Meteorological Institute
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Downscaling near-surface atmospheric fields with multi-objective Genetic Programming

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COSMO/CLM/ART User Seminar 2015

Transregional Collaborative Research Centre 32

Motivation

The TR 32 combines monitoring, modelling and data assimilation to investigate **„Patterns in Soil-Vegetation-Atmosphere Systems“.**

TR 32

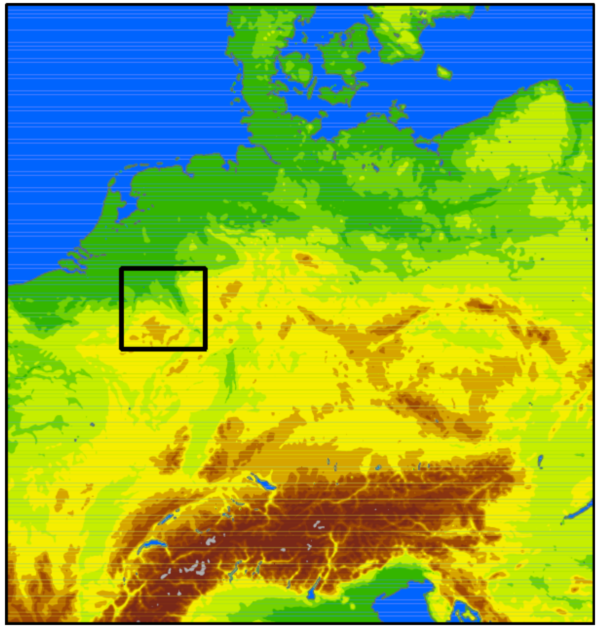

Figure: Main investigation area

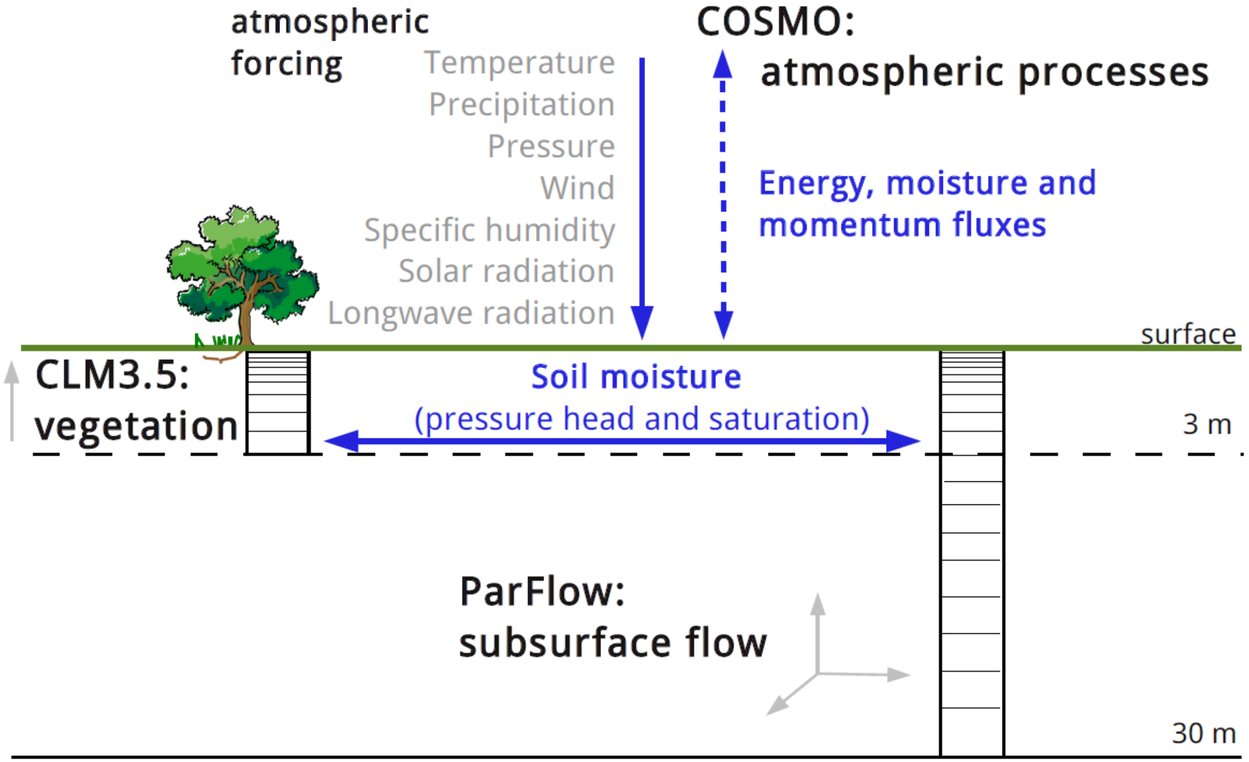

Figure: Sketch of TerrSysMP (Figure by J. Keune)

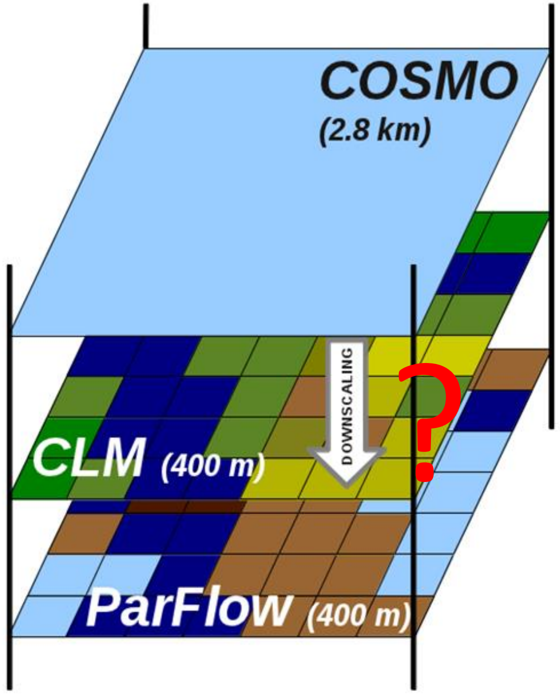

Figure: Illustration of scale gap.

Component models are usually operated at **different resolutions** in space and time.

Motivation

Downscaling approach by Schomburg et al.:

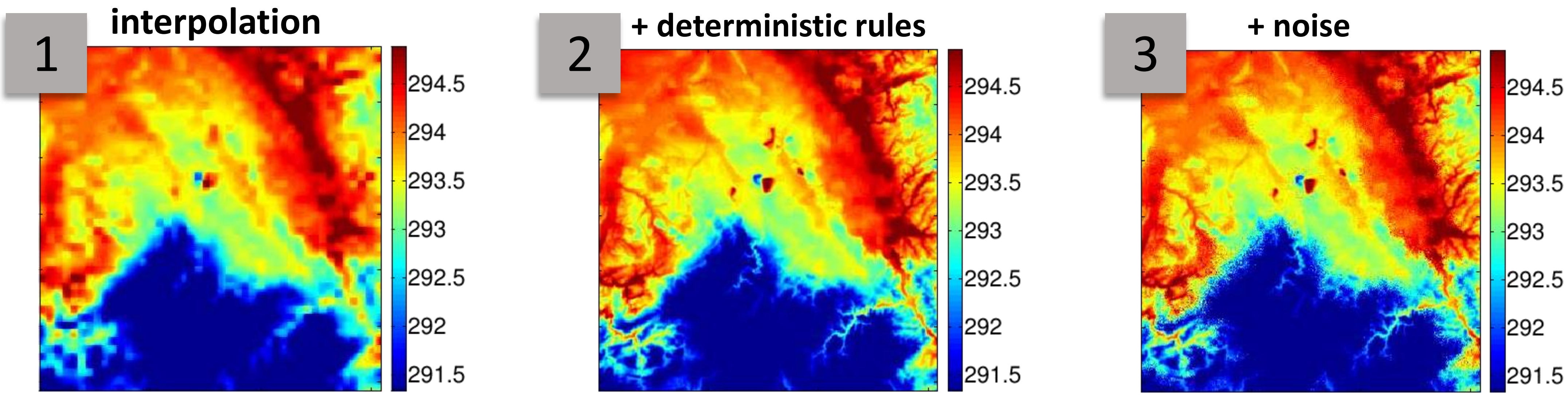

Figure: Downscaling scheme applied to a 10m-temperature field, 10:00 UTC, May 12th 2008, [K] (figures by A. Schomburg).

Motivation

Downscaling approach by Schomburg et al.:

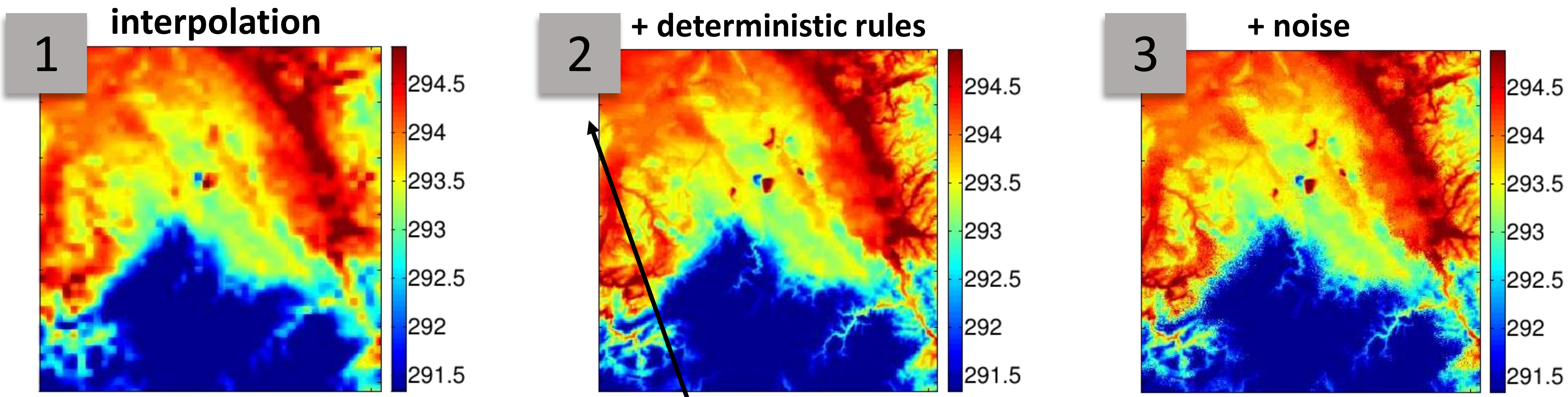

Figure: Downscaling scheme applied to a 10m-temperature field, 10:00 UTC, May 12th 2008, [K] (figures by A. Schomburg).

coarse atmospheric model output (temperature, wind, …)

+

fine-scale surface information (orography, roughness length…)

penalized linear regression

e.g.

if T_{gr105} < 0.0058 K/m

T*= - 0.0084 K/m x HSURF*

downscaled atmospheric field

Motivation

Downscaling approach by Schomburg et al.:

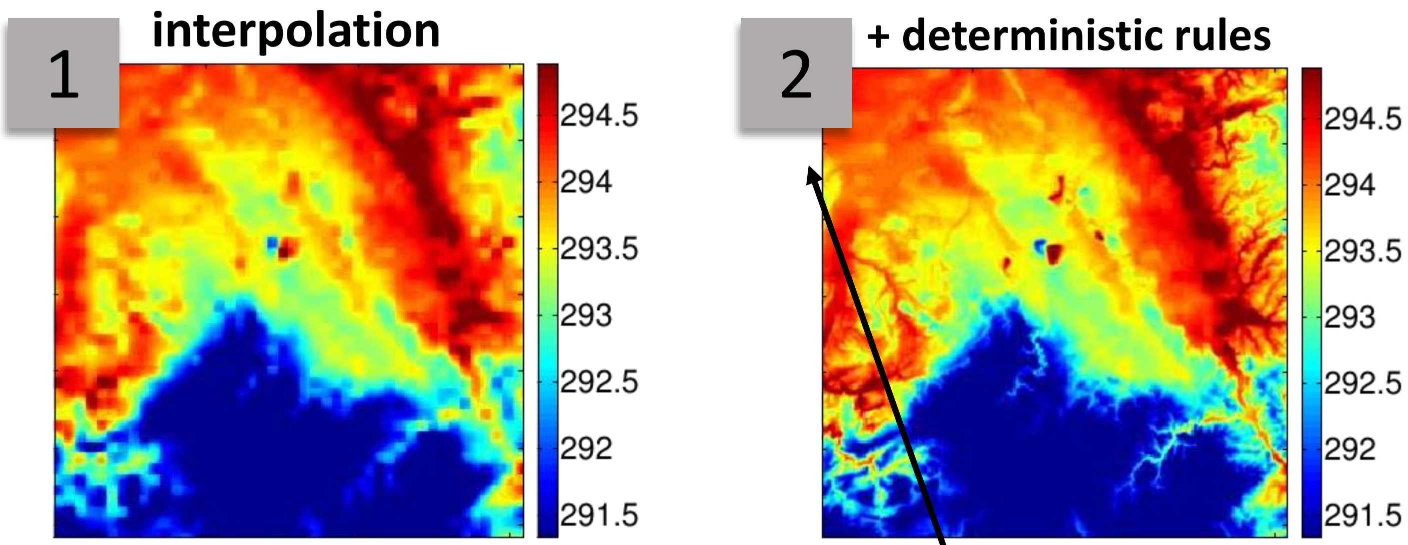

Figure: Downscaling scheme applied to a 10m-temperature field, 10:00 UTC, Ma

Step 2 currently available?

- pressure ✓
- **temperature** (✓)
- specific humidity
- wind speed
- longwave radiation (✓)
- dir. shortwave radiation (✓)
- dif. shortwave radiation (✓)
- precipitation

coarse atmospheric model output (temperature, wind, …)

\+

fine-scale surface information (orography, roughness length…)

penalized linear regression →

e.g.
if T_{gr105} < 0.0058 K/m
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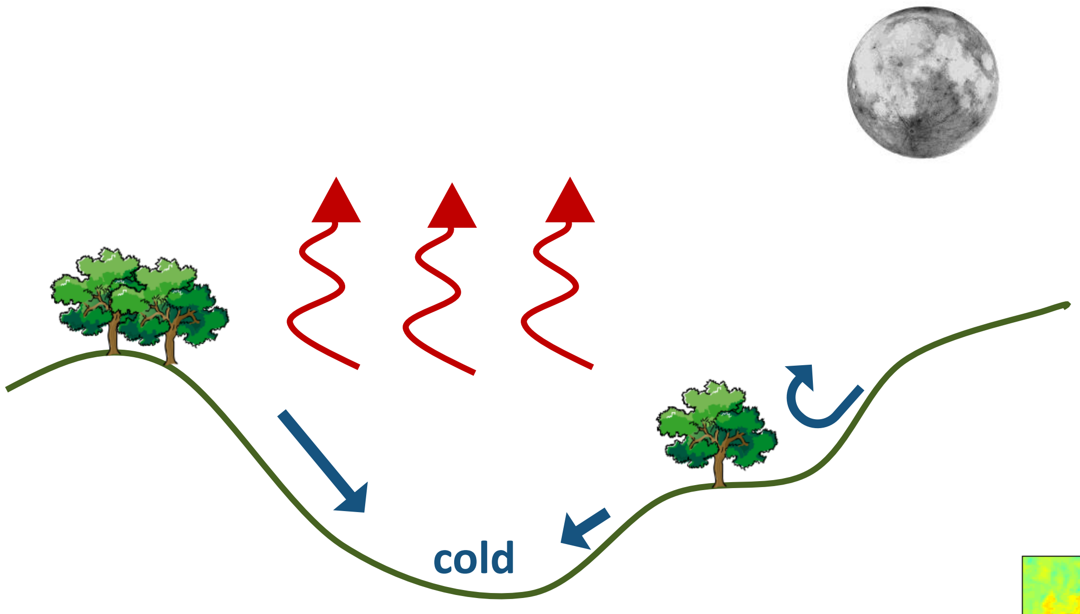
downscaled atmospheric field

Improving temperature downscaling with multi-objective GP

- Theory
  - Genetic Programming for Downscaling
- Results
  - Overview
  - Clear-sky situation
  - Cloudy situation

Improving temperature downscaling

In clear sky nights temperature inversions cause cold air to drain into the valleys.



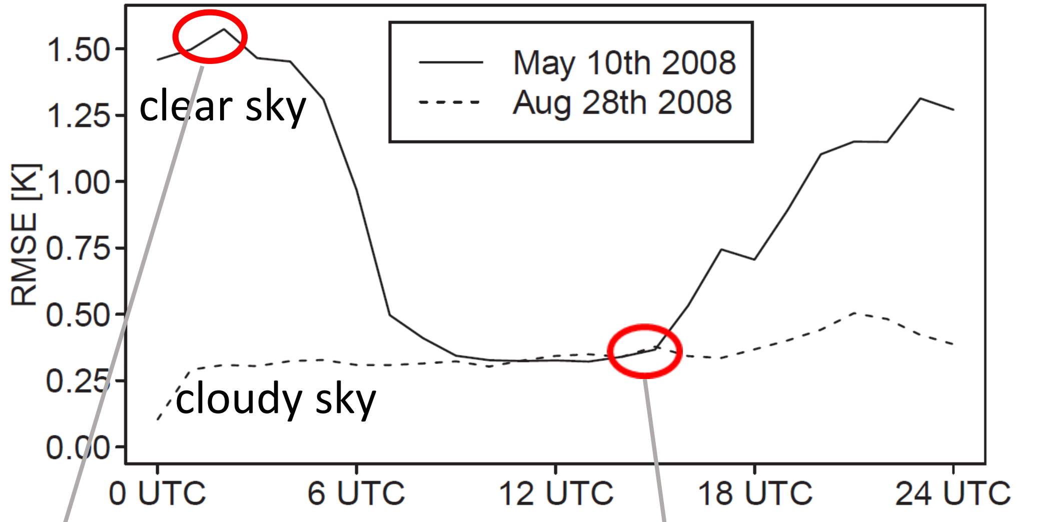
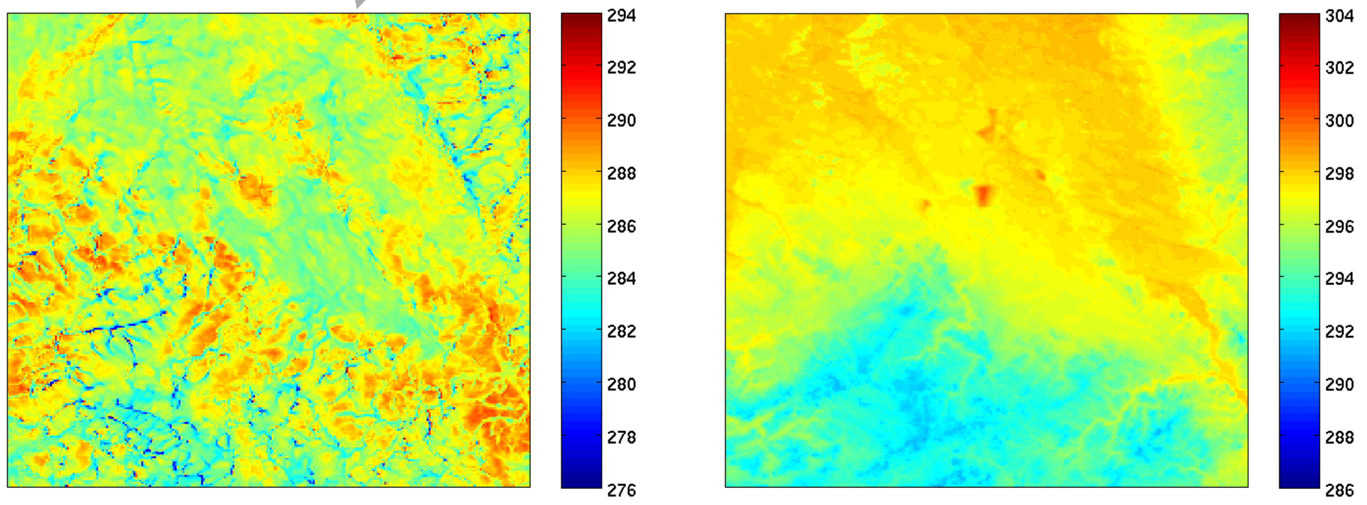


Fig: Diurnal cycle of RMSE between high-resolution (400m) and coarse near-surface temperature field.

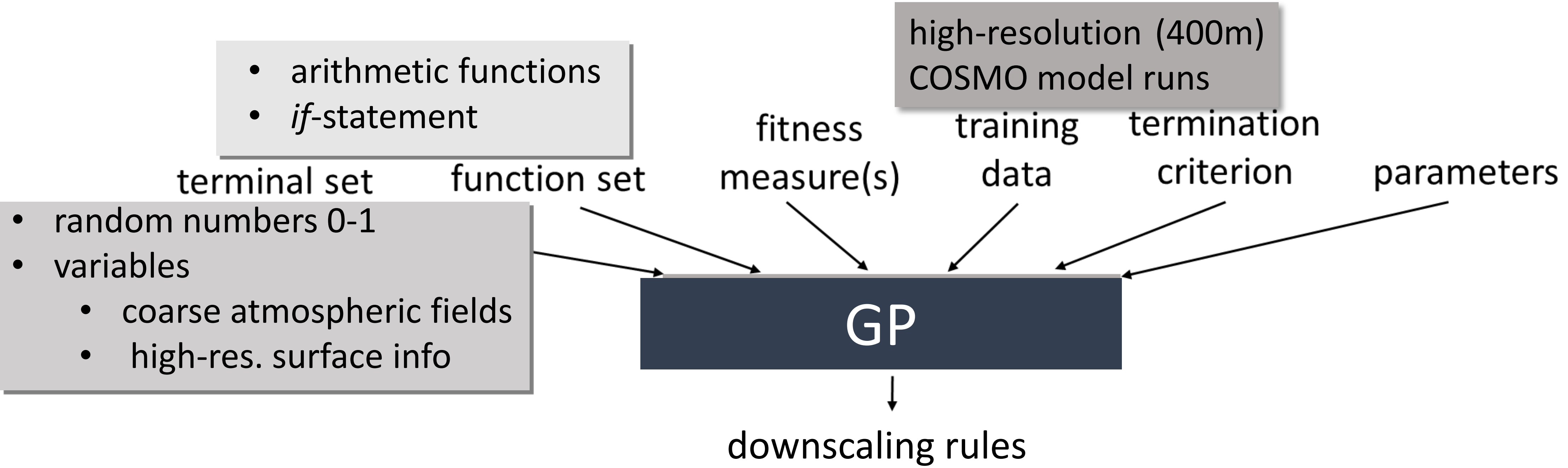


Genetic Programming (GP)

- Machine learning method based on the concept of **natural evolution.**
  - A generation of solutions (downscaling rules) is evolved.
  - The better a candidate solution performs the more likely it contributes to the next generation („survival of the fittest“).
- Advantages of using GP to search for downscaling rules:

  + include **nonlinear** and **multivariate** relations

  + solutions (downscaling rules) take form of equations or code.



GP for Downscaling

- GP/GEP has been applied to downscaling of GCM output to a station or catchment mean by Coulibaly (2004) and Hashmi et al. (2011).
  -> **We require spatial fields not single grid points**!
- Exact fit not possible.
  -> Fit reasonable **trade-off between exact fine-scale pattern and spatial variance**.

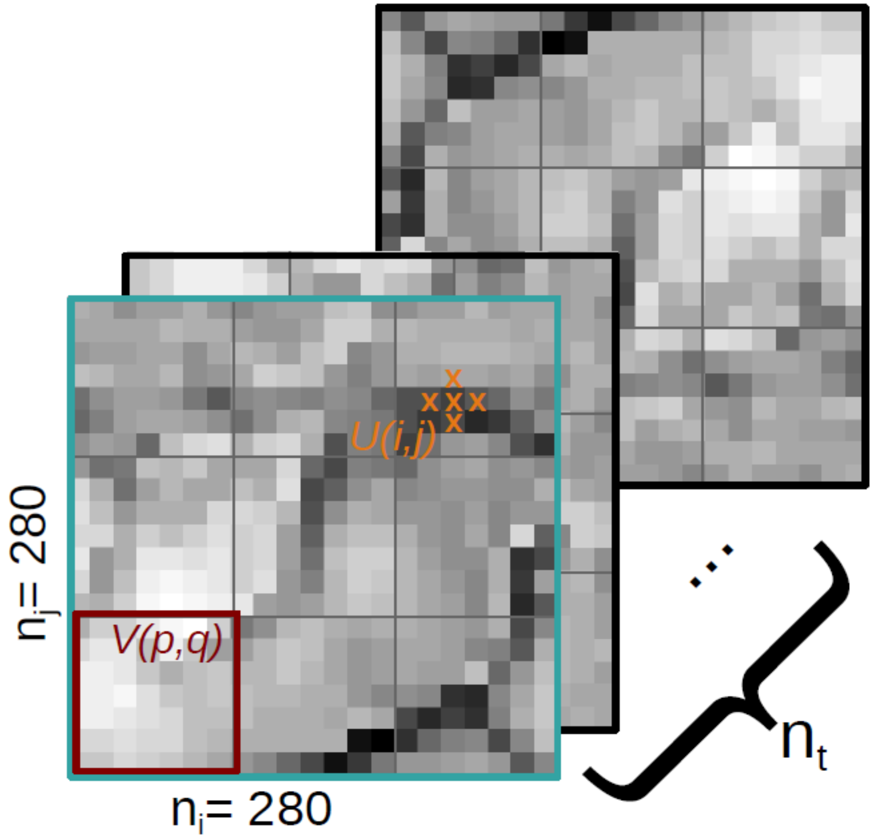
Multiple Objectives:

1. RMSE
calculated at each pixel (i,j) incorporating neighborhood U(i,j)

2. ME(STD)
calculated from the standard deviation within coarse pixels

3. IQD
(integrated quadratic distance) calculated from the histogram distributions of the full fields (bin width=0.25K)

4. SIZE
(complexity) of the downscaling rules

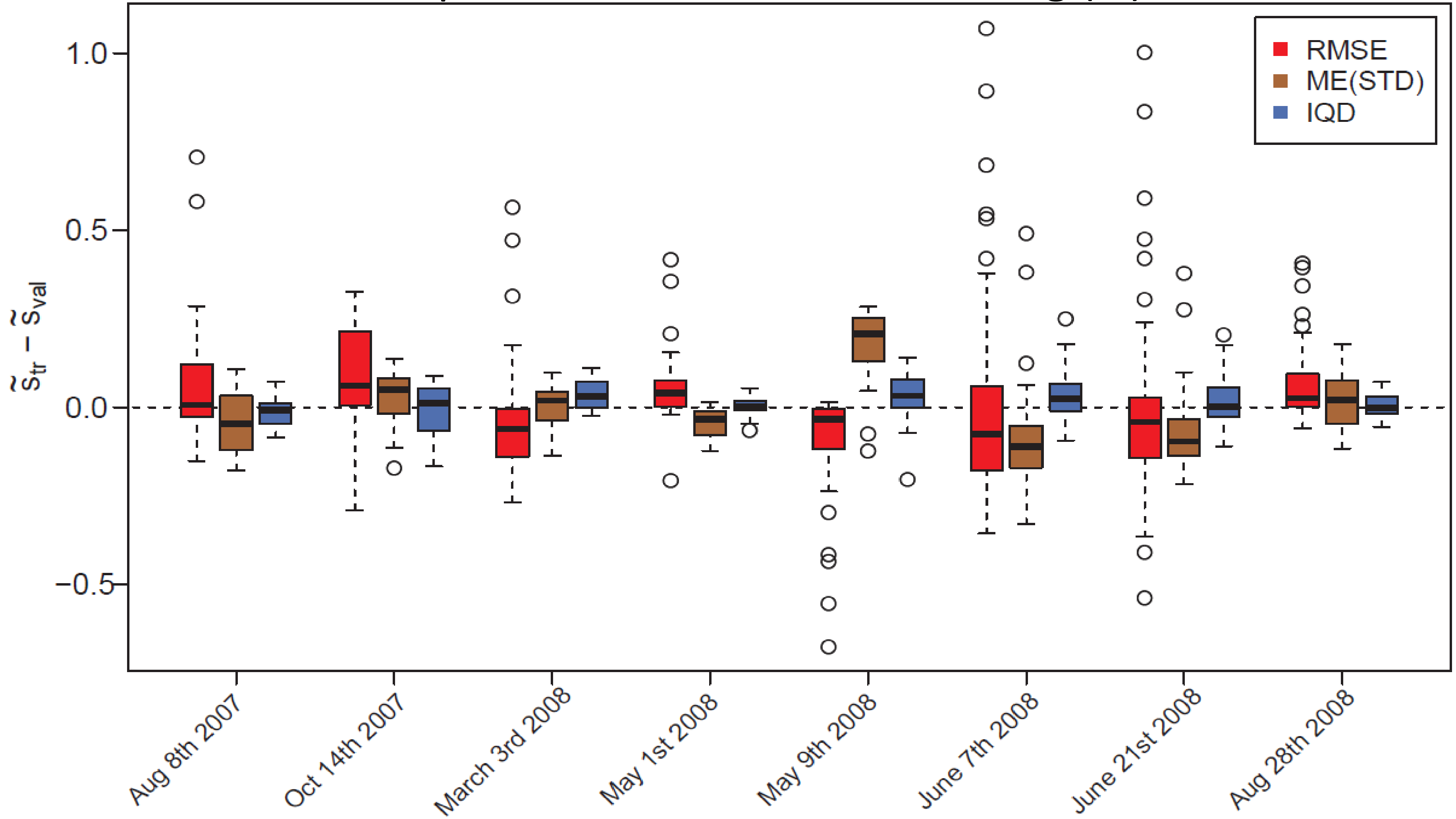


Results

We have carried out **8 GP runs** in total, each leaving out a different day of the training data set (cross-validation).

Each run returns **50 potential downscaling rules**.

Difference in relative performance between training (tr) and validation (val) data sets:



>0

performance on tr better than on val

< 0

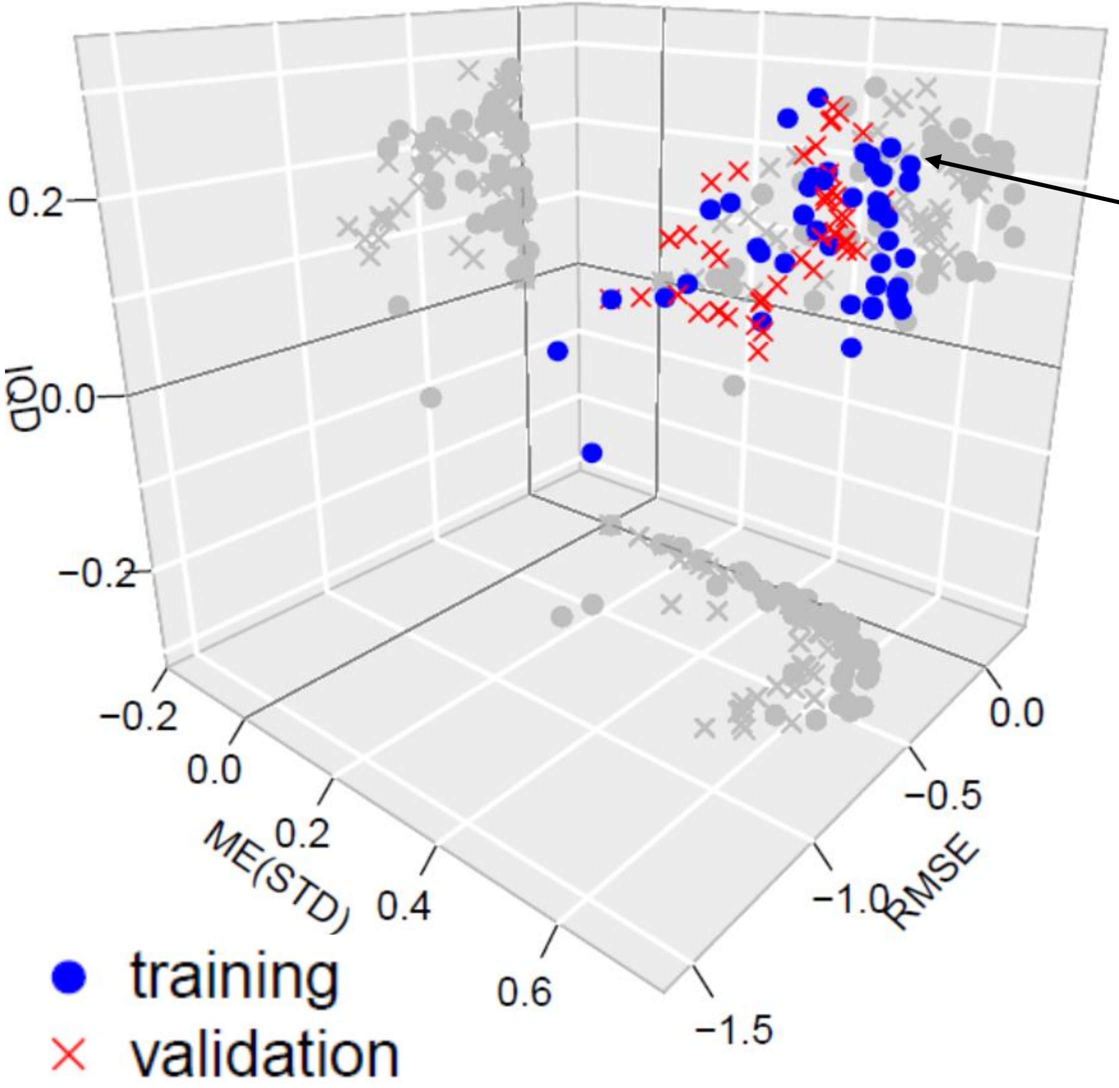
performance on val better than on tr

Results

Relative performance:

1 perfect downscaling
0 as good as predicting 0
-1 error doubled

*Validating on October 14th 2007 (**clear sky**)*



Example of a downscaling rule:

$$\begin{aligned}
&\text{if } HSURF_a > 0.98\\
&\text{then } HSURF_a \times T_{gr60}\\
&\text{else } HSURF_a \times T_{gr110}\\
&+ \text{ if } T_{gr25} > T_{gr110}\\
&\quad \text{then if } 0.83 > T_{gr25}\\
&\qquad\quad \text{then } w_v\\
&\qquad\quad \text{else } Topo_2\\
&\quad \text{else } w_v
\end{aligned}$$

Relative performance:

	RMSE	ME(STD)	IQD
training	-0.18	0.53	0.21
validation	-0.49	0.56	0.09

Results

- a daytime temperature field under clear-sky conditions

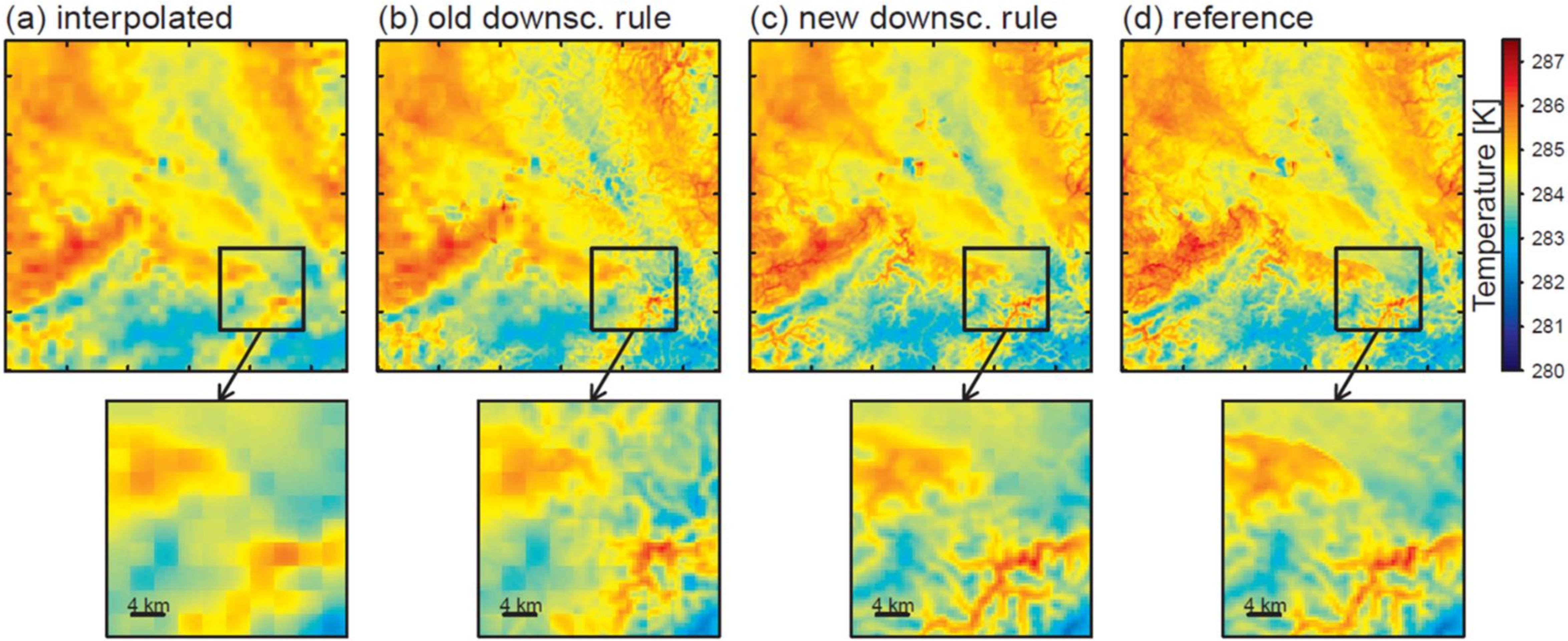
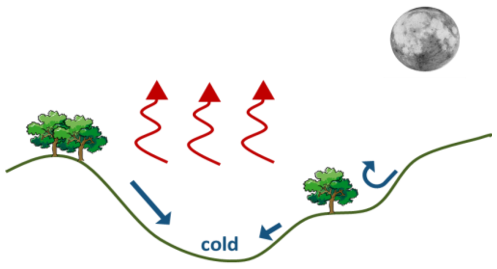


Figure: Near-surface temperature field on October 14th, 2007 at 11:00 UTC. The upper figures show the full fields (i.e.,112 x 112 km); the bottom figures show a zoom in on an area of 28 x 28 km.

Results

- a nighttime temperature field under clear-sky conditions



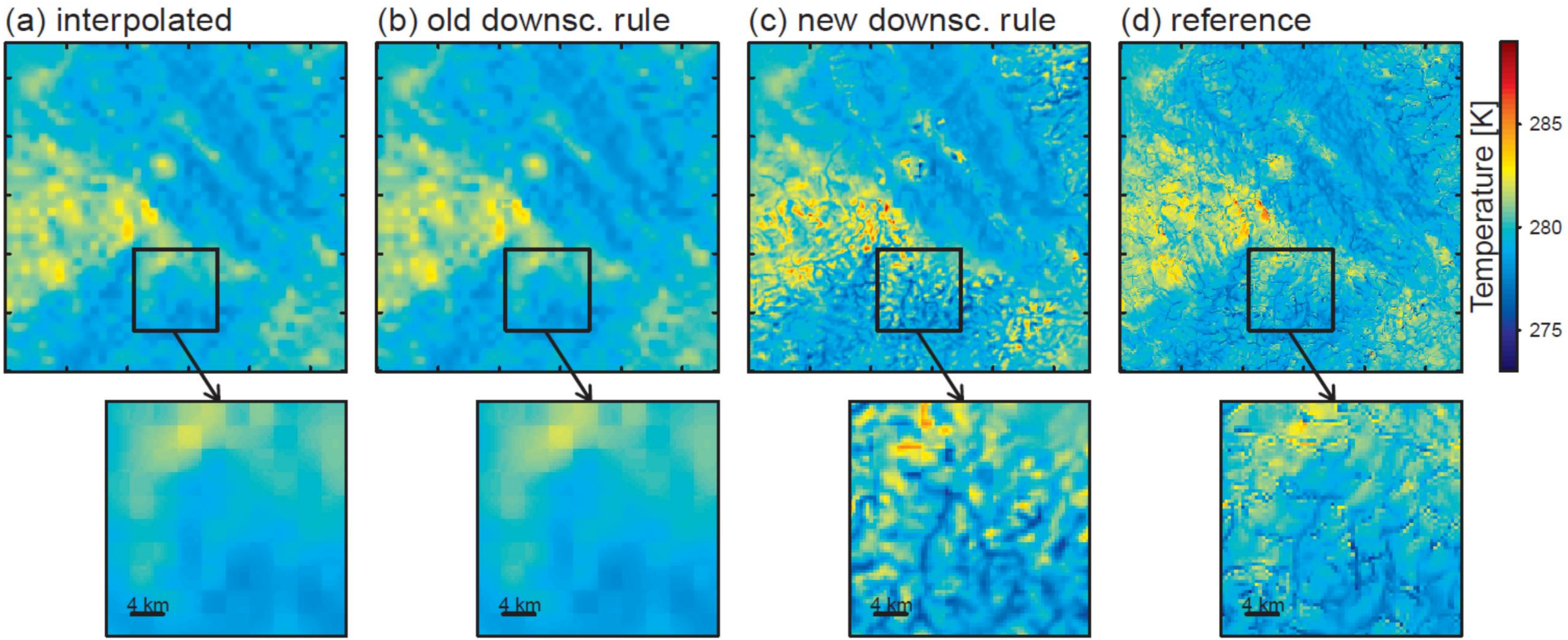
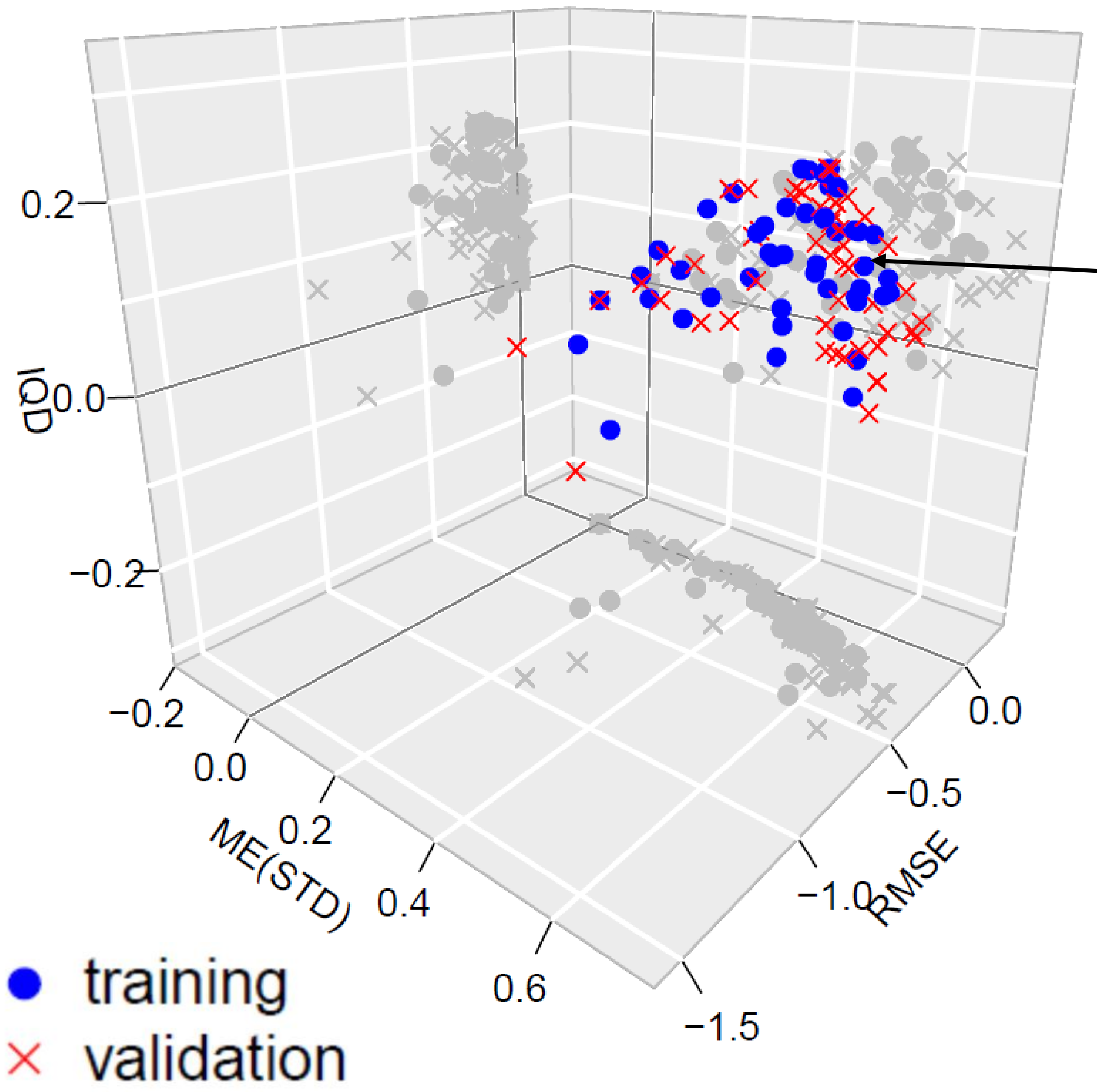


Figure: Near-surface temperature field on October 14th, 2007 at 23:00 UTC. The upper figures show the full fields (i.e.,112 x 112 km); the bottom figures show a zoom in on an area of 28 x 28 km.

Results

*Validating on May 1st 2008 (**clouds and precip.**)*



Relative performance:

1 perfect downscaling
0 as good as predicting 0
−1 error doubled

Example of a downscaling rule:

$$if\ \ T_{gr105} < HSURF_a \times T_{gr25}$$
$$HSURF_a \times T_{gr60}$$
$$else\ 0.17623$$

Relative performance:

	RMSE	ME(STD)	IQD
training	-0.23	0.58	0.10
validation	-0.31	0.63	0.06

Results

- a daytime temperature field under cloudy conditions

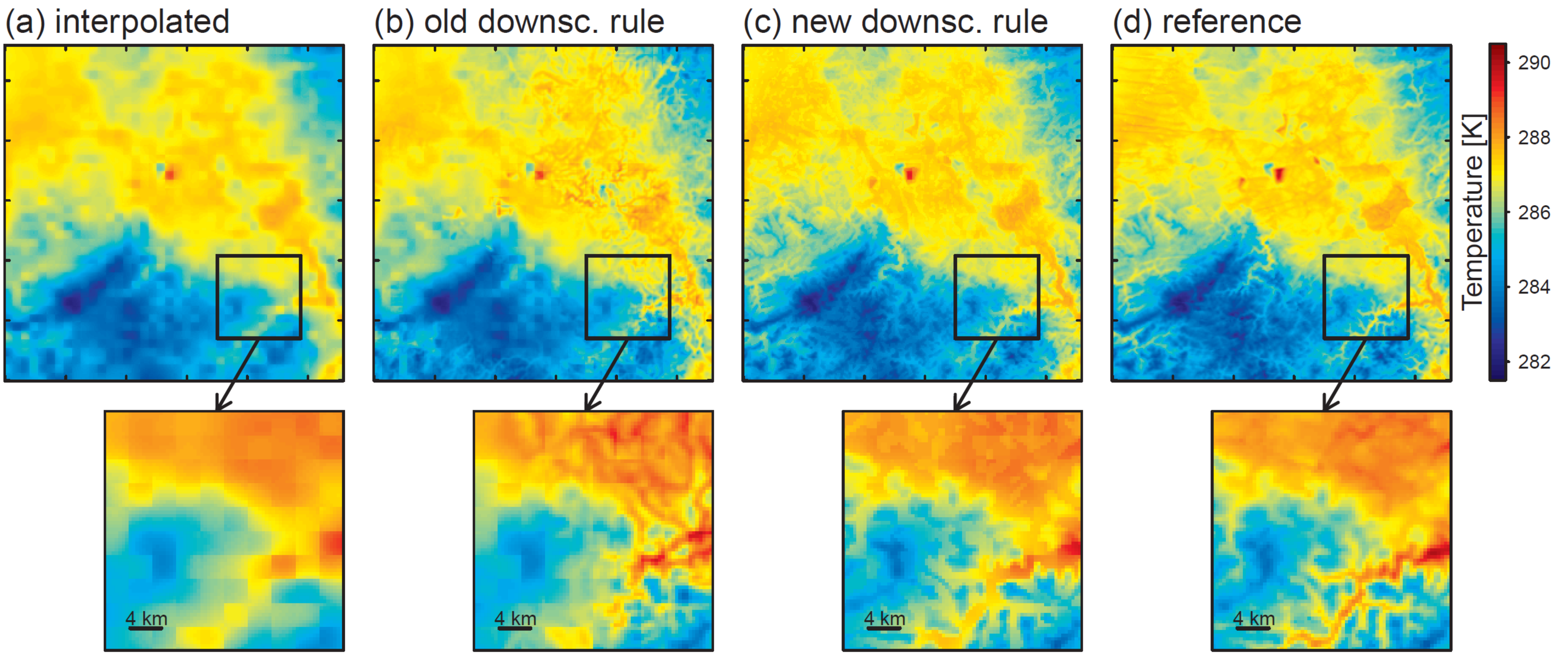


Figure: Near-surface temperature field on May 1st, 2008 at 12:00 UTC. The upper figures show the full fields (i.e.,112 x 112 km); the bottom figures show a zoom in on an area of 28 x 28 km.

Results

- a nighttime temperature field under cloudy conditions

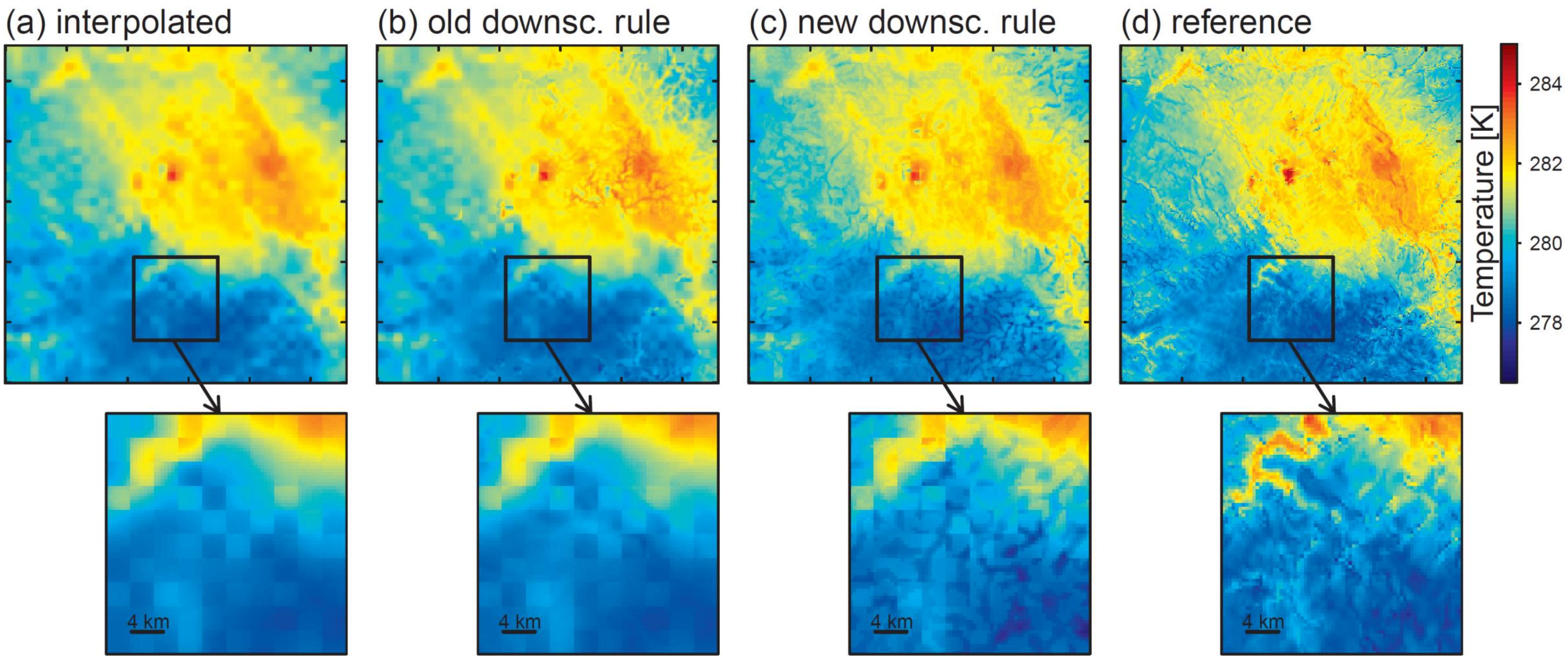


Figure: Near-surface temperature field on May 2nd, 2008 at 1:00 UTC. The upper figures show the full fields (i.e.,112 x 112 km); the bottom figures show a zoom in on an area of 28 x 28 km.

Conclusion and Outlook

Conclusion:

- We have introduced multi-objective Genetic Programming for downscaling near-surface atmospheric fields.
- We have shown that for temperature **more complex processes** can be accounted for than with linear regression.

Outlook:

- Expand training data set.
- Apply multi-objective GP based search algorithm to **all variables** required by land-surface and subsurface models.
- **Implement** new downscaling into coupled modeling platform TerrSysMP.

References

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- Zitzler, E., Thiele, L., 1999. Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach. Evol. Comput. 3 (4), 257–271.

Thank you for your attention!

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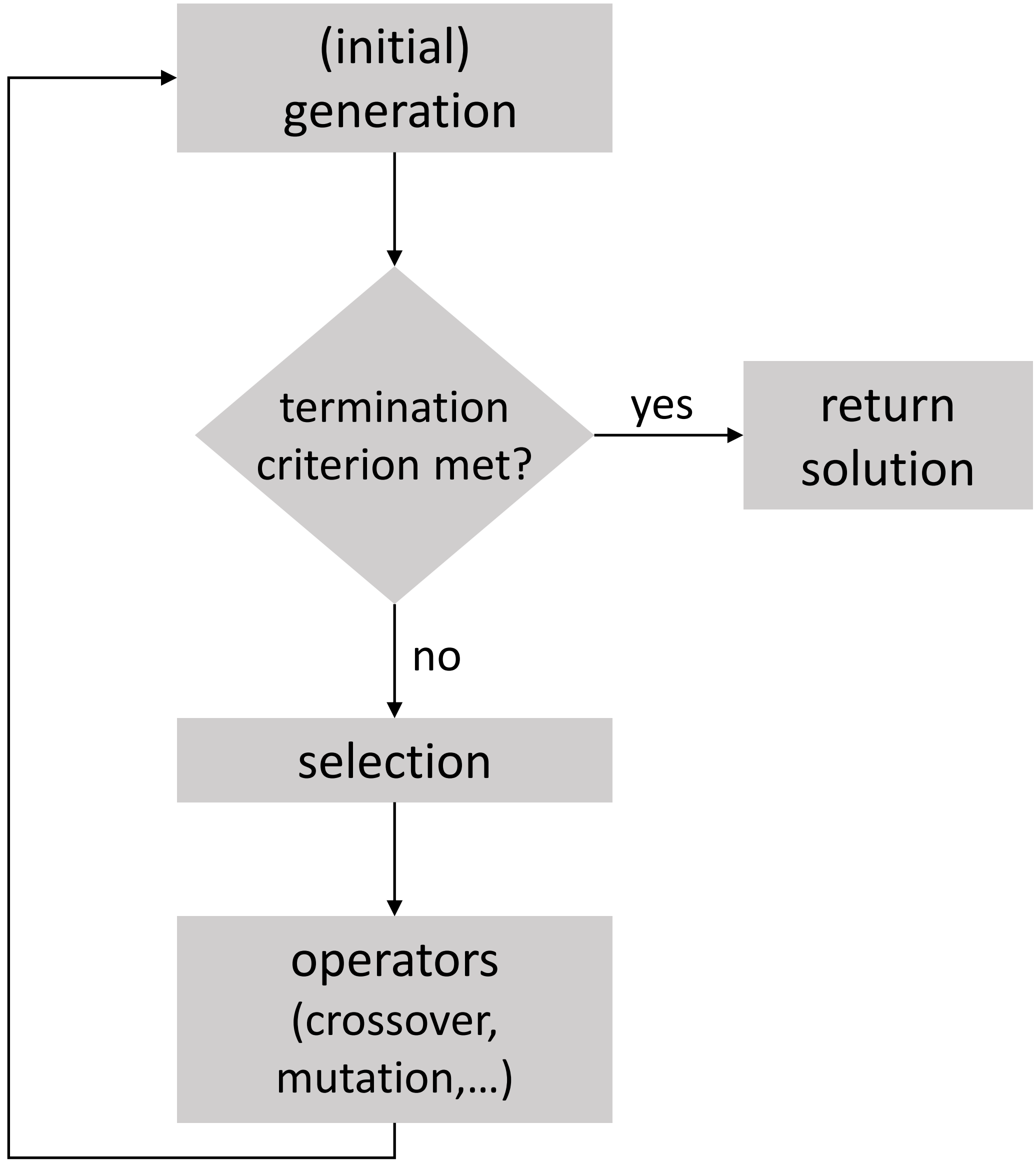
Appendix Predictors

Weather information (coarse)	
T	near surface temperature
T_{gr25}	vert. temp. gradient of lowest 2 layers ($\approx 25m$)
T_{gr60}	vert. temp. gradient of lowest 3 layers ($\approx 60m$)
T_{gr110}	vert. temp. gradient of lowest 4 layers ($\approx 110m$)
w_v	near surface vertical windspeed
w_h	near surface horizontal windspeed
R_{net}	net radiation
Surface information (high-res.)	
$HSURF_a$	topographic height anomaly
$Topo_1$	mean height difference to neighboring grid points
$Topo_{1a}$	anomaly of $Topo_1$
$Topo_2$	slope to lowest neighboring grid point
$Topo_3$	slope to highest neighboring grid point
$Topo_4$	number of direct neighbors lower than grid point
PLC	plant cover
RH	roughness length
ALB	albedo

Appendix Training Data Set

Date	Weather	Time steps used in GP runs
27 Aug. 2007	varying cloud cover, no precipitation	3:00-4:00, 15:00-16:00
14,(15) Oct. 2007	clear sky	11:00-12:00, 23:00-24:00
10 March 2008	strong winds, variable clouds and precipitation	10:00-11:00, 22:00-23:00
(1),2 May 2008	clouds and precipitation	0:00-1:00, 12:00-13:00
(9),10 May 2008	clear sky	1:00-2:00, 13:00-14:00
7,(8) June 2008	convective clouds and precipitation	5:00-6:00, 17:00-18:00
21 July 2008	synoptically driven stratiform rainfall	9:00-10:00, 21:00-22:00
28 Aug. 2008	cloudy, some rain	7:00-8:00, 19:00-20:00

Appendix Genetic Programming (GP)



- Downscaling rules are developed over several generations.
- Each generation consists of a large number of candidate rules.
- A new generation is created by applying so called genetic operators to the parent generation.
- The better a candidate downscaling rule performs the more likely it contributes to the new generation.

Appendix GP for Downscaling

GP/GEP has been applied to **downscaling of GCM output to a station** or catchment mean by *Coulibaly (2004)* and *Hashmi et al. (2011).*

Summary of results of the two studies in comparison with SDSM by Wilby et al.:

Study	Predictant		RMSE GP/GEP	RMSE SDSM	Variables used GP/GEP	Variables used SDSM
Coulibaly (2004)	T_{max}	training	3.54	-	2	6
		testing	3.59	4.07		
	T_{min}	training	4.65	-	2	6
		testing	4.57	5.14		
Hashmi et al. (2011)	precip.	training	5.23	5.61	7	10
		testing	5.35	6.03		

Appendix Multi-objective (Pareto) approach

- With multiple (conflicting) objectives often **no solution optimal with respect to all objectives**.
- Instead there is a set of **Pareto optimal** solutions, in which no solution is optimal in an absolute sense, i.e. with respect to all objectives

- The **Strength Pareto Approach (SPEA)** uses the concept of Pareto optimality for fitness calculation.
- SPEA implies 2 changes to traditional GP:
  - Returns not one final solution, but a **set of (e.g. 50) Pareto optimal solutions**.
  - **Fitness calculation based on comparison** between individuals not absolute objectives.

We have carried out 8 GP runs in total, each leaving out a different day of the training data set (cross-validation).

Each run returns 50 potential downscaling rules.

Appendix Results

We calculate the **relative performance** for a downscaling rule α concerning an objective s_i as:

$$\tilde{s}_i(\alpha) = 1 - s_i(\alpha)/s_i(0)$$

Where $s_i(0)$ is the objective when predicting no anomalies, i.e. 0 everywhere.

$\tilde{s}_i(\alpha) = 1$	perfect downscaling
$\tilde{s}_i(\alpha) = 0$	as good as predicting 0
$\tilde{s}_i(\alpha) = -1$	error doubled

Validating on October 14th 2007