CLIMATE INTERPOLATION
MATHEMATICAL NOTES ON METHODS
PART2

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NCEAS, July 22, 2012

Notes assembled during the production of the climate interpolation review.

CLIMATE INTERPOLATION
NCEAS ROUNDTABLE
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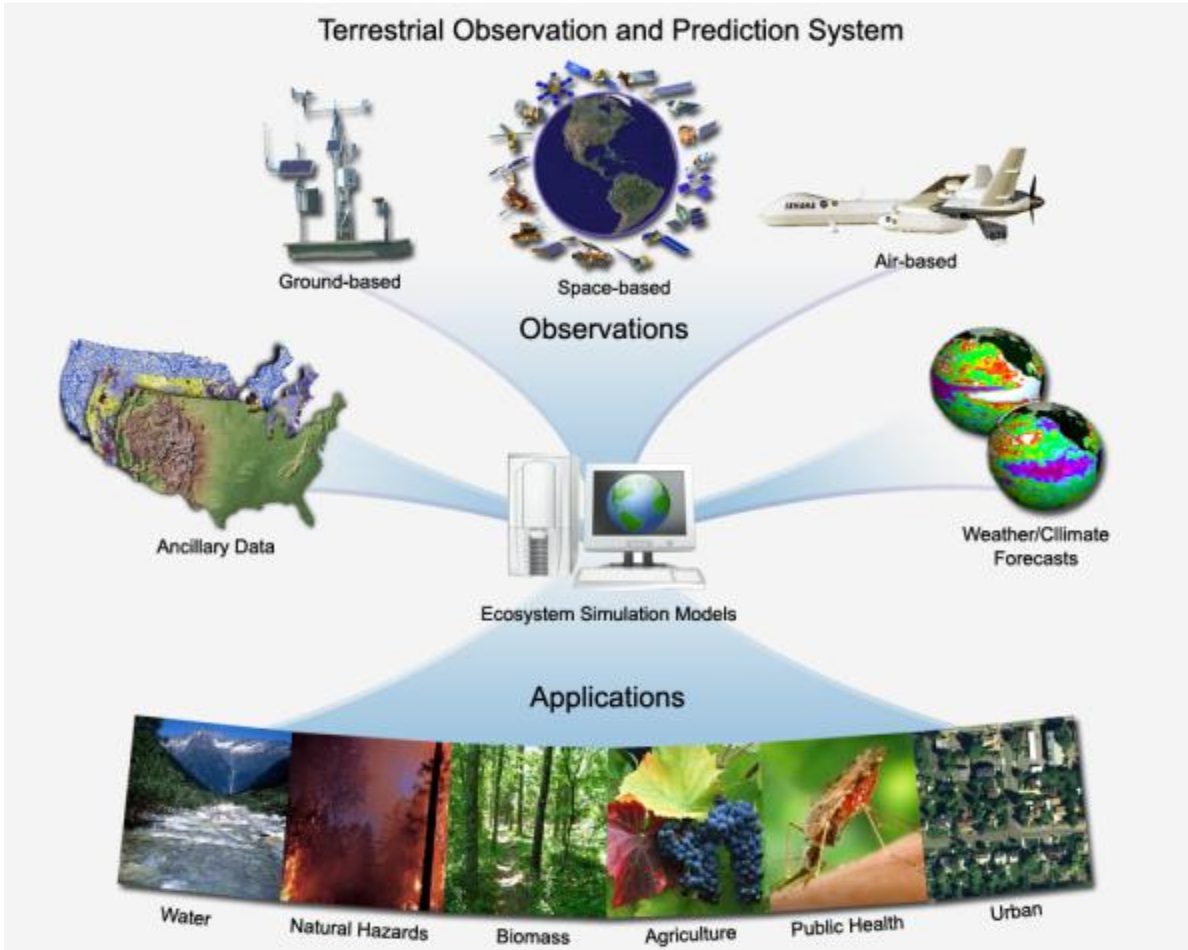
NCEAS, June 29, 2012
Santa Barbara, CA

Notes assembled during the production of the climate interpolation review.

CLIMATE INTERPOLATION

…just one piece of a large environmental monitoring "system"



http://ecocast.arc.nasa.gov/im/topsover.png

Goal: Create a continuous set of environmental layers that can be used for many applications such as species modeling.

DOWNSCALING AND AGGREGATION

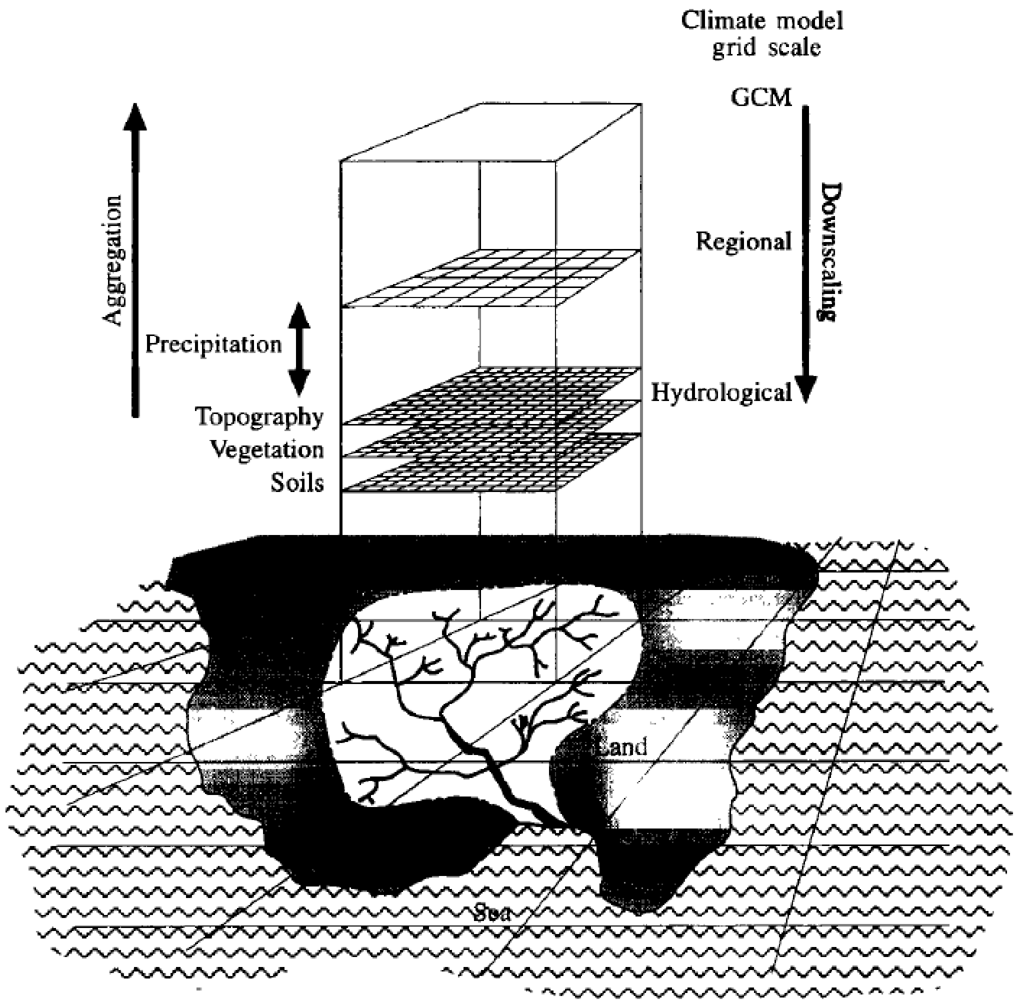


Figure 1 Conceptualization of downscaling and aggregation between atmospheric and hydrologic models
Source: Modified after Hostetler (1994)

USE OF THIS DATA SET FOR ECOLOGY

Derivation of bioclimatic variables more relevant to the biology of plants and animals….

→ Extreme events and bioclimatic variables difficult to derive for coarse temporal product…

→ Minimum temperature in a day may affect presence and absence of organisms…

MOTIVATION: WHY DO WE CARE ABOUT ENVIRONMENTAL DATA?

"In particular, the possibility of development of general, predictive models that are able to extrapolate across space or time to predict biodiversity phenomena on novel landscapes may be heavily contingent on the appropriate choice of environmental data sources."
Peterson et al. 2008:

→ Peterson et al. 2008 presents a study with 6 datasets prepared for comparison…

Data 1 and data 2

- Dataset 1 and 2 use WorldClim data at 0.0416 deg and 0.167 deg spatial resolution: WC1 and WC2

- With the following bioclimatic variables from WC: mean annual temperature, mean diurnal temperature range, isothermality, temperature seasonality, tmax of warmest month, tmin of the coldest month, temp. annual range, annual mean precip., precp of wettest month (prcp_max of months), prcp of driest month, prcp seasonality.

Dataset 3

- Uses IPCC 2001 data variables

  Tav annual, Trange_day, frost free days, Pav annual, monthly Tmin annual, monthly Tmax annual, vapor pressure and wet days,
- Resolution: 0.5 deg resampled at 0.05deg

Dataset 4

- Data from Center for Climate Research (CCR, University of Delaware) Feddema et al. 2006.

  Tav annual, Trange_day, Pav annual, Actual evapotranspiration (AET), Potential Evapotranspiration (PET), moisture deficit and surplus, soil moisture, tmax of the warmest month
- Resolution: 0.5 deg resampled at 0.05deg

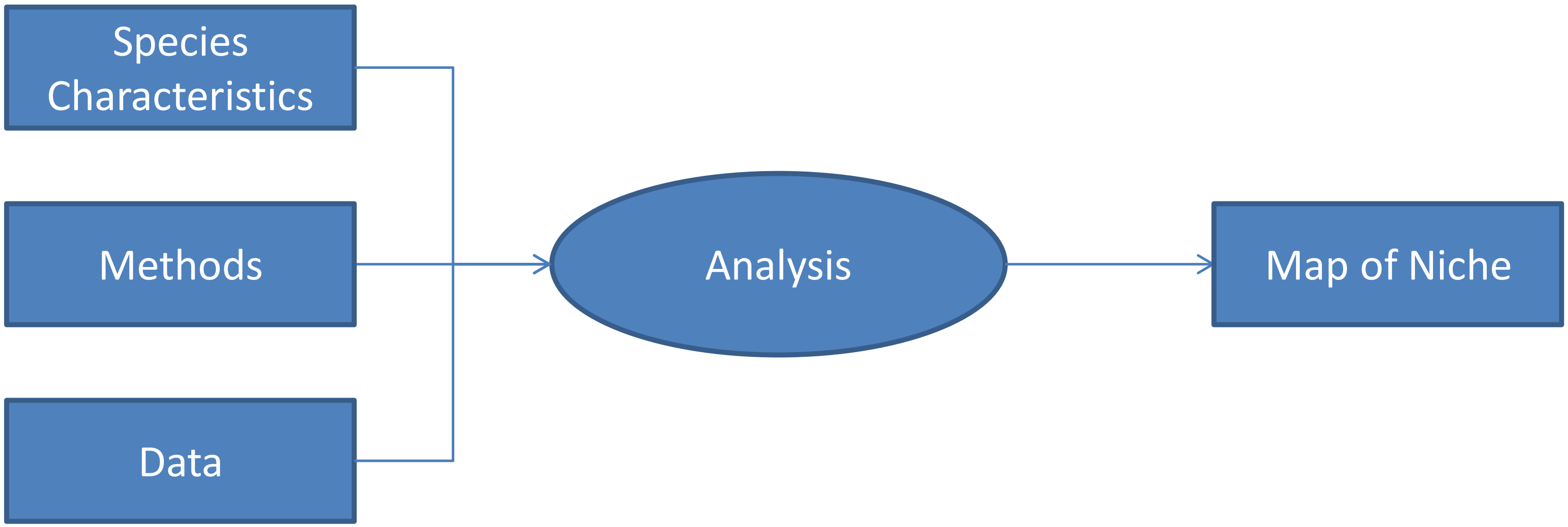
Dataset 5

- NDVI monthly AVHRR (Tucker 1979).
- Resolution: 0.08 deg. → data used in the same native resolution…

Dataset 6

- Use WorldClim data at 1 km spatial resolution: WC1 and WC2
- Variables used: annual mean precipitation, annual mean temperature, minimum temperature of coldest month, maximum temperature of the warmest month.

SPECIES NICHE MODELING



"In any case, the biological explanations for the non-predictivity between distributional areas suggested previously(Fitzpatrick et al. 2007) (and, in fact, in other recent contributions of the same nature; Broennimann et al. 2007) do not appear necessary –rather, methodological considerations suggest that the choice of environmental data sets may be responsible for the lack of correspondence."

WWW ⇔ WWG

What-We-Want : a map of the potential and actual distribution of the species of interest.
What-We-Get : a map that approximates the potential and actual distribution of the species
a map whose distribution may be influenced by Methods and Data more than the biology of the species.

INTERPOLATION PROBLEM

Predict response values at unknown location within a bounded domain.

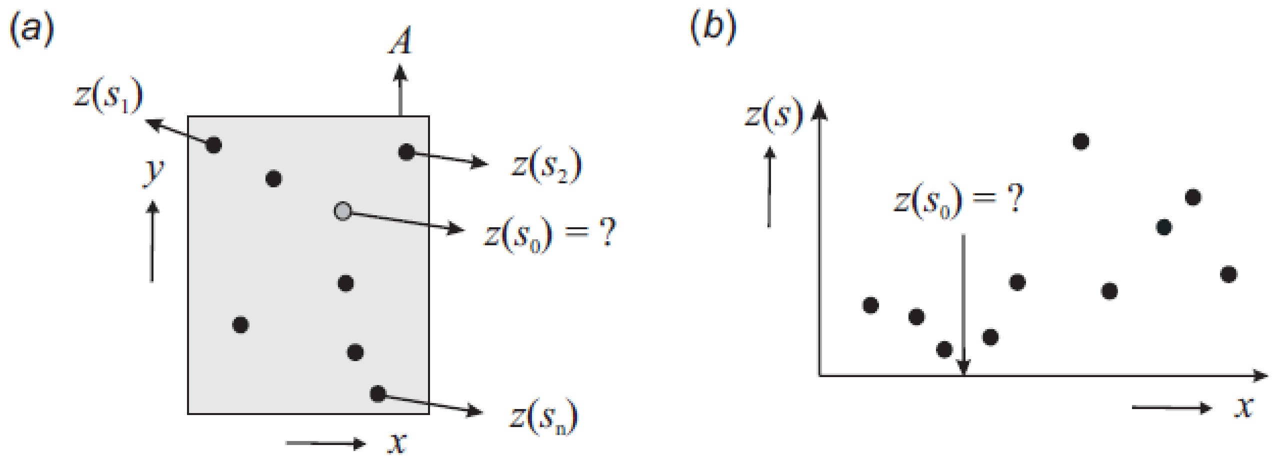


Fig. 1.7: Spatial prediction is a process of estimating the value of (quantitative) properties at unvisited site within the area covered by existing observations: (a) a scheme in horizontal space, (b) values of some target variable in a one-dimensional space.

Hengl et al. 2009:10

→ Use neighboring observations as the best "guess" i.e. prediction value.

INTERPOLATION METHODS

1. Environmental correlation/gradients methods

Use covariates (x1,…,xn) related to the response variable of interest (y) (Hengl et al. 2009).
Example: multiple linear regression

2. Geostatistical methods/Moving averages

Use response observations (yi) from sampled locations to predict unknown values of the response (y0) in another location.
Example: Kriging, IDW (Attore et al. 2007)

3. Hybrid methods

Use a mixture of environmental correlation and geostatistical methods (Stahl et al. 2006, Daly et al. 1994, Daly et al. 2002)
Example: GWR, Regression Kriging, PRISM, GAM with TPS and interactive lat-long term (Hutchinson et al. 1995)

4. Machine Learning methods

Based on the framework of pattern recognition, the goal is to learn typical patterns from a training dataset to predict the response value given the pattern in a set of features (i.e. covariates).
Example: Neural Network: MLP (Attore et al. 2007), regression trees

5. Anomaly-Climatology Based

Based on separating the temporal variability in different components: a normal and an anomaly.
This is a multi-step approach: model normal and model anomaly separately and add the results together to get the final result.

GLOBAL VERSUS LOCAL COMPONENTS

Local to Global: bottom up approach i.e. from local variation to global trend reconstruction. This type of approach is related to the summation of filter or kernel functions R (**x**). The non-stationary component or trend function T (**x**) can be added afterward or is related directly to R (**x**): e.g. Thin Plate Splines, Regularized Tension Splines (RST).

Global to local: top to bottom approach, i.e. fit a trend function T (**x**) to represent the global variability and add local variability using a Kernel function R **(x)**: Universal kriging.

$$Z(s) = m(s) + \varepsilon'(s) + \varepsilon''$$

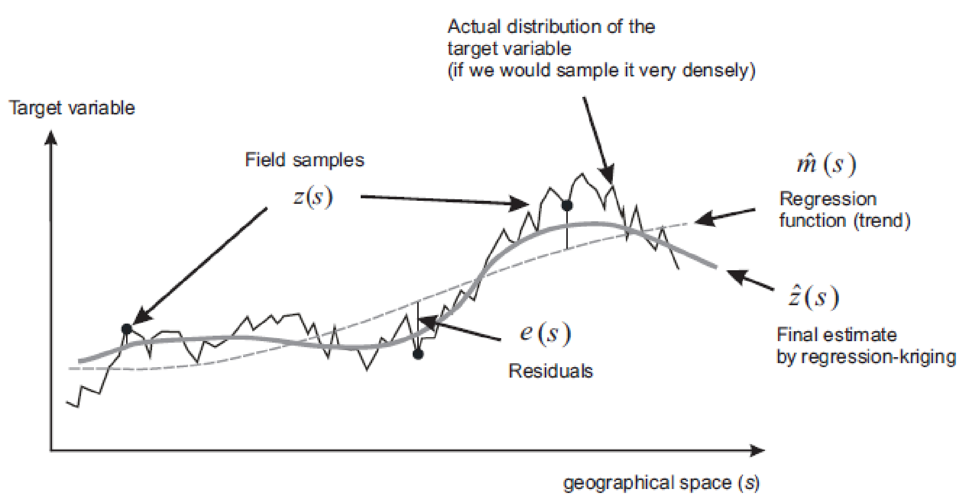


Fig. 2.1: A schematic example of the regression-kriging concept shown using a cross-section.

Global component:
T(x) = a0*+a1*x1 + …+am*xm +ε

Local component:
Σ R (x) : Sum of Kernel based estimations.

Sometimes it is possible to mathematical express the following:
Y = global + local
Y(x) = T(x) + Σ R (x)

Hengl 2009.

INTERPOLATION WITH GLOBAL AND LOCAL COMPONENTS

Local to Global: bottom up approach i.e. from local variation to global trend reconstruction. This type of approach is related to the summation of filter or kernel functions R (**x**). The non-stationary component or trend function T (**x**) can be added afterward or is related directly to R (**x**): e.g. Thin Plate Splines, Regularized Tension Splines (RST).

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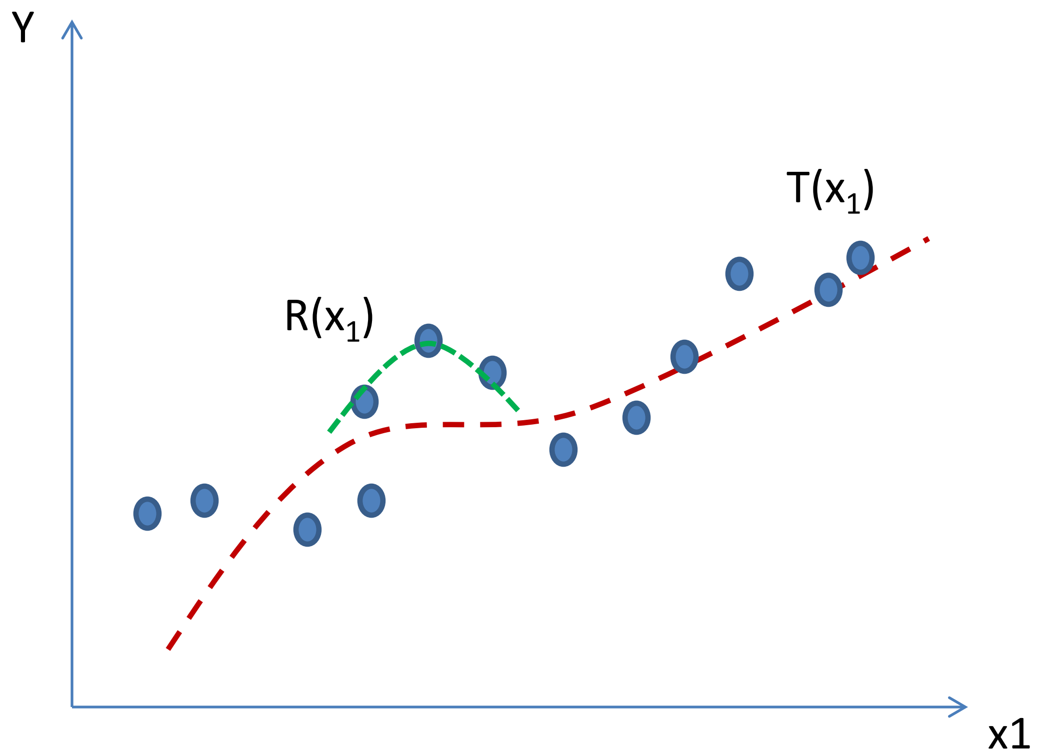


Global component:
T(x) = a0*+a1*x1 + …+am*xm +ε

Local component:
Σ R (xn) : Sum of Kernel based estimations.

Sometimes it is possible to mathematical express the following:
Y = global + local
Y(x) = T(x) + Σ R (x)

m: number of covariates
n : number of observations

Hybrid methods METHODS

Weights can be dependent on the spatial structures and/or covariates

a_i = coefficients

$y0 = \Sigma a_i * y_i$

$y = \Sigma a_i(x_{ij}) * y_i$

a(ri) : term dependent on a kernel function with r being the distance. e.g. IDW, Simple Kriging

$a(x_{ij})$: term dependent on covariates: e.g. PRISM with the distinction that PRISM includes a master/trend equation

EQUIVALENCE BETWEEN TPS AND KRIGING IN 2D

Using the concept of duality the general solution to TPS can be written as:

$$f(x) = \sum_{j=1}^{M} a_j \phi_j(x) + \sum_{i=1}^{n} b_i \psi(r_i)$$

m= the number of covariates

n = the number of points

Hutchinson et al. 1994

In two dimensions

For the interpolating spline, we have (Duchon, 1975):

$$\sigma(x) = \sigma(u, v) = \boxed{a_0 + a_1 u + a_2 v} + \boxed{\sum_{\alpha=1}^{n} b^{\alpha} r_{\alpha}^{2} \log r_{\alpha}} \quad (10)$$

where

$$r_{\alpha}^{2} = (u - u_{\alpha})^2 + (v - v_{\alpha})^2$$

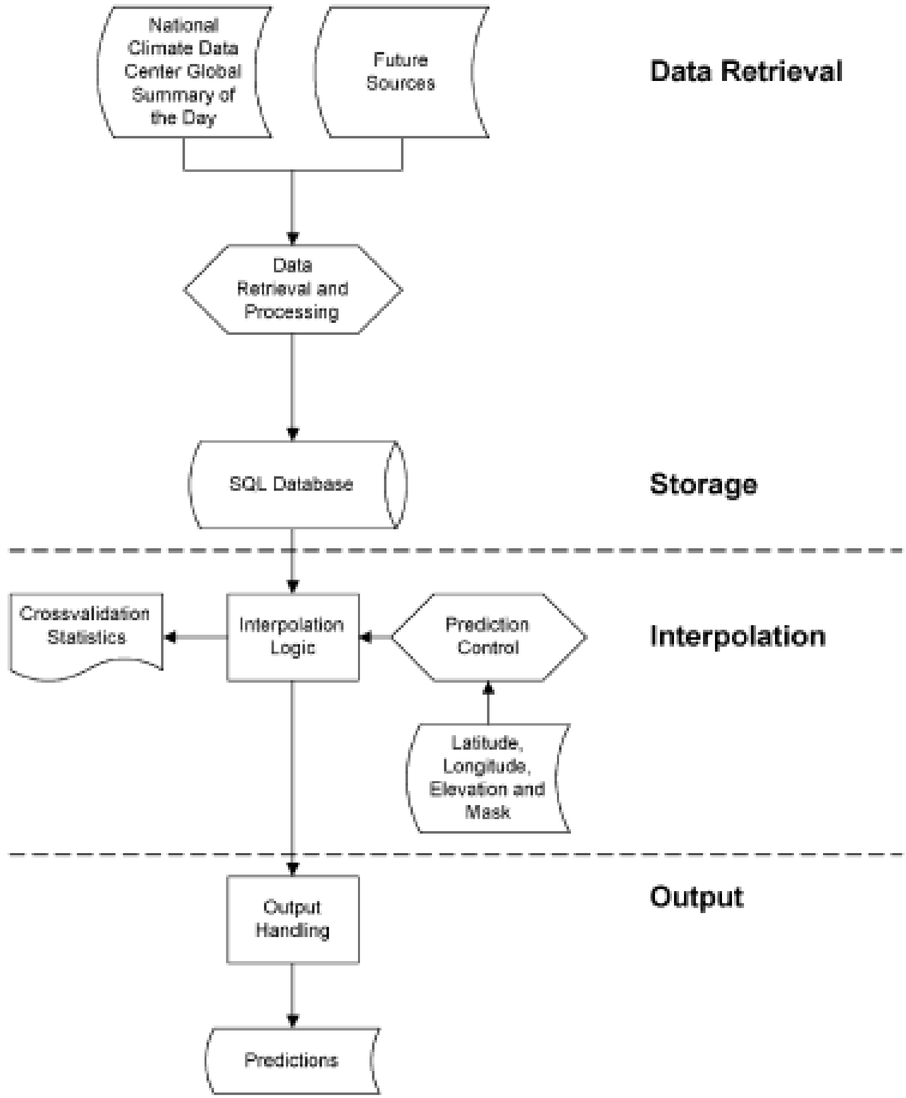
Global component from trend analysis

Local component from the covariance structure

Dubrule et al. 1984

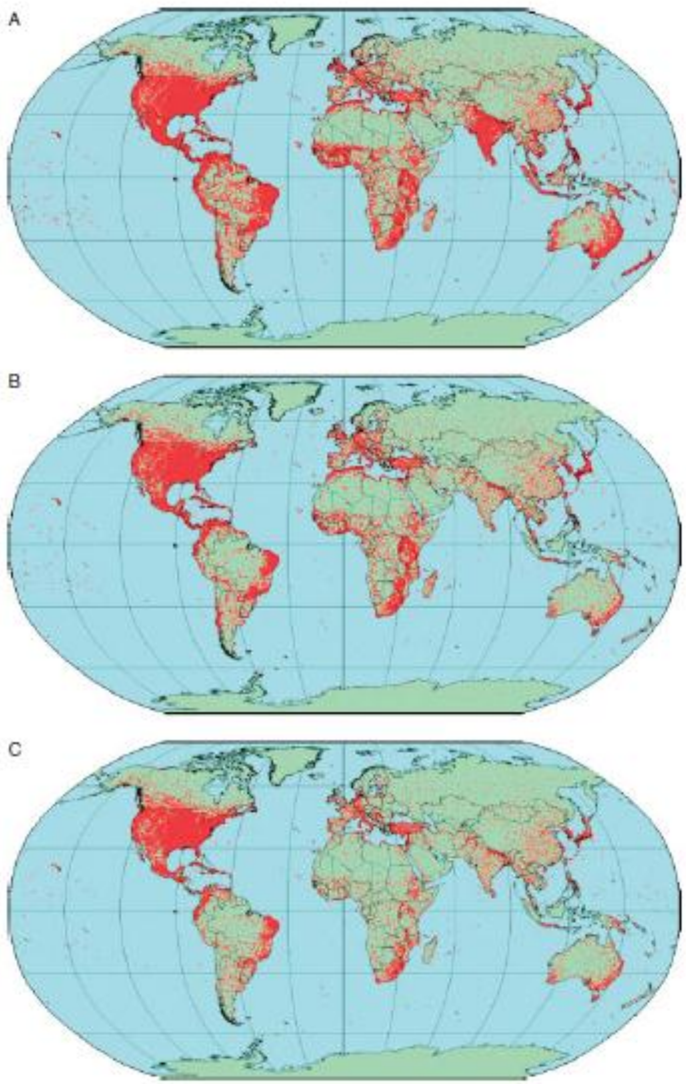
ENVIRONMENTAL DATASET PRODUCTION: TYPICAL WORK FLOW

Jolly et al. 2005



Workflow from SOGS (Jolly et al. 2005) used in NASA Terrestrial Observation and Prediction System (Nemani et al. 2009).

SCARCITY-WORLDCLIM STATION DATA DISTRIBUTION



Networks are typically sparse but improving constantly. For instance, compared to WorldClim New et al. 2002 had:

- 57% of the precipitation station of WorldClim
- 52% of mean temperature of WorldClim
- 74% of the temperature range of WorldClim

Figure 1. Locations of weather stations from which data was used in the interpolations. (A) precipitation (47 554 stations); (B) mean temperature (24 542 stations); (C) maximum or minimum temperature (14 930 stations). This figure is available in colour online at www.interscience.wiley.com/ijoc

EXAMPLE: DATABASE ASSESSMENT

→ Example of WWW

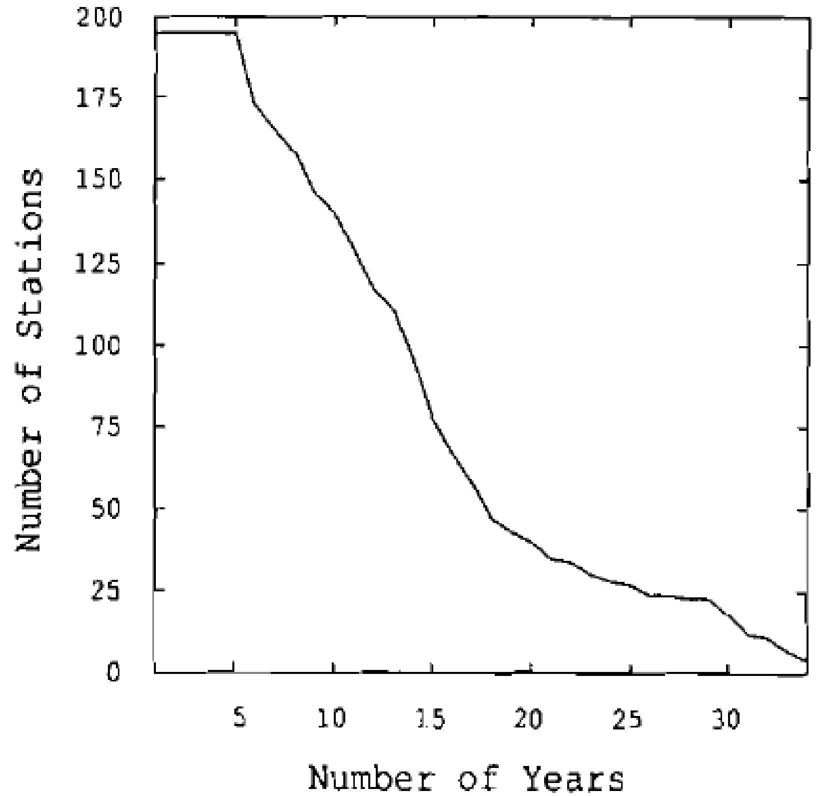
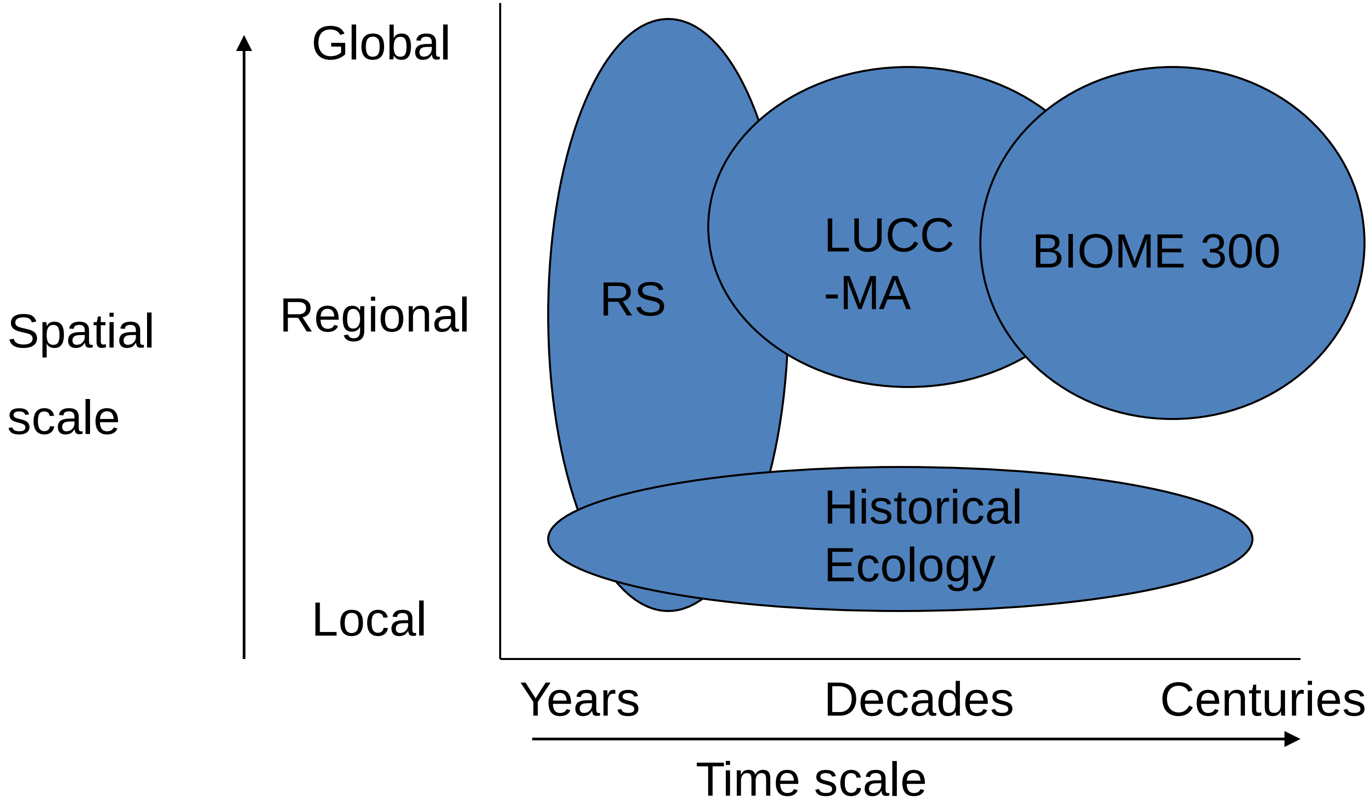


Figure 2. Number of stations for each length of record. Each station had at least 5 years of record.

Hutchinson 1995

Loss of records when doing averages over long periods…Scarcity made

Using GIS and RS to investigate EARTH SYSTEM and H-E relationship



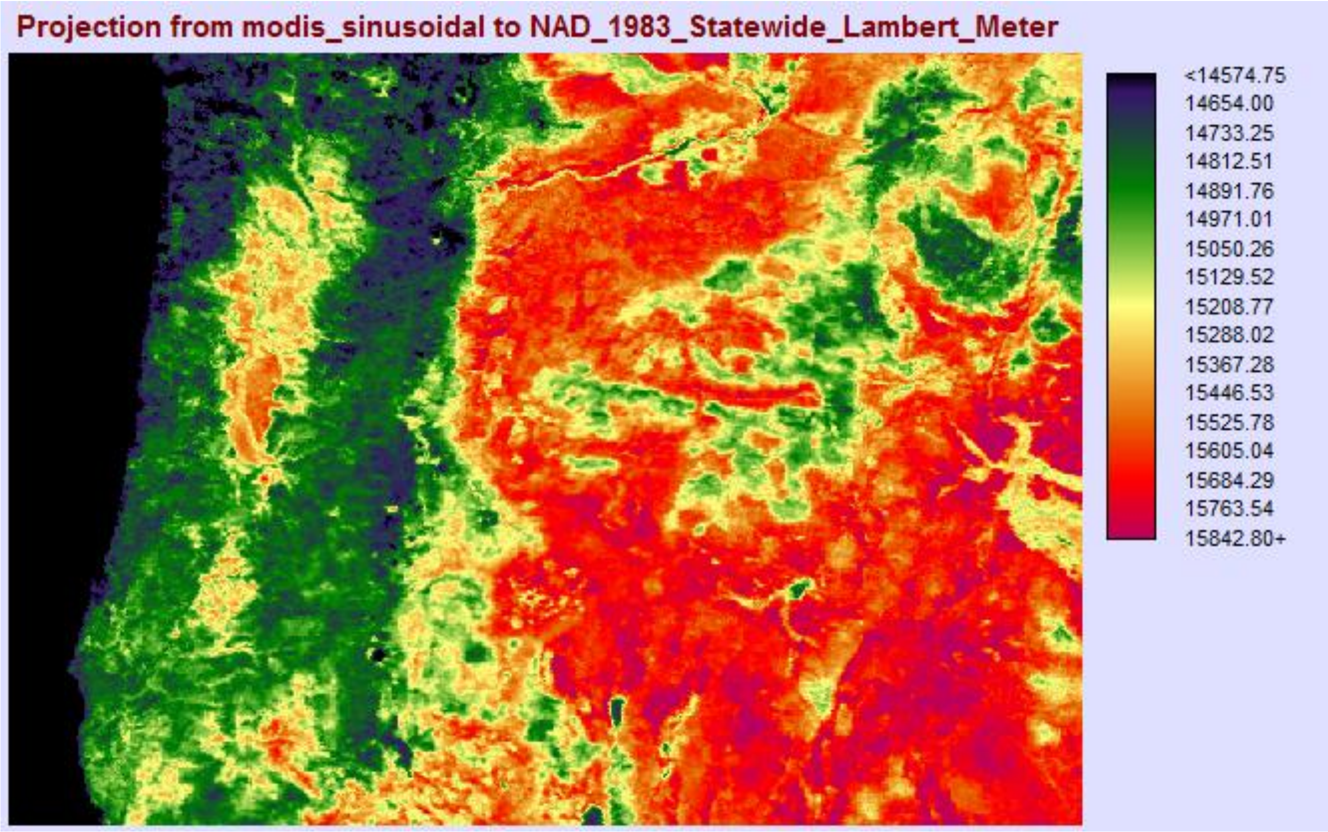
"Much of the promise of the new remote sensing techniques comes from expanding the areal extent of studies so that regional-scale phenomena such as land-use change can be addressed. The very advantages of small-scale studies (intimacy with informants, richness of the social network, insights into household structure) limit the ability of investigators to examine larger-scale phenomena.Remote Sensing`s larger spatial capabilities expand the kinds of questions that can be studied"p.94 People and Pixels.

Graphic p.11 LUCC Lambin and Geist 2006 fig.2.1

OREGON MODIS LAND SURFACE TEMPERATURE

An example of the average for day 244 (Sept 1, 2010)

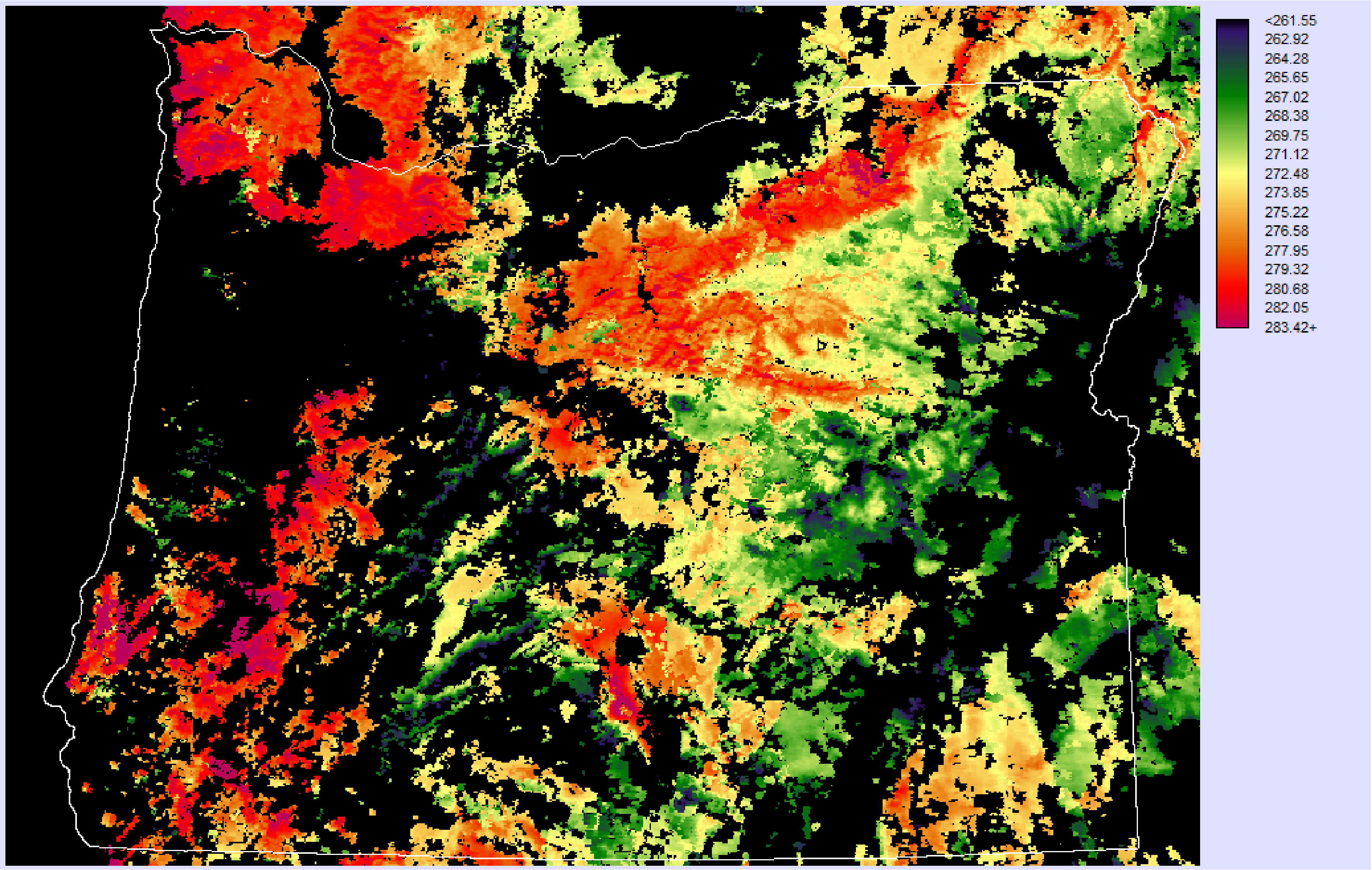
→ WWW=WWG



Average for day 244 over 2001-2010: the LST values need to be rescaled (multiplication factor is 0.02).

OREGON- DAILY MEAN FOR DOY 001

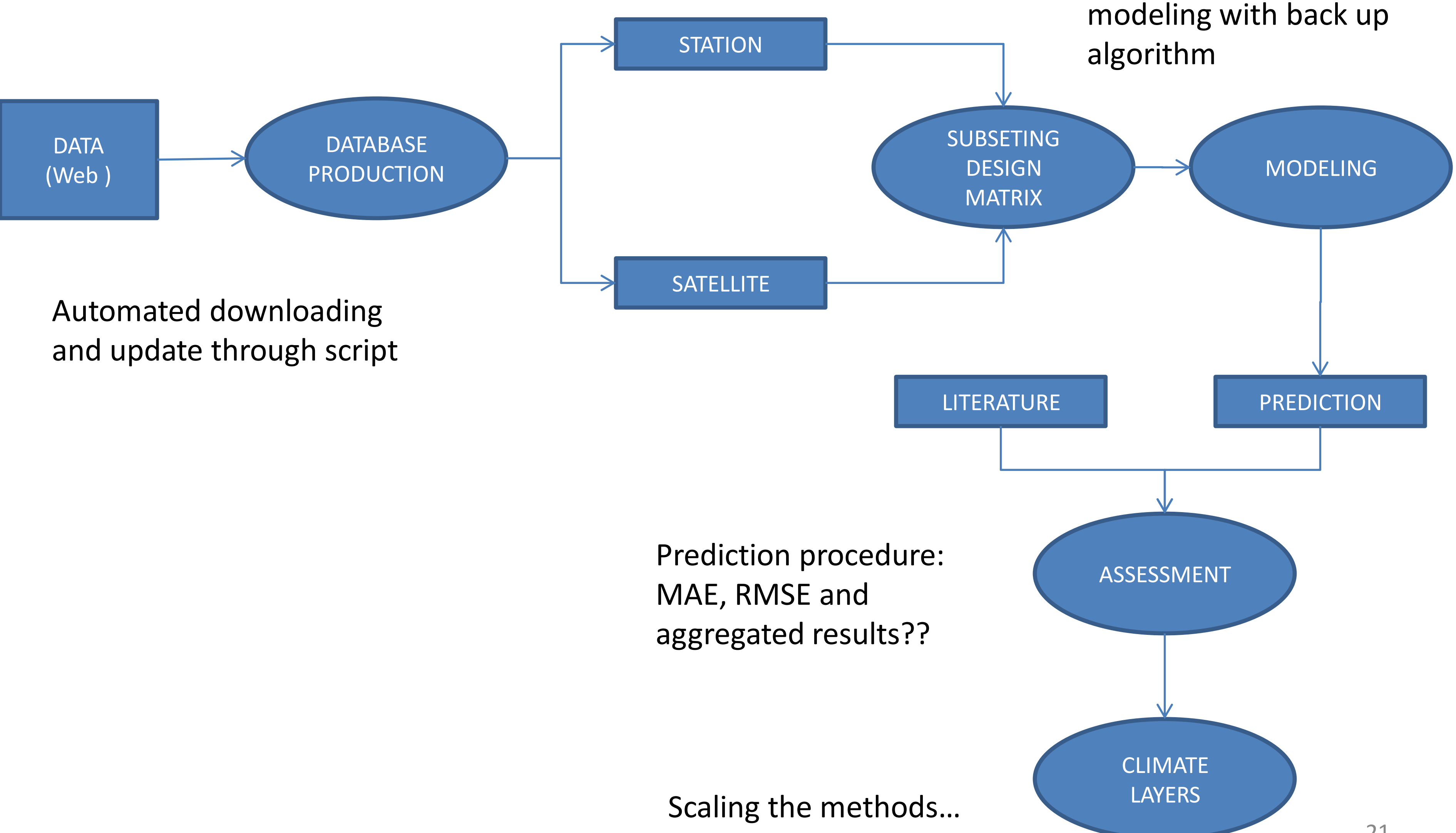
→ WWW WWG



mean_day001_rescaled.rst

GENERAL TEMPLATE

Automated subsetting and modeling with back up algorithm



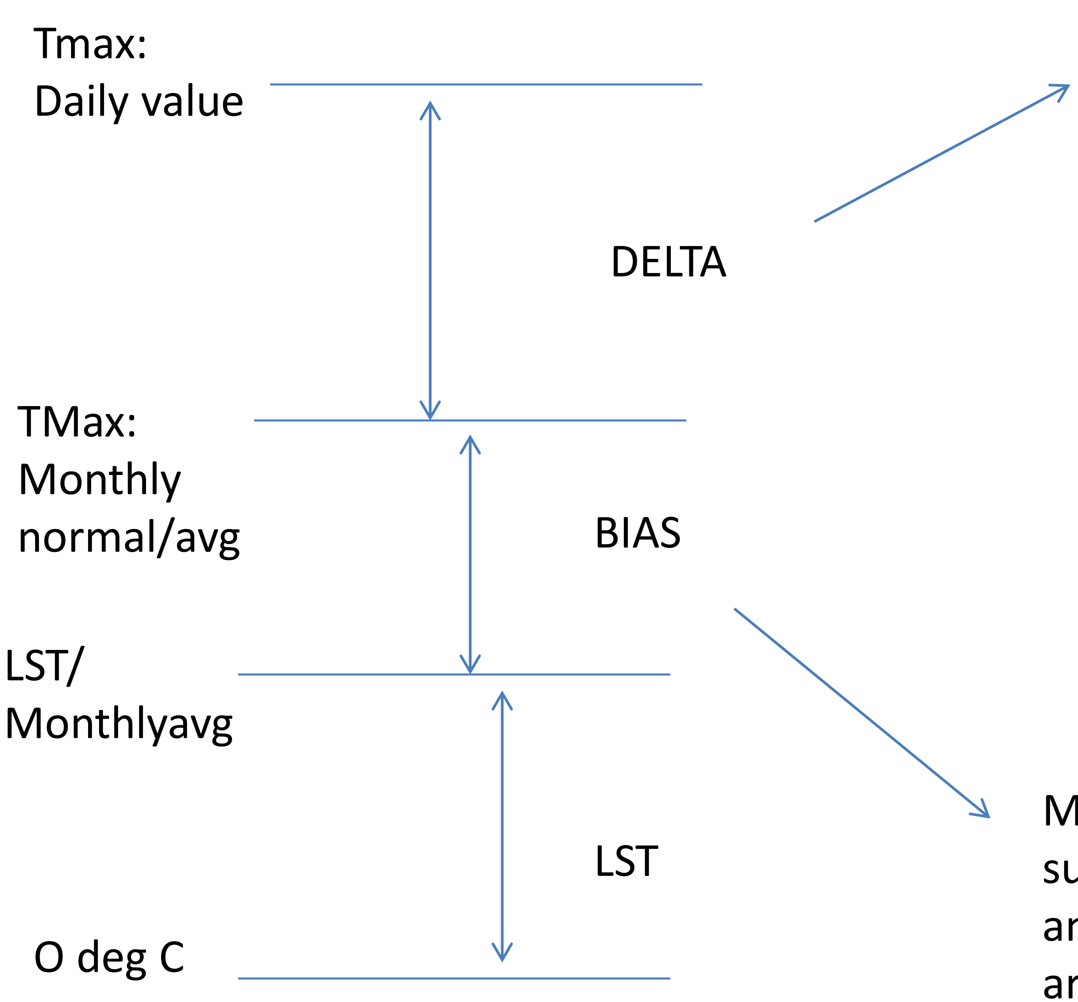
Automated downloading and update through script

Prediction procedure: MAE, RMSE and aggregated results??

Scaling the methods… next steps

Climatology Aided Interpolation through Fusion of Satellite and Stations observations

Strategy: divide the variability in a long term component and a daily component.



Harder to predict with static covariates: auto-interpolation seems appropriate

Variability may be due to daily weather phenomena (air masses and front, local convection)

Variability may be due to diff between skin and air temp. This is the long term component of tmax.

May plug in modeling of surface through elevation and other covariates that are static??

Main idea: Interpolation quality decreases when predictions are made far from stations

→ Use the spatial structure from the satellite

SURVEY OF METHODS

Methods	Weighted average and weighting function for observations	Covariates used as predictors	Global trend/ Component/spatial hetoerogenity	Automated	Studies
IDW	Fixed, distance based	No/Yes	No/yes	Yes	Shepard 1968, Renka 1984, Wilmott et al. 1995, Thorton et al. 1997, ,Doson and Marks 1997,
Simple Kriging	Data/empirical and distance based	No	Null trend	Sometime: automated fit of variogram	Philipts et al. 1992, Garen et al. 1994, Dingman et al. 1988, Hevesi et al. 1992
Ordinary Kriging	Data/empirical and distance based	No	Constant trend	Sometime: automated fit of variogram	Jolly et al. 2005 (SOGS),
Universal Kriging/ Regression Kriging	Data/empirical and distance based	Yes	Trend modeled by coordinates or covariates	Sometime: automated fit of variogram	Hengl et al. 2007, Attore et al 2007.
Co-Kriging	Data/empirical	Yes	Yes, when drift modeled	Sometime: automated fit of variogram	
Localized Kriging	Data/empirical and distance based	Yes/No	May include trends	No/yes	
GWR	Fixed, distance based	No/yes	No trend	Yes	Llyod 1999, Brundson 1999
GAM/Spline/ TPS	Fixed,Solution from optimization	No	Non linear trend estimation	Yes	Wahba &Wendelberger, Hutchinson et a. 1995, New et al. 199, New et al. 2002, Hijmans et al. 2005
PRISM	Yes, empirical or expert based	Yes, though weigths	No	No, Knowledge based system +statistical methods	Daly et al. 1994,Daly et al. 2002
CAI/Anomaly	Dependent on method	Dependent	Yes/No	Yes	Willmott et al. 1985,Haylock et al. 2008
LM and GLM	No but can be included making it GLS	Yes	Yes	Yes	Jarvis and Stuart 2001, Bolstad et al. 1998, Xia et al.

COMMON ISSUES AND STRATEGIES FOR INTERPOLATION

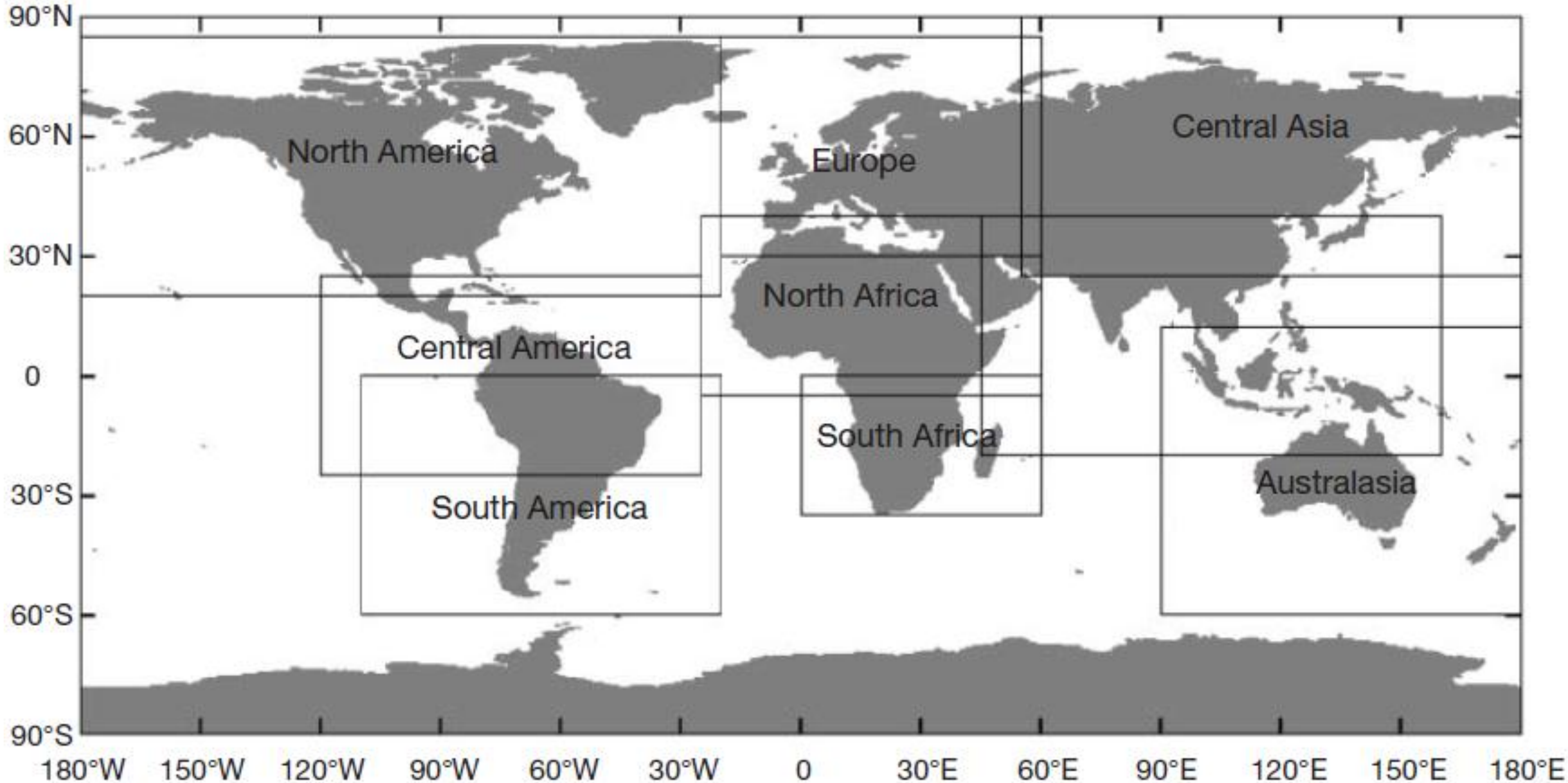
CLIMATE INTERPOLATION: ISSUES	Strategies
Sparse and unequal density of station network	Include data such as satellite information, evaluate accuracy from the network. Assemble data from many alternative sources
Large Geographical variability and non-stationary	Divide the study area in multiple subregions, use a model with local adjustment
Database Quality and Completeness	Multiple screening with possibility of following WMO or NCDC procedures. Extend temporal period or spatial area.
Validation in a sparse data context	Use cross-validation, evaluate accuracy by average gridding
Automation and incorporation of human expert knowledge	Reduce manual fitting of parameters. Increase human input in validation.

Table 2
SOGS cross-validation results for each of the five key weather variables for the Continental United States for 2002 using ordinary kriging, the truncated Gaussian filter and inverse distance weighting

	Ordinary kriging		Truncated Gaussian filter		Inverse distance weighting	
	MAE	Bias	MAE	Bias	MAE	Bias
Tmax (°C)	1.6	0.03	1.9	−0.01	1.9	0.11
Tmin (°C)	1.9	0.01	2.0	0.01	2.0	0.02
Precipitation (cm)	0.48	0.35	0.49	0.29	0.47	0.27
VPD (Pa)	293.1	−196.6	167.5	7.2	141.6	9.1
Solar radiation (W/m^2)	43.5	−3.4	47.7	−8.7	43.1	−4.2

The main message:
There is no single best method that can be applied in all situations, accuracy is largely dependent on case by case basis with the most important factors being the density of the station network and the variability of the study area.

LARGE STUDY AREA: TILING



"Spatial domains or tiles over which the interpolations of surface climate data…" New et al. 2002

SURVEY OF STUDIES

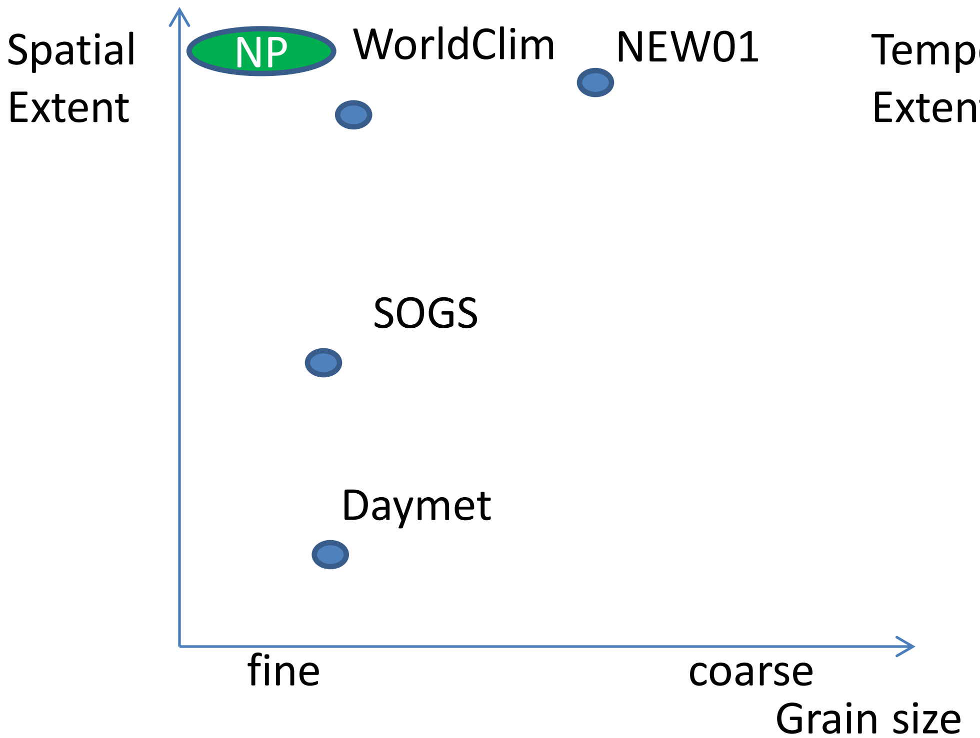
Name	Spatial extent	Temporal extent	Method	Temporal resolution	Spatial resolution	Variables	Accuracy	Explanation
PRISM	USA	1980-2010	Regression, GWR, mixed	Monthly	4km	Tmax, tmin, precipitation	MAE=1.6 C	This MAE is reported for Coastal California only. There is no full report of MAE or RMSE
Daymet	World	1980-2008	Truncated Gaussian Filter	Daily	10minutes	Tmax, tmin, precipitation, radiation, humidity		
SOGS-TOPS	CA,North America, World	1982-2012?	OK, Truncated Gaussian Filter, IDW	Daily	1km (CA), 8km (USA), 0.5 deg (World)	Tmax, tmin, precipitation, shortwave radiation, Vapor Pressure Deficit	MAE: 1.6 for Tmax OK, 1.9 Tmin OK, 48 mm precip (OK)	There were three methods used and the reported accuracy is for the 2002 run from Jolly et al. 2005. OK had the lowest MAE
WorldClim	World	1950-2000	GAM/TPS	Monthly	1km	Tmax, tmin, precipitation	0.5-2	The MAE in Oregon is about 0.5 for 10 degree squares
Willmott 1985	World	1881-1990	IDW	??	??		1.3-1.9C	
Willmott 1995	World	1881-1990	CAI-IDW	Annual	?		0.75-.1.5	
Haylock et al. 2008	Europe	1950-2006	CAI: TPS+Kriging with drift	Daily	0.1 or 25km?		0.5-1C	
NEW99	World	1961-1990	TPS	Monthly	0.5 deg	*Pcp,wdf,RH,sun,Trange,gff,w_speed*		
NEW01	World	1961-1990	TPS	Monthly	10’	*Pcp,wdf,RH,sun,Trange,gff,w_speed*		

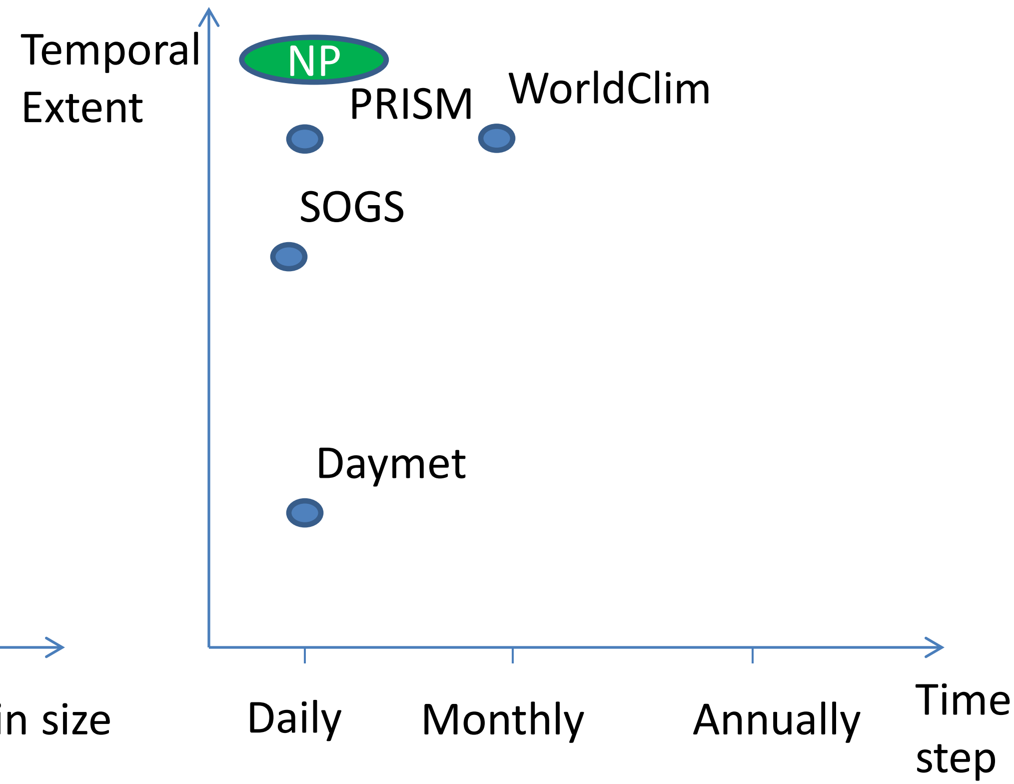
TPS often used in global studies:
Global studiesNEW01, WorldClim.

SURVEY OF STUDIES

Name	Spatial extent	Temporal extent	Method	Temporal resolution	Spatial resolution	Variables	Accuracy	Explanation
HadGHCND	World	1946-2000	ADW	Daily	2.5 lat By 3.75 long	Tmax, Tmin		
Thorton et al. 1997	Northestern USA	One year	IDW: truncated Guassian	Daily	?	*Pcp,wdf,RH,sun,Trange,gff,w_speed*	?	
Feng et al. 2004	China	1951-200						
Groot and Orlandi 2003	Europe	1975-2000	Nearest Neighbour, IDW		50km	*Temperature and precipitation*	?	?
Hewitson and Crame	South Africa	1950-2000	Conditional Interpolation		0.1 deg	*Precipitation*	?	?
Stahl et al. 2006	British Colombia Canada	1965-2000	IDW, Kriging, Mulitple regression	Daily				
McKenney et al. 2006	Canada-USA	1901-2000	TPS	monthly	?	*PRCP, tmax,tmin*	MAE: 1-1.5C, 20-40 PRCP	

SURVEY OF STUDIES





N.P. : New Product from NCEAS-IPLANT-NASA

WWW→ finer resolution smaller time steps with products covering the world and long time period.

SURVEY OF ACCURACY PROCEDURES

Procedures	**Studies**
1.Report fit metric	everywhere
2.Data partitioning/hold out	Price et al. 2000, Vicente-Serrano et al. 2003, Hijmans et al. 2005, Attore et al. 2007, McKenney et al. 2006.
3.Cross-validation	Jolly et al. 2005, Willmott and Matsuura 1995, New 1999 etc.
4.Grid aggregation	Hijmans et al. 2005, Hosfra et al. 2008, Haylock et al. 2008
5.Error uncertainty	Hijmans et al. 2005, Daly et al. 2002,
6.Error regression study	Thorthton et al. 1997, Price et al. 2000, Stahl et al. 2006.
7.Visualization /mapping of errors/residuals	Hijmans et al. 2005, Jarvis and Stuart 2001
8. Product comparison	Hijmans et al. 2005, Daly et al. 2002, New et al. 2002,…

→ Cross-validation more common than hold out.
→ Product comparison often used.
→ Uncertainty not often reported

SURVEY OF ACCURACY PROCEDURES

Problem with data partitioning

→ The density of the network is the most important factor in the accuracy and holding out data will result in a decrease in accuracy (New et al. 2001, Stahl et al. 2006, Hutchinson et al. 1995)

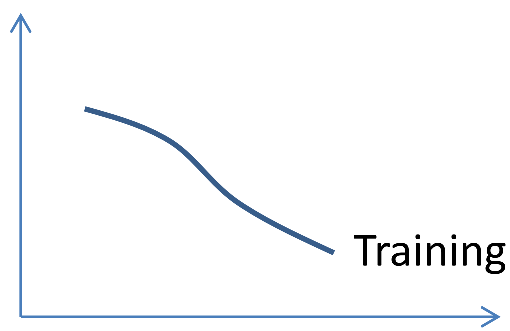
→ There is spatial autocorrelation in the dataset so that the effective number of observations retained by hold out is lower.

→ Accuracy may depend on the validation sample being chosen with areas lacking validation station. This means that random sampling may not be appropriate (Attore et al. 2007, Hutchinson et al. 1995).

Possible solutions:

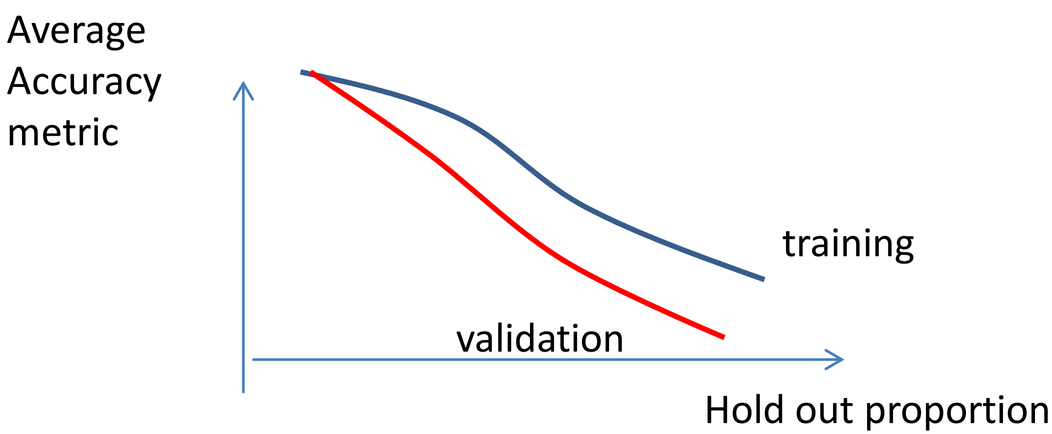
→ Assess the effect of partitioning by varying the hold out proportion and provide an estimate of increase in accuracy for decreasing hold out. This assessment should include multiple hold out for each proportion

If we decide not to do hold out we should at least provide a justification.

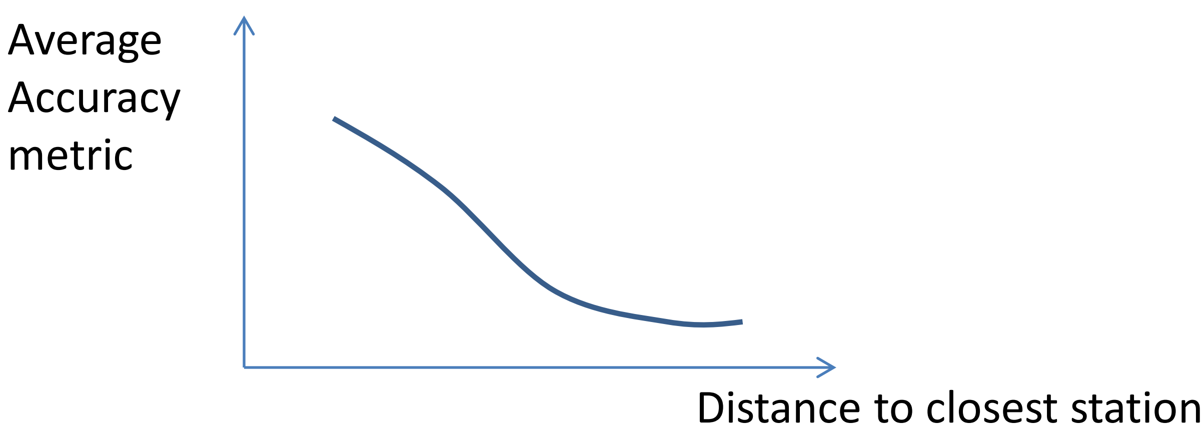


ACCURACY PROCEDURES

→ Provide a graph of the difference between accuracy of the validation and testing data set. The idea is that the accuracy may be over-evaluated in unknown locations due to overtraining/overfitting.



→ Stratified or systematic sampling to take into account the spatial configuration of stations.
→ Sampling taking into account spatial autocorrelation: range based limit?
Assessment of spatial autocorrelation by distance category?

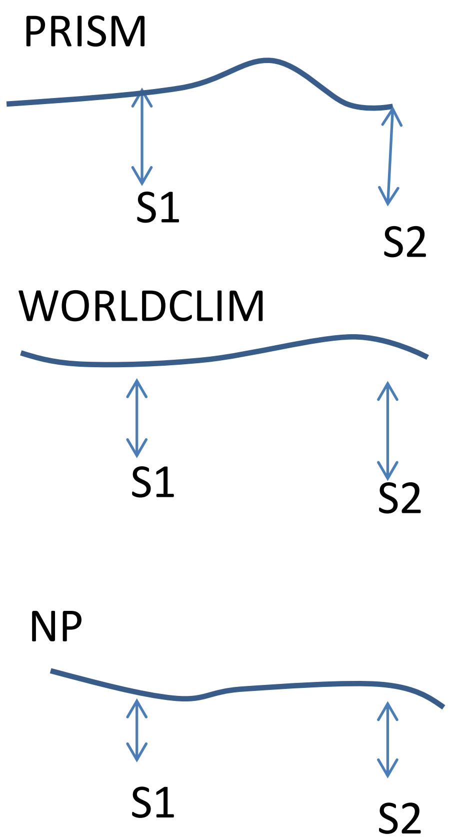


COMPARISON TO OTHER PRODUCTS

This approach is very common in the literature.

→ Issue : similarities and/or dissimilarities among product do not imply accurate results.
: visual comparison is a poor tool of map comparison (Pontius et al.)

→ Solution : provide inter comparison to a more "neutral" reference surface i.e. the station network. This would be an approach similar to New et al. 2002.



Note that:

1. Products may not cover the same extent so a common area must be chosen. This may not reflect the overall accuracy.
2. Products may not have been produced at the same spatial resolution. This means that coarsening may be necessary.
3. Products may not have been produced at the same temporal resolution. Aggregation in time may be necessary.

S1: station number 1

UNCERTAINTY ASSOCIATED TO PREDICTION

Uncertainty of prediction relate to the “precision” of the prediction in terms of a confidence interval around the predicted values (Hengl 2009).

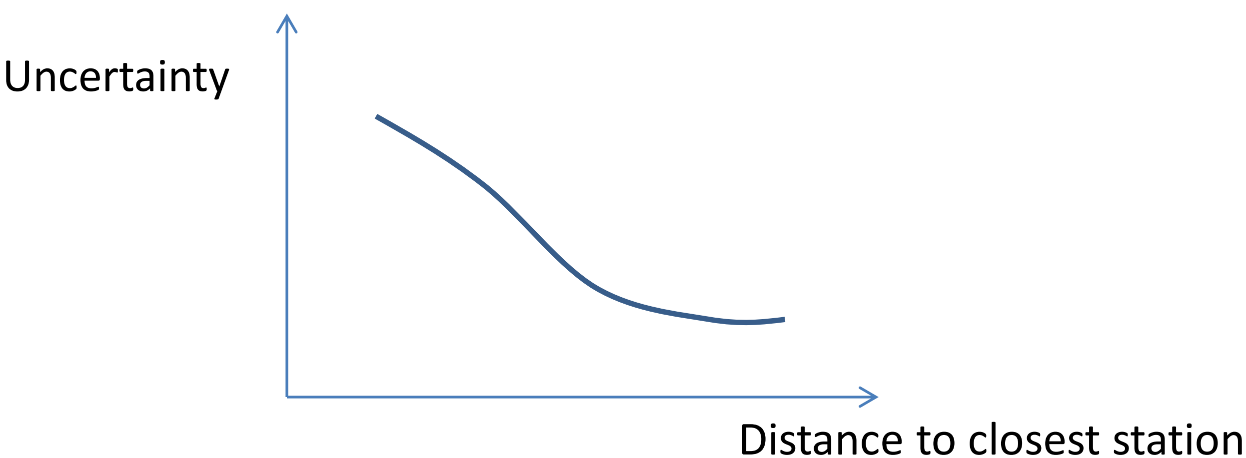
In some cases, uncertainty is not produced by the method. For Kriging, regression and GAM methods however there uncertainty bands are available.

Note that:

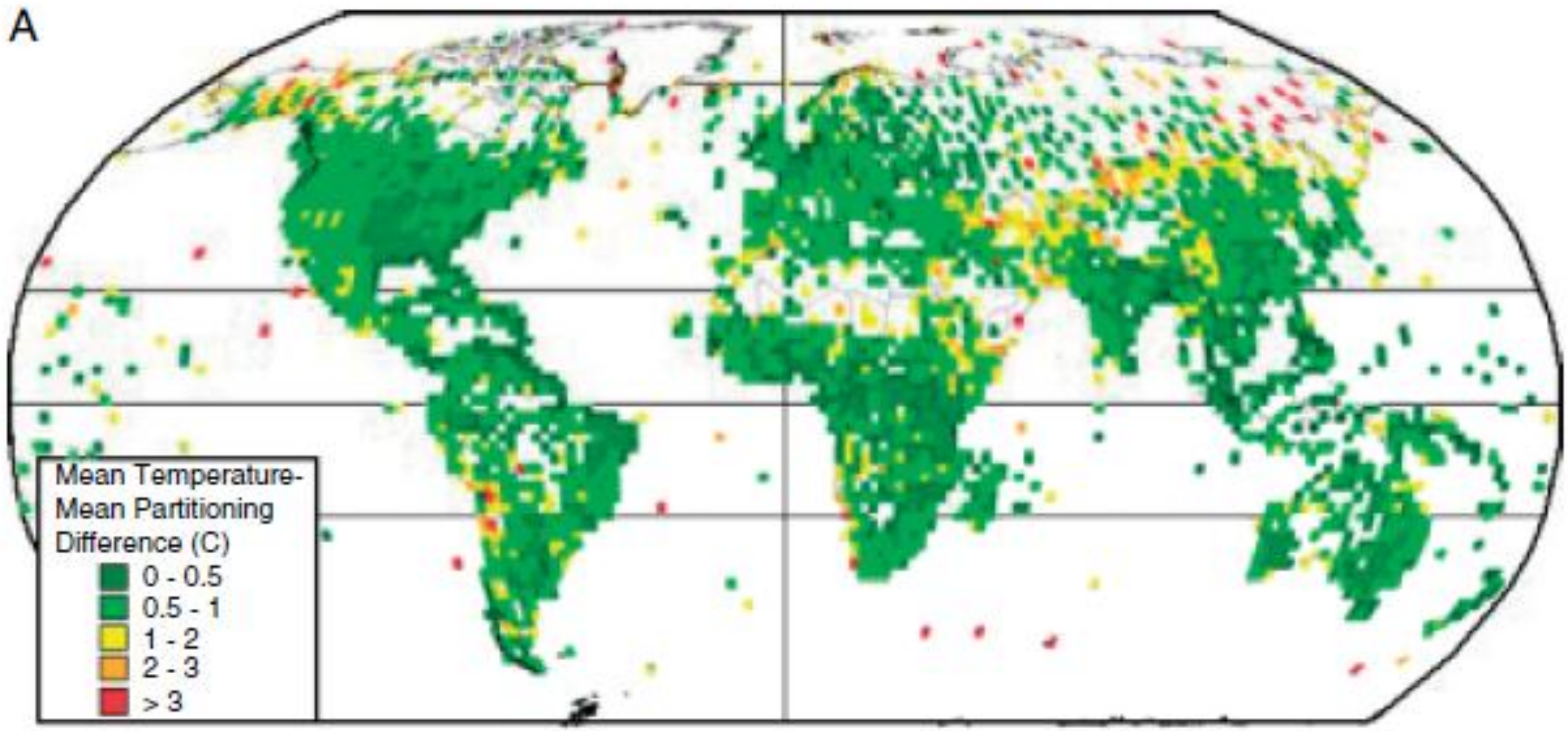
1. We can provide a report of how the uncertainty vary in terms of spatial configuration (map)

2. Uncertainty can be described in terms of the various input covariates.

3. Uncertainty can be described in terms of distance to station points.



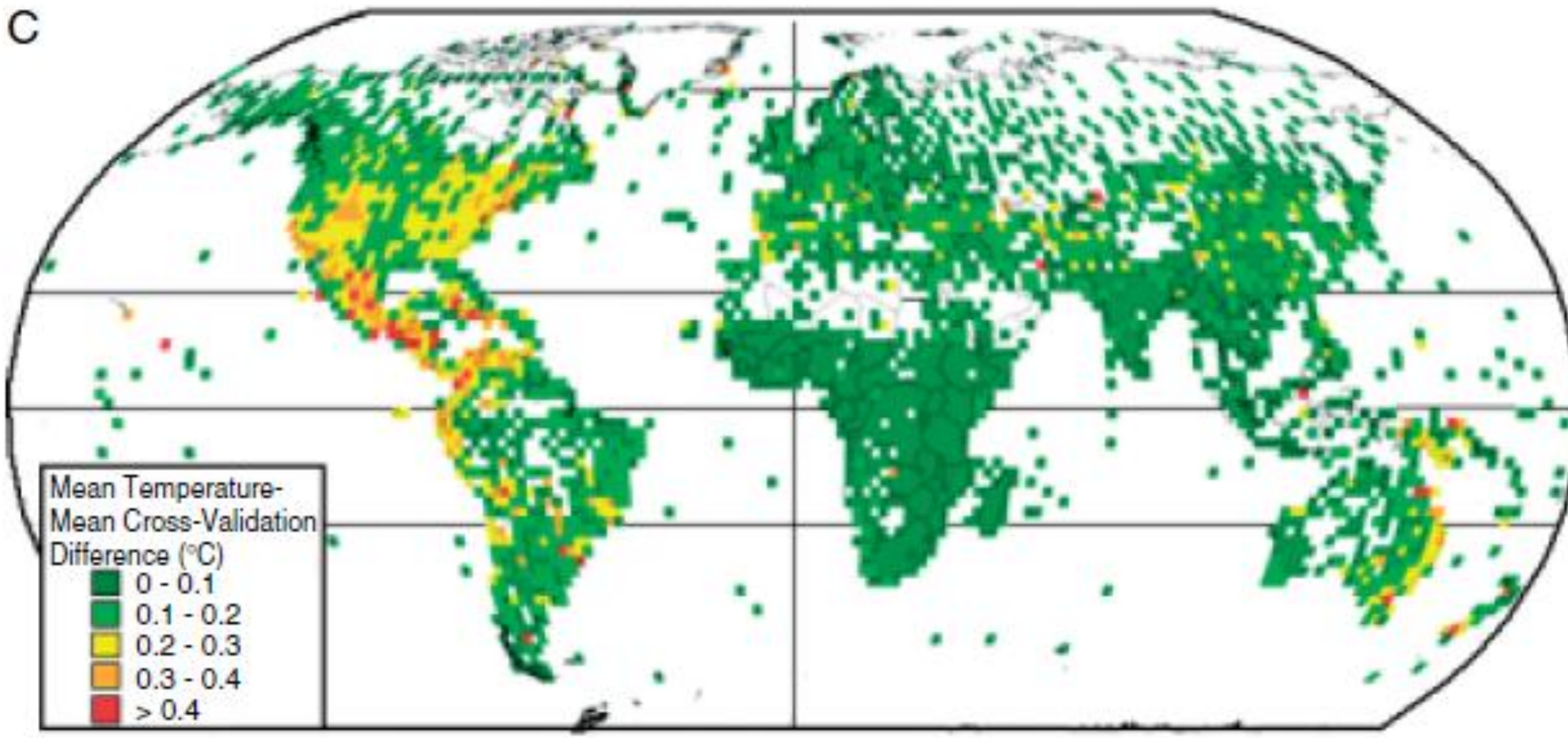
EXAMPLE OF VALIDATION: WORLDCLIM



Hijmans et al. 2005: Mean difference in temperature for the validation data set? This is an average across 12 months within 2x2 degrees cells.

"We also partitioned the stations into a test and training set, each containing a random set of half the stations." Hijmans et al. 2005

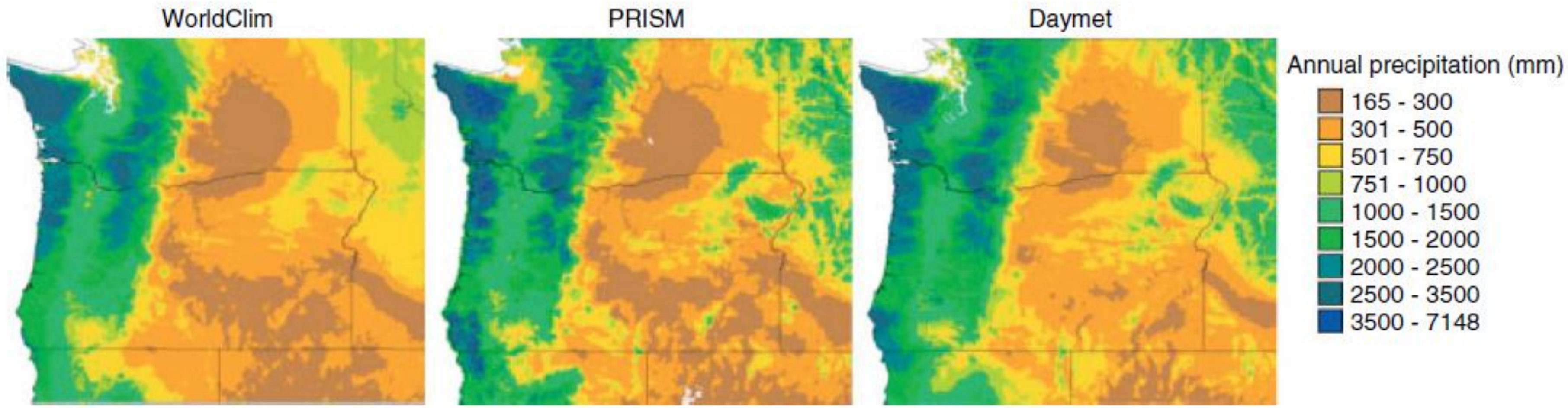
EXAMPLE OF VALIDATION: WORLDCLIM



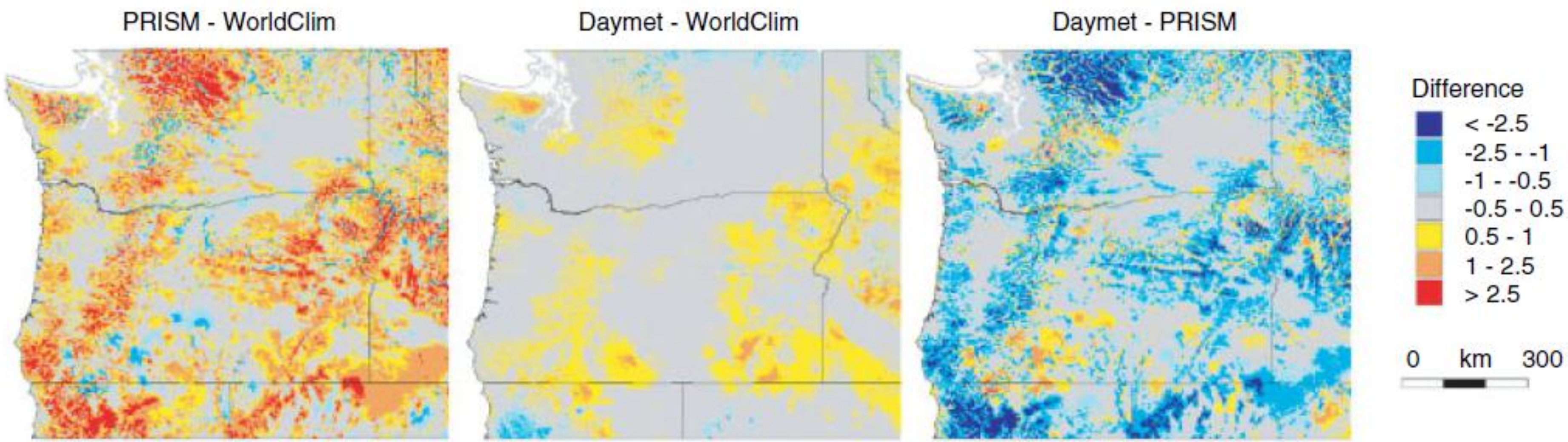
Hijmans et al. 2005: Mean difference in temperature for cross validation data set.
This is an average across 12 months within 2x2 degrees cells.

→ Crossvalidation has smaller errors in general.

EXAMPLE OF VALIDATION: WORLDCLIM



Spatial pattern: comparison among products (Hijmans et al. 2005)



Differences: comparison among products (Hijmans et al. 2005)

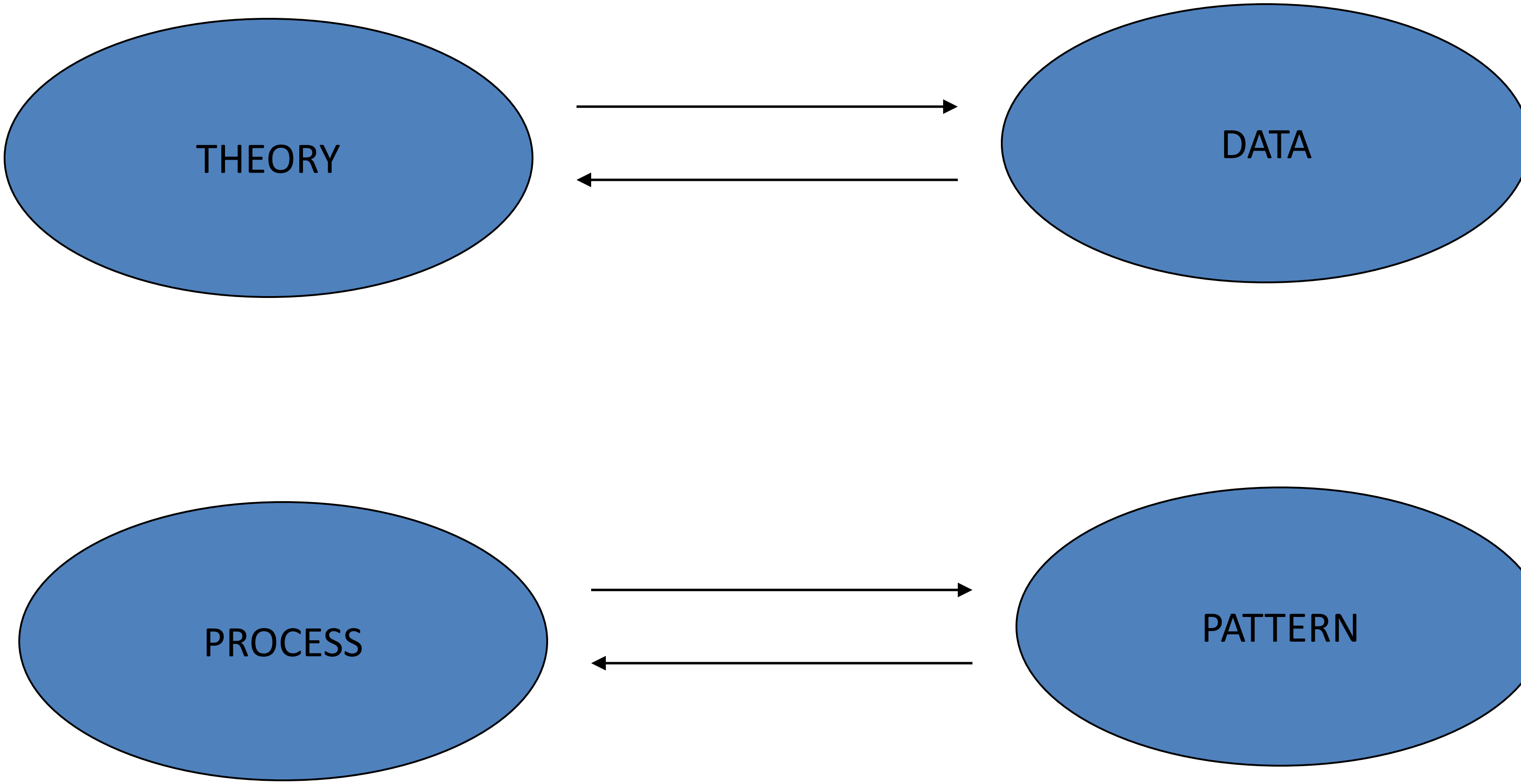
ISSUES FOR DISCUSSIONS

1) How can researchers deal with validation in species modeling or climate interpolation when faced with small input datasets (e.g. stations, presence-absence).

2) How can the satellite spatial pattern be captured to improve air temperature predictions?

3) How can researchers separate the effect of model, data and biological characteristics on the results?

HOW DO WE STUDY THE EARTH SYSTEM and create KNOWLEDGE?



WORLDCLIM: HIJMAN ET AL. 2005

- Time period: 1950-2000
- Time resolution: monthly time steps
- Spatial extent: global
- Spatial resolution: 1 km
- Variables: tmin, tmax, prcp
- Methods: ANUSPLIN
- Co-variates: elevation, lat, lon
- Accuracy: cross-validation and data partioning (50%)

NCEAS-IPLANT-NASA PRODUCT

- Time period: 1970-2010
- Time resolution: daily time steps
- Spatial extent: global
- Spatial resolution: 1 km
- Variables: tmin, tmax, prcp
- Methods: to be determined
- Co-variates: elevation, lat, lon, distoc, aspect, LST, land cover, Canopy Height
- Accuracy: to be determined--cross-validation and data partitioning?

MOTIVATION—CLIMATE LAYERS DOWNSCALING AND AGGREGATION

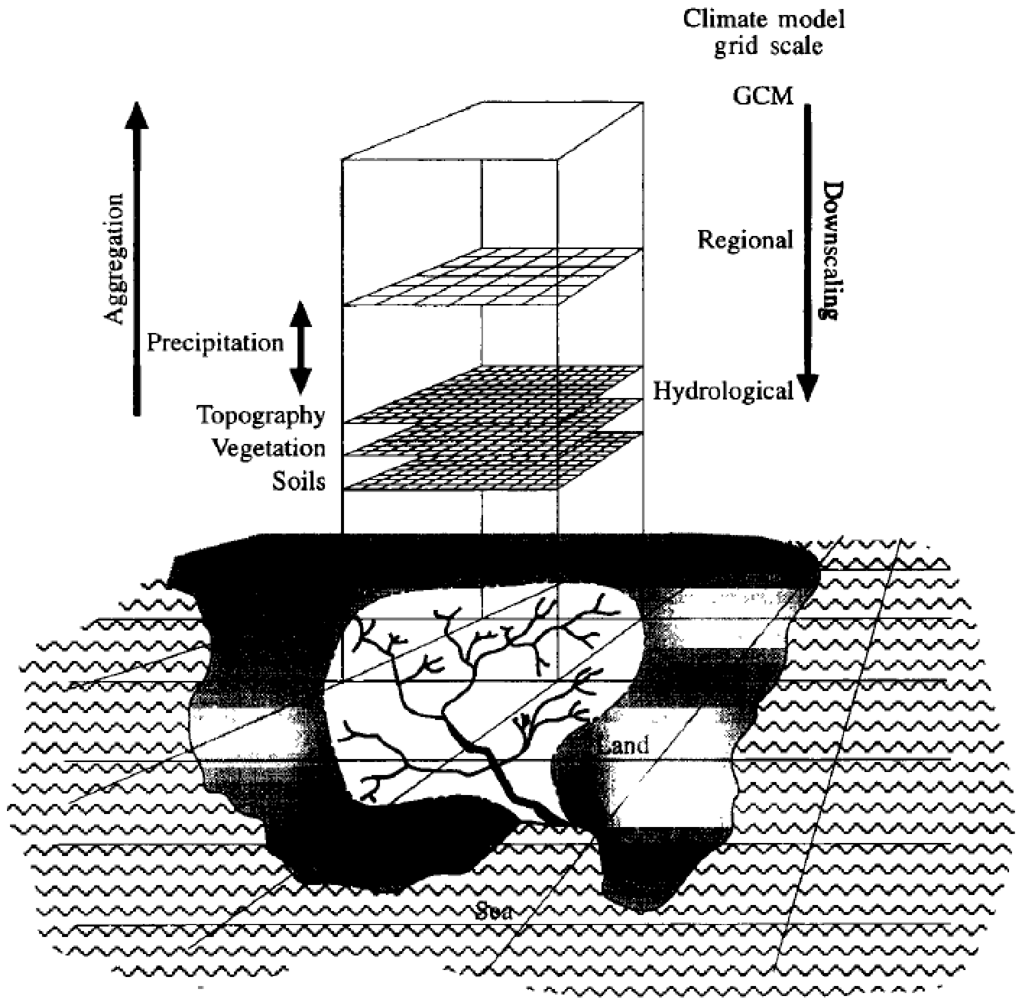


Figure 1 Conceptualization of downscaling and aggregation between atmospheric and hydrologic models
Source: Modified after Hostetler (1994)

WHY USE STATION DATA TO CREATE DAILY SURFACES??

General Circulation Models (synoptic meteorology)
- Use principles of physics (conservation laws: mass, momentum, energy) to model motion of fluid (the atmomsphere)
- typically at 1 degree scale or coarser often global
- May be at very fine time steps (hours, day, week)
- Forecast usually stops at 2 weeks because of divergence and chaotic behaviour of dynamical models, computer intensive

Interpolation and downscaling (mesoscale meteorology)
- 1 km to 100km using meteorological station data
- No direct modeling of fluid to predict temp and prcip
- Local convection and cloud can be resolved, influence of mountain, coastal proximity, land cover and other environmental covariates.

Land-Atmosphere model (micro scale meteorology)
- 10 km or less: this is the scale of organisms (plant&animals)
- Predict temp and humidity in micro climate scale
- Modeling of fluxes, typically through flux towers

"Spatial climate patterns are most affected by terrain and water bodies, primarily through the idrect effects of leevation, terrain-induced cliamte transitions, cold air drainage and inversions, and coastal effects. The imporatnace of these factors is generally lowest at scales of 100km and greater, and becomes greatest at less than 10km. Escept in densley populated rigons of developed countries, typical station spacing is on the order of 100km. Regions without major terrain features which are at least 100km from climatically important coastlines can be handled adequatley by most interpolation techniques." Daly et al. 2006

MOTIVATION—CLIMATE LAYERS DOWNSCALING AND AGGREGATION

→ Hydrological and ecological applications require fine grained resolution data.

→There is a mismatch between data produced by GCM which are typically at the scale of 100 km (degree scale) and other datasets needed at 1km or less.

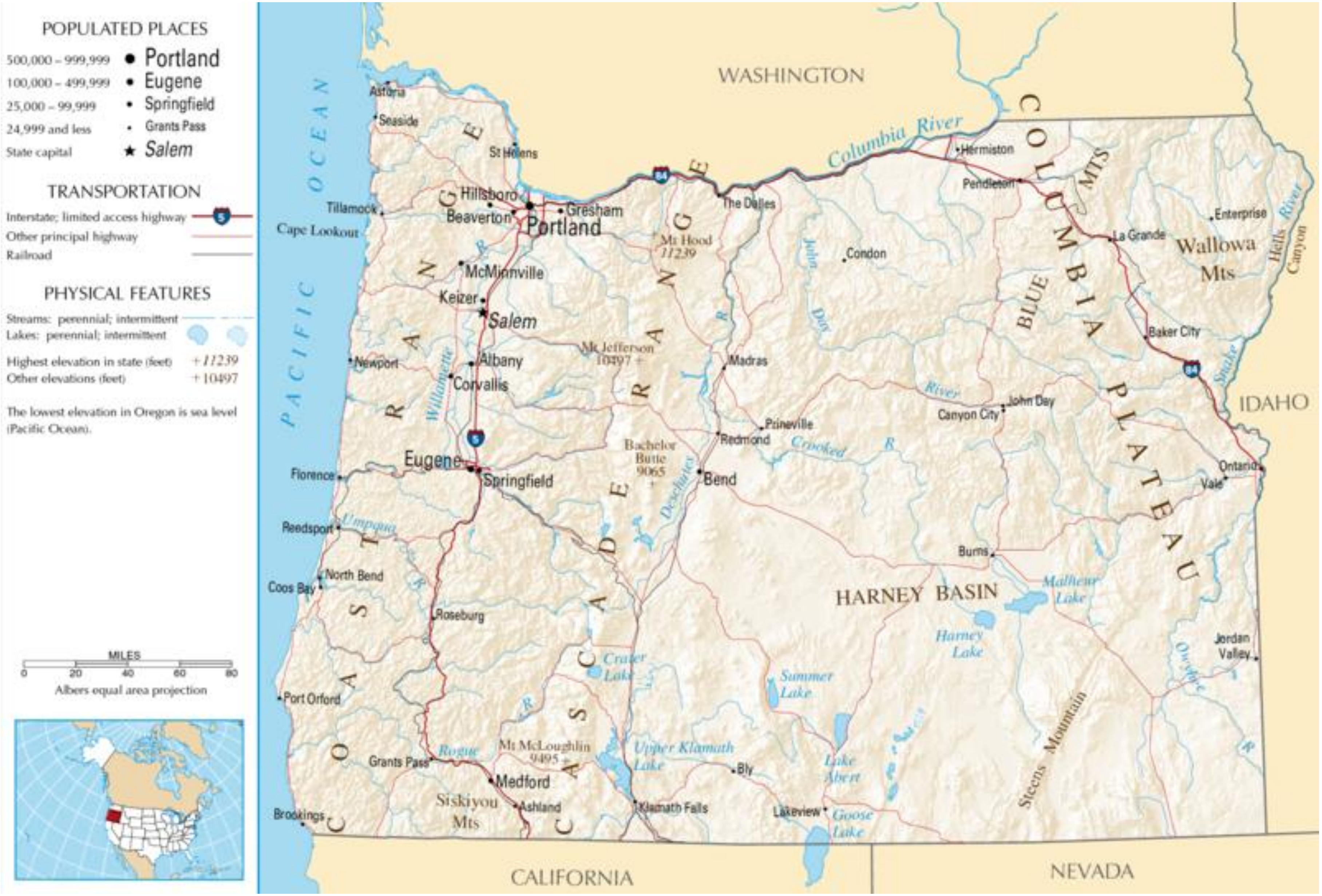
For example, hydrological models are frequently concerned with small, sub catchment (even hill slope) scale processes, occurring on spatial scales than those resolved in GCMs. GCMs deal most proficiently with fluid dynamics at the continental scale and parameterize regional and smaller-scale processes. These scale-related sensitivities and mismatch problems are further exacerbated because they usually involve the most uncertain components of climate models, water vapour and cloud feedback effects (Rin et al., 1992). As Hosteler (1994) has observed, the greatest errors in the parameterizations of both GCMs and hydrological models occur on the scale(s) at which climate and terrestrial impact models interface. These mismatch problems, which affect both the temporal and spatial dimension, have important implications for the credence of impact studies derived by the output of models of climate change, especially as research into potential human-induced modifications to hydrological and ecological cycles is assuming increasing significance." Wilby and Wigley 1997

The **synoptic scale** in meteorology (also known as **large scale** or **cyclonic scale**) is a horizontal length scale of the order of 1000 kilometres (about 620 miles) or more.[1] This corresponds to a horizontal scale typical of mid-latitude depressions (e.g. extratropical cyclones). Most high and low-pressure areas seen on weather maps such as surface weather analyses are synoptic-scale systems, driven by the location of Rossby waves in their respective hemisphere. Low-pressure areas and their related frontal zones occur on the leading edge of a trough within the Rossby wave pattern, while surface highs form on the back edge of the trough. Most precipitation areas occur near frontal zones. The word *synoptic* is derived from the Greek word συνοπτικός (*sunoptikos*), meaning *seen together*.

Microscale meteorology is the study of short-lived atmospheric phenomena smaller than mesoscale, about 1 km or less.[1] These two branches of meteorology are sometimes grouped together as "mesoscale and microscale meteorology" (MMM) and together study all phenomena smaller than synoptic scale; that is they study features generally too small to be depicted on a weather map. These include small and generally fleeting cloud "puffs" and other small cloud features.[2] Microscale meteorology controls the most important mixing and dilution processes in the atmosphere.[3] Important topics in microscale meteorlogy include heat transfer and gas exchange between soil, vegetation, and/or surface water and the atmosphere caused by near-ground turbulence. Measuring these transport processes involves use of micrometeorological (or flux) towers. Variables often measured or derived include net radiation, sensible heat flux, latent heat flux, ground heat storage, and fluxes of trace gases important to the atmosphere, biosphere, and hydrosphere.

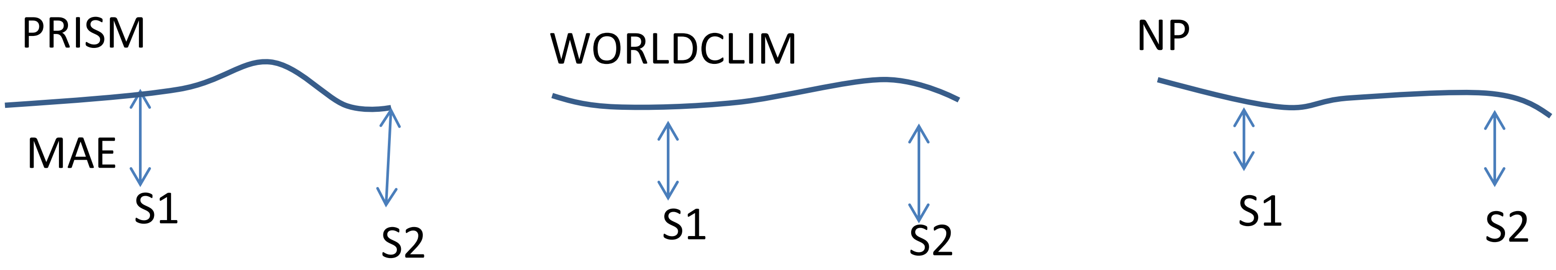
http://en.wikipedia.org/wiki/Microscale_meteorology

http://en.wikipedia.org/wiki/Synoptic_scale



http://upload.wikimedia.org/wikipedia/commons/e/e4/Map_of_Oregon_NA.png

COMPARISON TO OTHER PRODUCTS



SN: station number N NP: new product

The scale of the mismatch between GCM and interpolation at sation level seems to be the mesoscale meteorology:

Mesoscale meteorology *is the study of [weather systems smaller than synoptic scale systems but larger than microscale and storm-scale cumulus systems. Horizontal dimensions generally range from around 5 kilometers to several hundred kilometers. Examples of mesoscale weather systems are sea breezes, squall lines, and mesoscale convective complexes.Vertical velocity often equals or exceeds horizontal velocities in mesoscale meteorological systems due to nonhydrostatic processes such as buoyant acceleration of a rising thermal or acceleration through a narrow mountain pass.] Wikipedia: http://en.wikipedia.org/wiki/Mesoscale_meteorology*