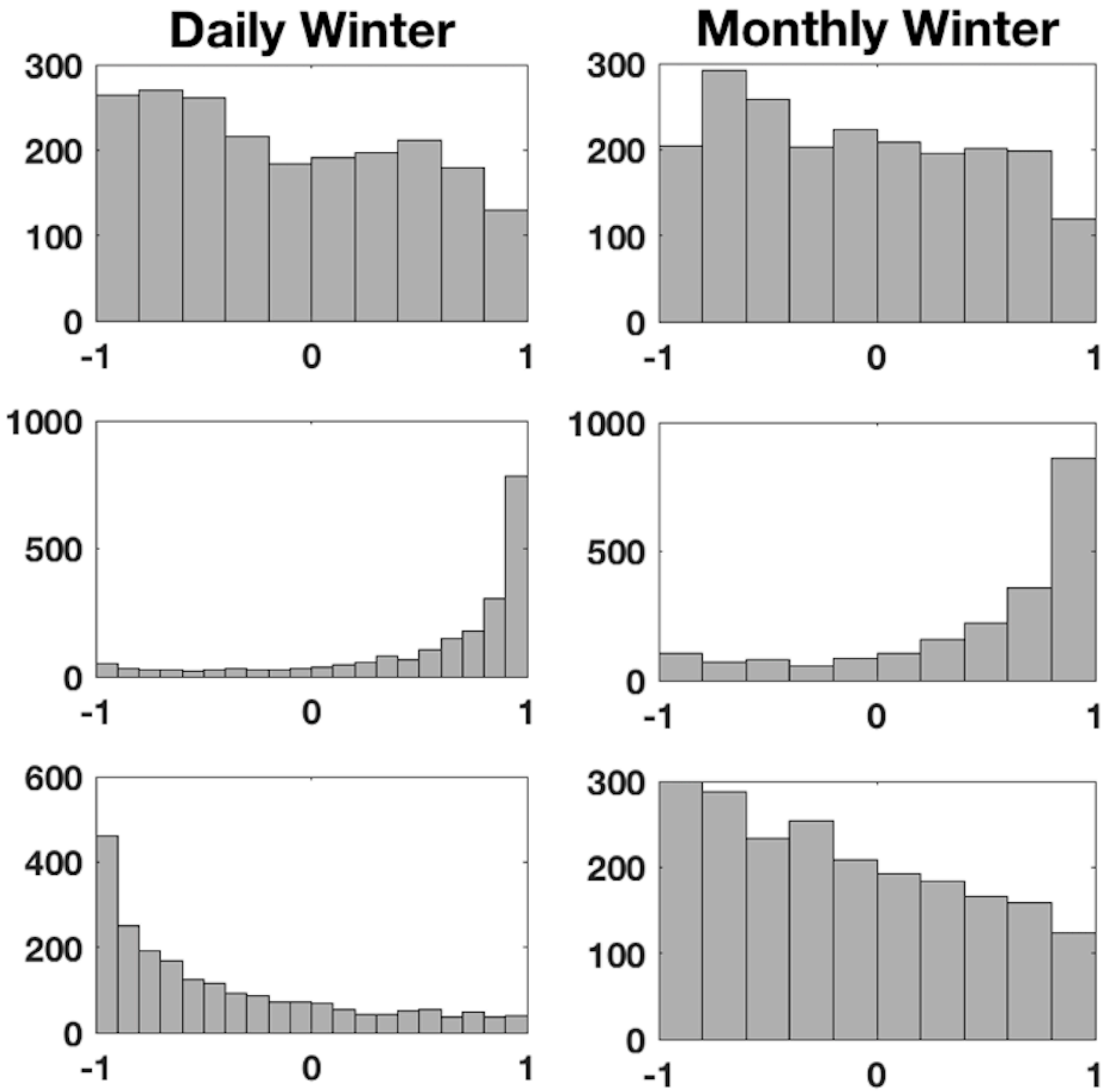
Terrain

$\rho(\Pi(\theta), \sigma(\theta))$

U Variability

$\rho(\Pi(\theta), kurt(\theta))$

U Distribution



direction of Low/High Predictability

direction of

- **more/less complex terrain**
- **less/more variable fluctuation**
- **non-Gaussian/near-Gaussian**

Rank correlation coefficient

$\rho \to 1$ Directional maxima (minima) tend to align

$\rho \to -1$ Directional maxima (minima) tend to be orthogonal

$\rho \to 0$ No directional relationships

Idealized model

$$U(\theta) = Noise + Signal$$

- zero linear correlation with predictors
- Isotropic
- non-Gaussian

- Perfect linear correlation with predictors
- vary with direction
- Gaussian

$$\Pi(\theta) = corr^2(U(\theta), Signal)$$

Idealized model

$$U(\theta) = U_x + g(\theta)U_y,$$

Noise **Signal**

$$\Pi(\theta) = corr^2(U, U_y) = \frac{G(\theta)}{\beta + G(\theta)}$$

$$\sigma(\theta) = \sqrt{V_x + V_y G(\theta)},$$

$$kurt(\theta) = \frac{K_x\beta^2 + G(\theta)^2 K_y + 6G(\theta)\beta}{\beta^2 + 2G(\theta)\beta + G(\theta)^2},$$

where,

$G(\theta) = g^2(\theta) \quad 0 \leq G(\theta) \leq 1$

$V_x =$ Variance of U_x (Noise)

$V_y =$ Variance of U_y (Signal)

$$\beta = \frac{V_x}{V_y}$$

$K_x > 3$ Kurtosis of U_x (Noise)

$K_y = 3$ Kurtosis of U_y (Signal)

Simulate metrics:

$$min(\sigma) = \sqrt{V_x + V_y G_{min}},$$

$$max(\sigma) = \sqrt{V_x + V_y},$$

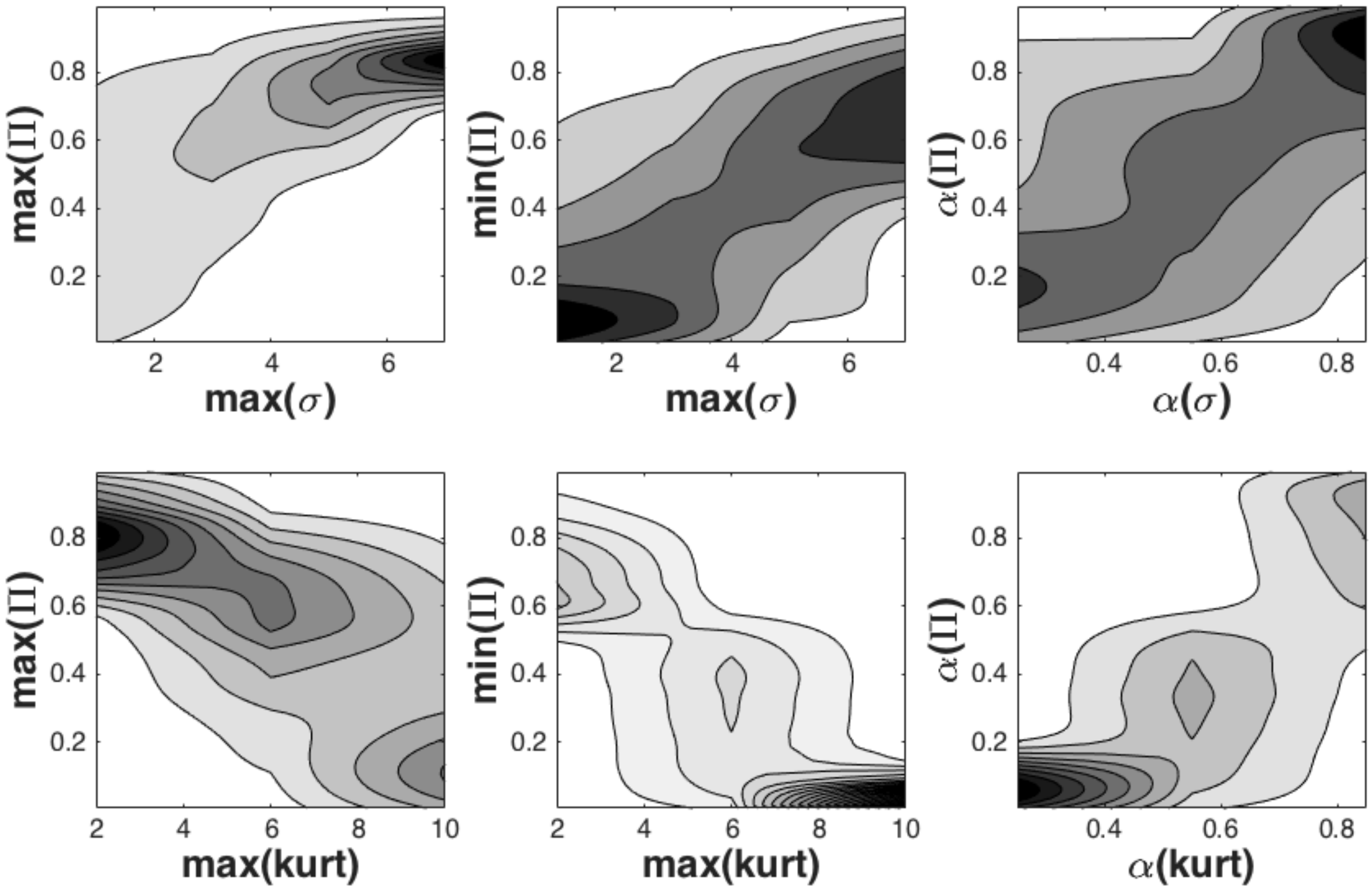
$$min(kurt) = \frac{K_x\beta^2 + K_y + 6\beta}{\beta^2 + 2\beta + 1},$$

$$max(kurt) = \frac{K_x\beta^2 + G^2{}_{min}K_y + 6G_{min}\beta}{\beta^2 + 2G_{min}\beta + G^2{}_{min}},$$

$$min(\Pi) = \frac{G_{min}}{\beta + G_{min}},$$

$$max(\Pi) = \frac{1}{\beta + 1};$$

Idealized model



Signal-to-noise ratio:

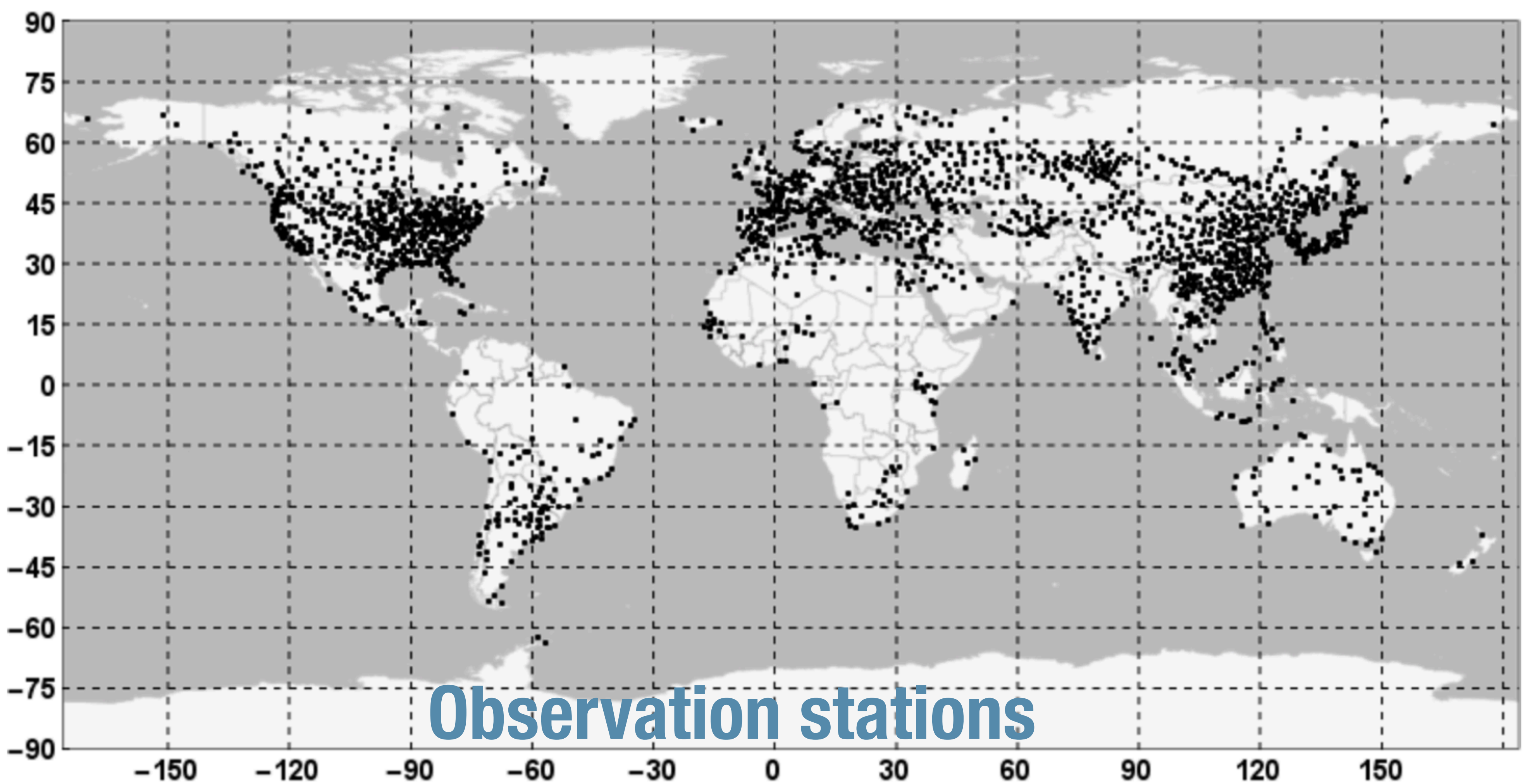
accounts for observed characteristics of linear predictability (e.g. predictive anisotropy)

Origin of the noise:

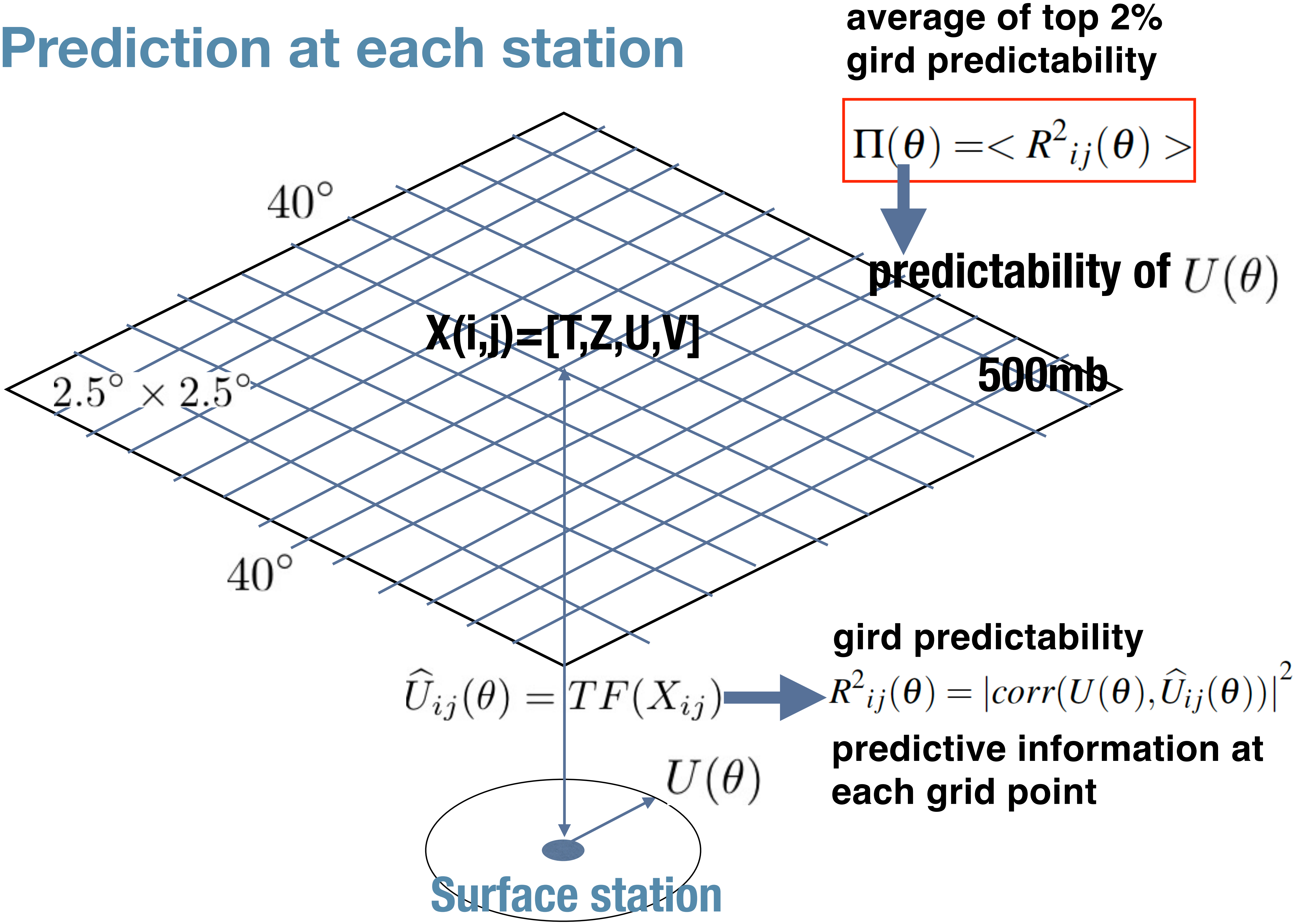
- physical factors?
- nonlinear predictor-predictand relationship?

Linear vs nonlinear TFs

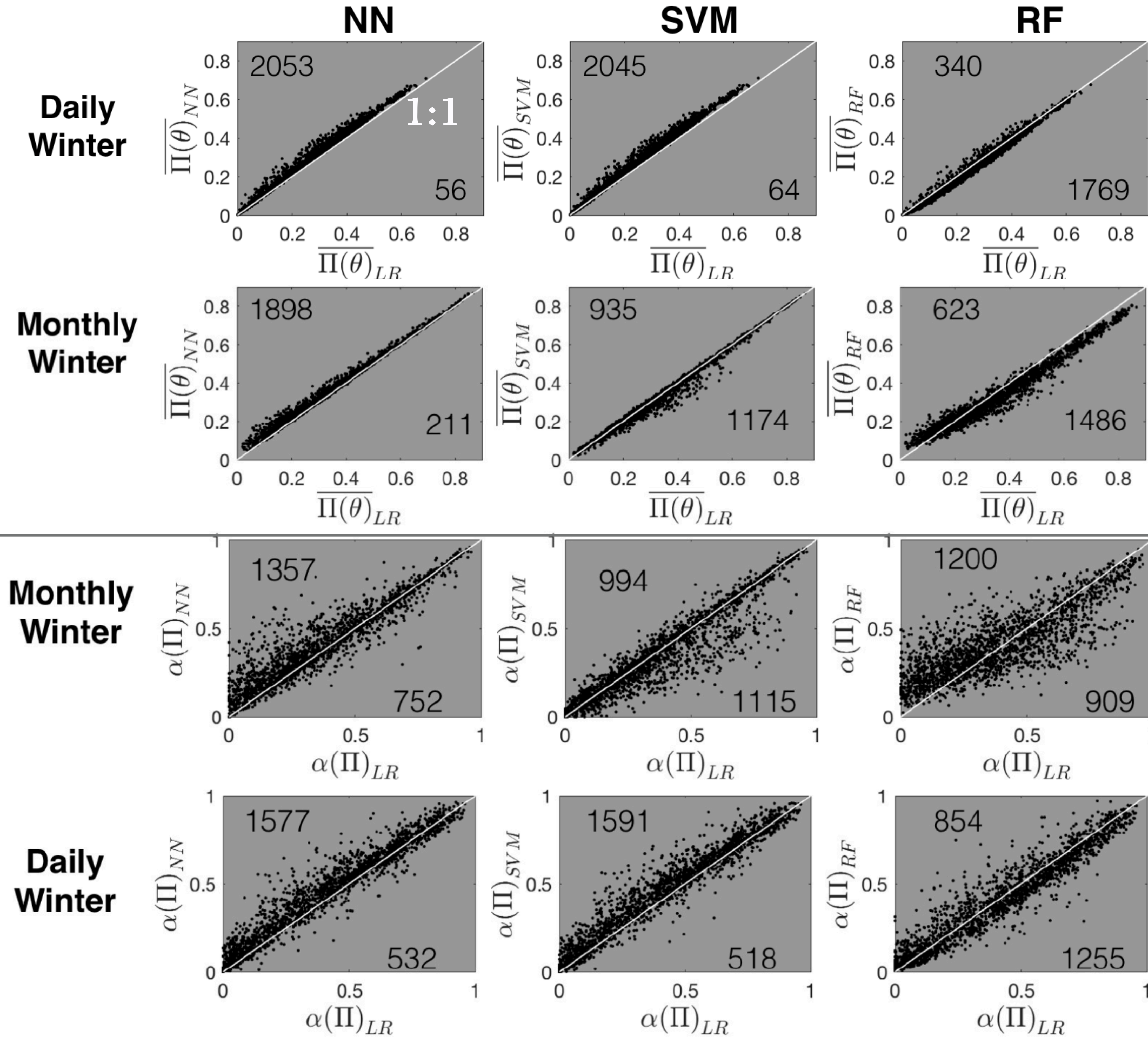
- Nonlinear prediction of surface wind components is carried out at the same 2109 stations
- Neural network (NN), Support vector machine (SVM), Random Forest (RF)



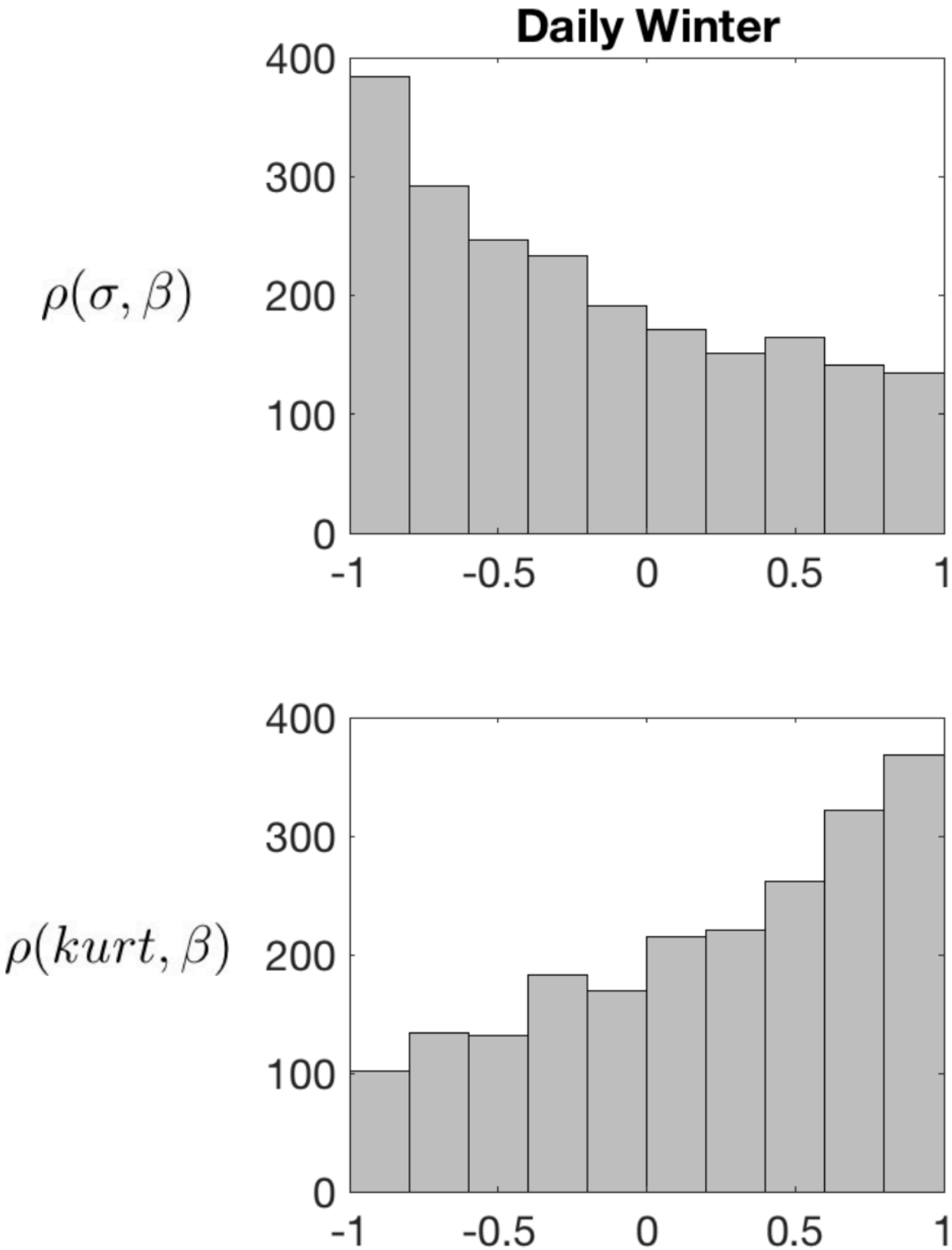
Prediction at each station



TF: nonlinear (NN, SVM, RF)



NN
SVM
RF
Daily Winter
Monthly Winter
Monthly Winter
Daily Winter
2053
56
1:1
2045
64
340
1769
1898
211
935
1174
623
1486
1357
752
994
1115
1200
909
1577
532
1591
518
854
1255
$\overline{\Pi(\theta)}_{NN}$
$\overline{\Pi(\theta)}_{SVM}$
$\overline{\Pi(\theta)}_{RF}$
$\overline{\Pi(\theta)}_{LR}$
$\alpha(\Pi)_{NN}$
$\alpha(\Pi)_{SVM}$
$\alpha(\Pi)_{RF}$
$\alpha(\Pi)_{LR}$



$$\beta = \frac{\Pi(\theta)_{BestNL}}{\Pi(\theta)_{LR}}$$

Systematic improvement by NL
no substantial improvement by NL
e.g.,

$$\beta = 10 \qquad \Pi_{NL} = 0.1 \qquad \Pi_{LR} = 0.01$$

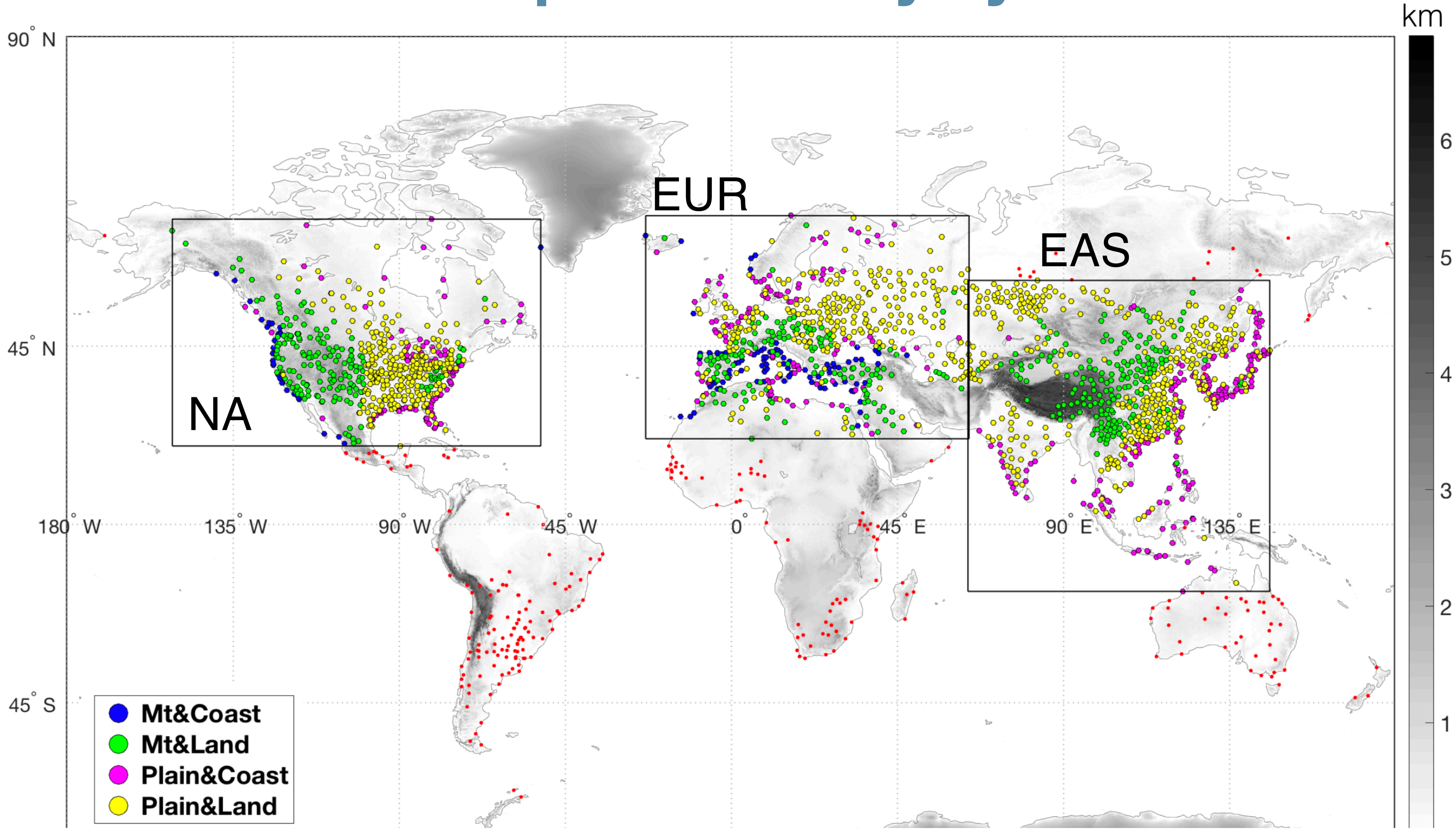
No compelling evidence to suggest that strong nonlinear relationships exist between large-scale predictors and surface wind components

predictive anisotropy (***contributing factors***)

- wrong functional form of TF (i.e. linear TF)? ✗
- physical factors?

Can **predictive anisotropy** be explained by some **unknown physical factors?**

Simulation of linear predictability by RCMs and Reanalysis

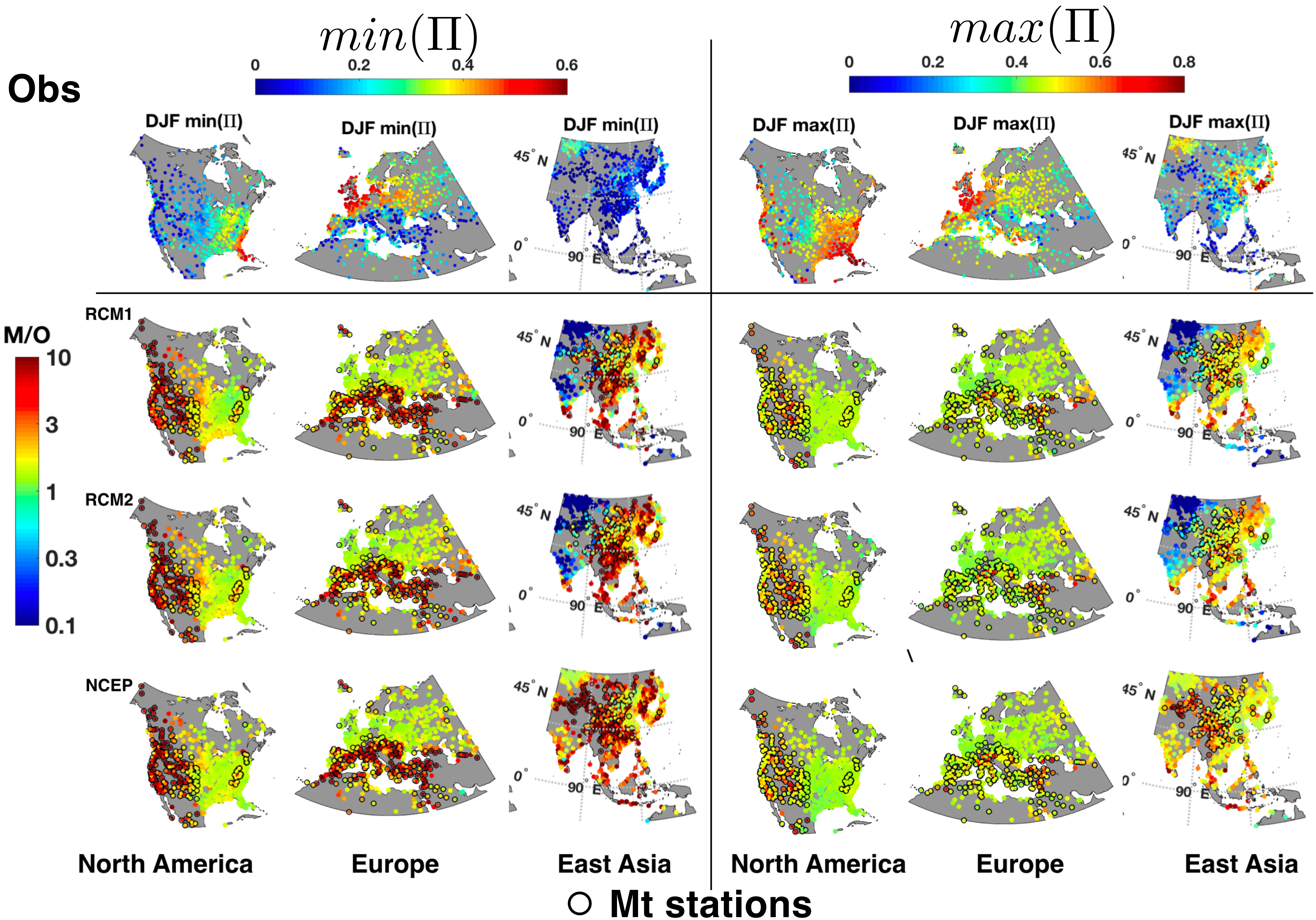


DJF, JJA

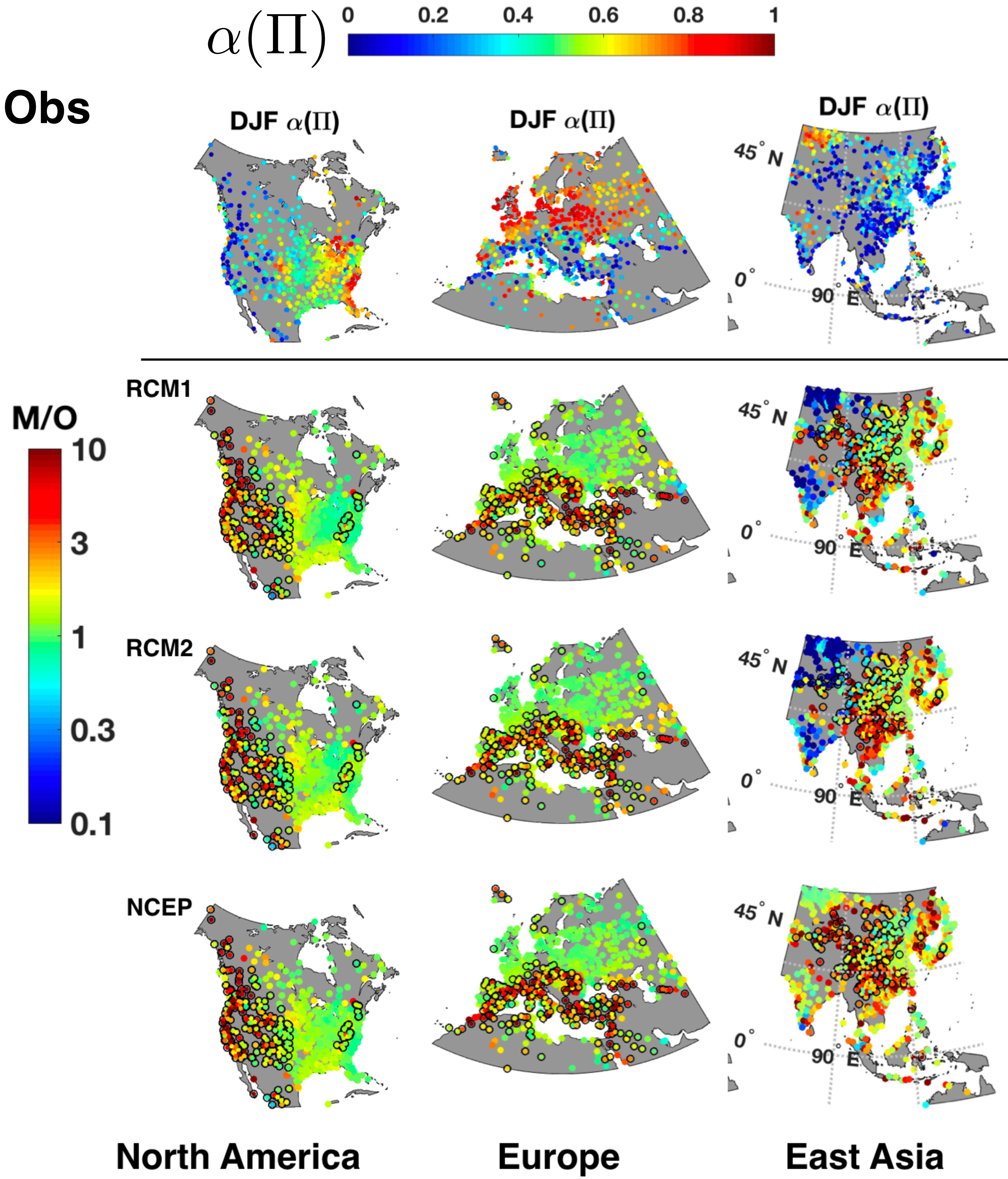
Daily

Labels	Driving reanalysis	Regional models	Modeling Group	Project	References
NA1	ECMWF-ERAINT	Canadian Regional Climate Model 4 (CanRCM4)	Canadian Centre for Climate Modelling and Analysis (CCCma)	CORDEX	Scinocca et al., 2016
NA2	NCEP2	Weather Research & Forecasting Model (WRF)	Pacific Northwest National Lab, US	NARCCAP	Mearns et al., 2007,updated 2014
EUR1	ECMWF-ERAINT	Rossby Centre regional atmospheric model (RCA4)	Swedish Meteorological and Hydrological Institute (SMHI)	CORDEX	Strandberg et al., 2015
EUR2	ECMWF-ERAINT	Canadian Regional Climate Model 4 (CanRCM4)	Canadian Centre for Climate Modelling and Analysis (CCCma)	CORDEX	Scinocca et al., 2016
EAS1	ECMWF-ERAINT	HadGEM3-RA	National Institute of Meteorological Research (NIMR), Korea	CORDEX	Davies et al., 2005
EAS2	NCEP2	Weather Research & Forecasting Model (WRF)	Seoul National University (SNU), Korea	CORDEX	Skamarock et al., 2005

NCEP2



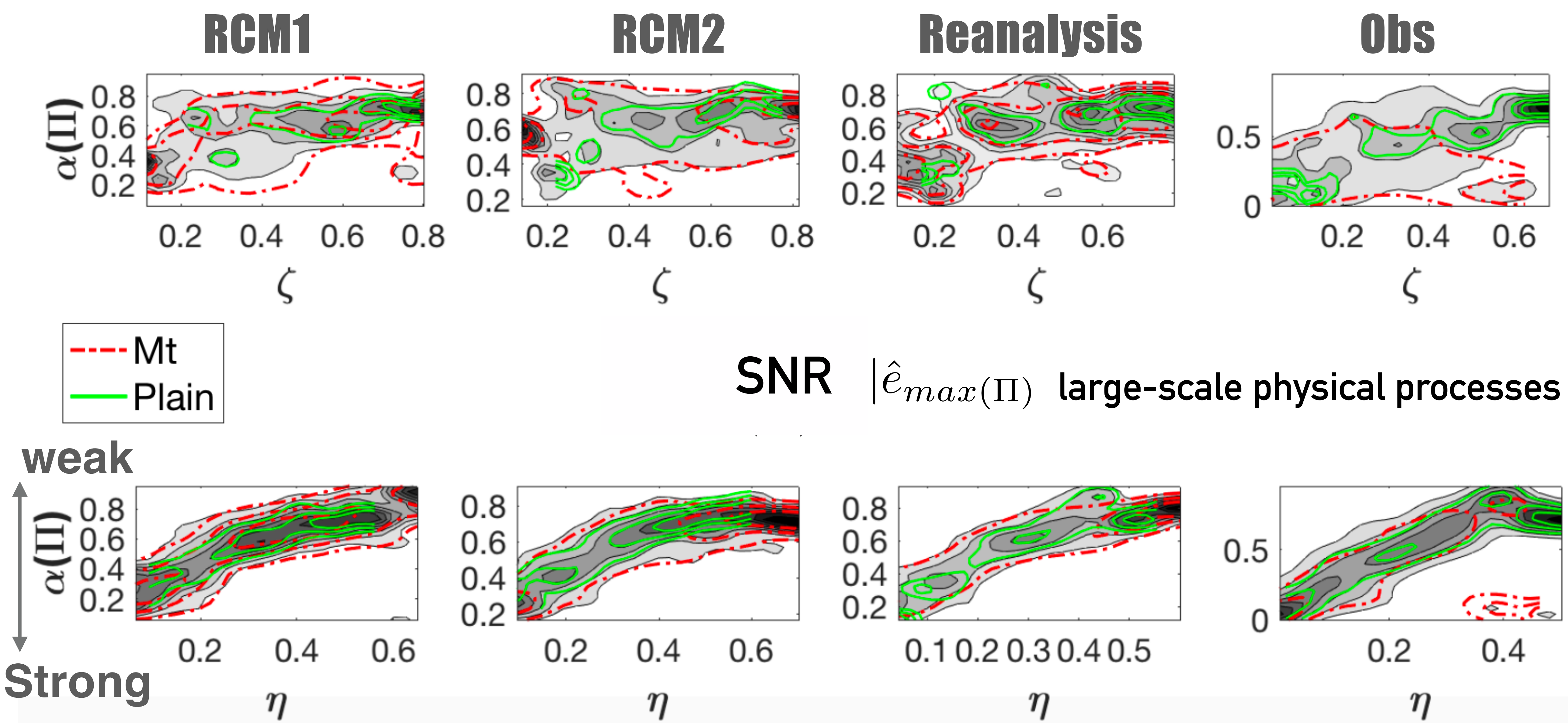
RCMs cannot capture small-scale physical processes (e.g. associated with surface heterogeneity)



Simulated predictive anisotropy is substantially weakened in mountainous region.

Small-scale physical processes (not captured by RCMs) contribute to predictive anisotropy

North America, (Europe, East Asia)



SNR $\left|\hat{e}_{max(\Pi)}\right.$ large-scale physical processes

SNR $\left|\hat{e}_{min(\Pi)}\right.$ small-scale physical processes

Predictive anisotropy can be explained by small-scale physical processes.

Conclusions

- Predictive anisotropy is a ***common*** feature
- Surface wind components are ***better predicted*** along the directions characterized by ***more variable*** and near ***Gaussian*** fluctuations.
- ***Poor predictability*** is often found in ***topographic complex*** regions (e.g. mountainous regions), along the directions of ***weak and non Gaussian*** fluctuations of surface wind components.
- ***No*** concrete evidence to show that the relationships between free-tropospheric predictors and surface wind components are ***nonlinear***.
- ***Small scale physical processes*** (not captured by RCMs) contribute to ***predictive anisotropy***.
- **Future study is needed to identify physical processes responsible for predictive anisotropy.**