Transformation of CarpatClim datasets to grid-box average datasets



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CarpatClim database

Daily gridded data series for basic meteorological variables in Carpathian Region (1961-2010)

Spatial resolution: 0,1°

Project of JRC (2011-2013) (10 participants)

Methodology: MASH for homogenization, MISH for gridding







http://www.carpatclim-eu.org/pages/home/



THE COMMONLY USED METHODS AND SOFTWARE

http://www.met.hu/en/omsz/rendezvenyek/homogenization_interpolation/software/

MASHv3.03

(Multiple Analysis of Series for Homogenization; Szentimrey, T.)

For homogenization, quality control and missing value completion of station daily data series

MISHv1.03

(Meteorological Interpolation based on Surface Homogenized Data Basis; *Szentimrey, T.and Bihari, Z.*)

For gridding (interpolation) of homogenized daily data series ORSZÁGOS METEOROLÓGIAI SZOLGÁLAT

The main features of MISHv1.03

I. Modelling system for climate statistical parameters in space (expected values, standard deviations, spatiotemporal correlations)

- Based on long homogenized data series and model variables.
- Modelling procedure must be executed only once before the interpolation applications.

II. Spatial interpolation system

- Additive (e.g. temperature) or multiplicative (e.g. precipitation) model and interpolation formula can be used depending on the climate elements.
- Daily, monthly, annual values and many years' means can be interpolated.
- Capability for application of background information such as satellite, radar forecast data.
- Capability for gridding of data series.

- COPERNICUS C3S_311a_Lot4 project: Climate monitoring products for Europe based on Surface in-situ Observations-evaluation of new E-OBS data set
- Transformation of CARPATCLIM dataset is necessary to comparisons
- MISH specialty
- that the necessary statistical parameters like spatial trend and correlation structure are modelled for a very dense half minutes grid and saved.
- These statistical parameters were modelled during also the construction of CarpatClim datasets and they were also outputs of our MISH procedure applied for gridding.
- -Using these saved parameters the transformation of CarpatClim datasets for grid-box average datasets is possible.

Additive model:

- The linear or additive model is appropriate in case of normal probability distribution.
- The spatial trend or median m(s)=E(s) were modelled for a very dense half minutes grid therefore we can transform the temperature CarpatClim gridpoint datasets for grid-box average datasets

Multiplicative model:

- In case of a quasi lognormal distribution (e.g. precipitation sum) we deduced a mixed additive multiplicative formula which is used also in our MISH system.
- The spatial median m(s) were modelled for a very dense half minutes grid therefore we can transform the precipitation CarpatClim gridpoint datasets for grid-box average datasets

For Example the Hungarian grid

The resolution is 0.1 degrees, but the modeling is 0.5 minutes. So, around a grid point, 169 modeled medianes are saved in a box.

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Assuming the linear model – in case of normal distribution - the appropriate additive meteorological interpolation formula is as follows,

$$\sum_{i=1}^{N} \lambda_i \left(E(\mathbf{s}_0) - E(\mathbf{s}_i) \right) + \sum_{i=1}^{M} \lambda_i Z(\mathbf{s}_i, t)$$

where $Z(s_0)$ predictand, s are the element of the given space domain \mathfrak{D}

 $Z(\mathbf{s}_i)$ (i=1,...,M) predictors

Where $\sum_{i=1}^{M} \lambda_i = 1$ and the λ_i (i=1,...,M) minimize the root-mean-square error and these are known functions of some climate statistical parameters

 $E(\mathbf{s}_i)$ (i=0,...,M) are the expected values or spatial trend values. (In case of normal distribution the expected value equals median.)

Mathematical background of transformation of gridpoint datasets for grid-box average datasets in case of additive model

$$\hat{Z}(\mathbf{s}_{0}) = \sum_{i=1}^{M} \lambda_{i} \left(E(\mathbf{s}_{0}) - E(\mathbf{s}_{i}) \right) + \sum_{i=1}^{M} \lambda_{i} Z(\mathbf{s}_{i})$$

Let $\mathbf{S}_{0,k} \in B(\mathbf{S}_0)$, (k=1,...,K) where $B(s_0)$ the gridbox round s_0 .

Then interpolated values within the gridbox are,

$$\hat{Z}\left(\mathbf{s}_{0,k}\right) = \sum_{i=1}^{M} \lambda_{i,k} \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_{i}\right) \right) + \sum_{i=1}^{M} \lambda_{i,k} Z\left(\mathbf{s}_{i}\right) \qquad (k = 1, ..., K)$$

Therefore the grid-box average is,

$$\hat{Z}_{Average}(\mathbf{s}_0) = \frac{1}{K} \sum_{k=1}^{K} \hat{Z}(\mathbf{s}_{0,k}) = \frac{1}{K} \sum_{k=1}^{K} \left(\sum_{i=1}^{M} \lambda_{i,k} \left(E(\mathbf{s}_{0,k}) - E(\mathbf{s}_i) \right) + \sum_{i=1}^{M} \lambda_{i,k} Z(\mathbf{s}_i) \right) \approx$$

as a consequence of the similar stochastic connection of the predictands within the grid-box with the predictors,

$$\approx \frac{1}{K} \sum_{k=1}^{K} \left(\sum_{i=1}^{M} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_i\right) \right) + \sum_{i=1}^{M} \lambda_i Z\left(\mathbf{s}_i\right) \right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{M} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{K} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{K} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_{0,k}\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{K} \frac{1}{K} \sum_{k=1}^{K} \lambda_i \left(E\left(\mathbf{s}_0\right) - E\left(\mathbf{s}_0\right) \right) + \hat{Z}\left(\mathbf{s}_0\right) = \sum_{i=1}^{K} \frac{1}{K} \sum_{i=1}^{K} \lambda_i \left(E\left(\mathbf{s}_0\right) - E\left(\mathbf{s}_0\right) \right) + \sum_{i=1}^{K} \sum_{i=1}^{K} \lambda_i \left(E\left(\mathbf{s}_0\right) + E\left(\mathbf{s}_0\right) \right) + \sum_{i=1}^{K} \sum_{i=1}^{K} \sum_{i=1}^{K} \lambda_i \left(E\left(\mathbf{s}_0\right) + E\left(\mathbf{s}_0\right) \right) + \sum_{i=1}^{K} \sum_{i=1}^{K$$

$$= \left(\overline{E}(\mathbf{s}_0) - E(\mathbf{s}_0)\right) + \hat{Z}(\mathbf{s}_0) = \left(\overline{m}(\mathbf{s}_0) - m(\mathbf{s}_0)\right) + \hat{Z}(\mathbf{s}_0)$$

 $\overline{m}(\mathbf{s}_0)$: the average of the medians in a BOX around \mathbf{s}_0 point

 $m(\mathbf{s}_0)$: median in the \mathbf{s}_0 point

 $\widehat{Z}(\mathbf{s}_0)$: the interpolated value from the CarpatClim gridpoint in the \mathbf{s}_0 point

Mathematical background of transformation of gridpoint datasets for grid-box average datasets in case of multiplicative model

$$\hat{Z}(\mathbf{s}_{0}) = \mathcal{G} \cdot \left(\prod_{q_{i} \in Z(\mathbf{s}_{i}) \geq \mathcal{G}} \left(\frac{q_{i} \cdot Z(\mathbf{s}_{i})}{\mathcal{G}} \right)^{\lambda_{i}} \right) \cdot \left(\sum_{q_{i} \in Z(\mathbf{s}_{i}) \geq \mathcal{G}} \lambda_{i} + \sum_{q_{i} \in Z(\mathbf{s}_{i}) < \mathcal{G}} \lambda_{i} \cdot \left(\frac{q_{i} \cdot Z(\mathbf{s}_{i})}{\mathcal{G}} \right) \right)$$

$$\mathcal{G} > 0, q_i > 0, \quad \lambda_i \ge 0 (i = 1, \dots, M) \qquad \sum_{i=1}^M \lambda_i = 1$$

During the construction of CarpatClim datasets we applied this interpolation formula with interpolation paramaters:

$$\mathcal{G} = m(\mathbf{s}_0), \quad q_i = m(\mathbf{s}_0)/m(\mathbf{s}_i)$$
 Where $m(\mathbf{s}_i), (i = 0, ..., M),$ are the spatial median values.

Let
$$\mathbf{S}_{0,k} \in B(\mathbf{S}_0)$$
, $(k=1,...,K)$ where $B(s_0)$ the gridbox round s_0 .

Then interpolated values within the gridbox are,

$$\hat{Z}(\mathbf{s}_{0,k}) = m(\mathbf{s}_{0,k}) \cdot \left(\prod_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})}\right)^{\lambda_{i,k}}\right) \cdot \left(\sum_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \lambda_{i,k} + \sum_{Z(\mathbf{s}_{i}) < m(\mathbf{s}_{i})} \lambda_{i,k} \cdot \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})}\right)\right)$$

Therefore the grid-box average is,

$$\hat{Z}_{Average}(\mathbf{s}_{0}) = \frac{1}{K} \sum_{k=1}^{K} \hat{Z}(\mathbf{s}_{0,k}) =$$

$$= \frac{1}{K} \sum_{k=1}^{K} m(\mathbf{s}_{0,k}) \cdot \left(\prod_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})} \right)^{\lambda_{i,k}} \right) \cdot \left(\sum_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \lambda_{i,k} + \sum_{Z(\mathbf{s}_{i}) < m(\mathbf{s}_{i})} \lambda_{i,k} \cdot \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})} \right) \right) \approx$$

as a consequence of the similar stochastic connection of the predictands within the grid-box with the predictors,

$$= \left(\frac{1}{K}\sum_{k=1}^{K} m(\mathbf{s}_{0,k})\right) \cdot \left(\prod_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})}\right)^{\lambda_{i}}\right) \cdot \left(\sum_{Z(\mathbf{s}_{i}) \ge m(\mathbf{s}_{i})} \lambda_{i} + \sum_{Z(\mathbf{s}_{i}) < m(\mathbf{s}_{i})} \lambda_{i} \cdot \left(\frac{Z(\mathbf{s}_{i})}{m(\mathbf{s}_{i})}\right)\right) = \frac{1}{K} \sum_{k=1}^{K} m(\mathbf{s}_{0,k})}{m(\mathbf{s}_{0})} \cdot \hat{Z}(\mathbf{s}_{0}) = \frac{\overline{m}(\mathbf{s}_{0})}{m(\mathbf{s}_{0})} \cdot \hat{Z}(\mathbf{s}_{0})$$

ANOVA (Analysis Of Variance)

$$Z(\mathbf{s}_{j},t) (j = 1,...,N; t = 1,...,n) - \text{data series} (\mathbf{s}_{j} : \text{location}; t : \text{time})$$

$$\hat{E}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} Z(\mathbf{s}_{j},t) (j = 1,...,N) - \text{temporal mean at location } \mathbf{s}_{j}$$

$$\hat{D}^{2}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} (Z(\mathbf{s}_{j},t) - \hat{E}(\mathbf{s}_{j}))^{2} (j = 1,...,N) - \text{temporal variance at location } \mathbf{s}_{j}$$

$$\hat{E}(t) = \frac{1}{N} \sum_{j=1}^{N} Z(\mathbf{s}_{j},t) (t = 1,...,n) - \text{spatial mean at moment } t$$

$$\hat{D}^{2}(t) = \frac{1}{N} \sum_{j=1}^{N} (Z(\mathbf{s}_{j},t) - \hat{E}(t))^{2} (t = 1,...,n) - \text{spatial variance at moment } t$$

$$\hat{E} = \frac{1}{N \cdot n} \sum_{j=1}^{n} \sum_{t=1}^{n} Z(\mathbf{s}_{j},t) = \frac{1}{N} \sum_{j=1}^{N} \hat{E}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} \hat{E}(t) - \text{total mean}$$

$$\hat{D}^{2} = \frac{1}{N \cdot n} \sum_{j=1}^{N} \sum_{t=1}^{n} (Z(\mathbf{s}_{j},t) - \hat{E})^{2} - \text{total variance}$$

Partitioning of Total Variance (Theorem)

$$\hat{D}^{2} = \frac{1}{N} \sum_{j=1}^{N} \left(\hat{E}(\mathbf{s}_{j}) - \hat{E} \right)^{2} + \frac{1}{N} \sum_{j=1}^{N} \hat{D}^{2}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} \left(\hat{E}(t) - \hat{E} \right)^{2} + \frac{1}{n} \sum_{t=1}^{n} \hat{D}^{2}(t)$$

$$\frac{1}{N} \sum_{j=1}^{N} (\hat{E}(\mathbf{s}_{j}) - \hat{E})^{2} - \text{spatial variance of temporal means}$$
$$\frac{1}{N} \sum_{j=1}^{N} \hat{D}^{2}(\mathbf{s}_{j}) - \text{spatial mean of temporal variances}$$
$$\frac{1}{n} \sum_{t=1}^{n} (\hat{E}(t) - \hat{E})^{2} - \text{temporal variance of spatial means}$$
$$\frac{1}{n} \sum_{t=1}^{n} \hat{D}^{2}(t) - \text{temporal mean of spatial variances}$$

Maximum temperature



 \widehat{E} (s_j) and the difference between the two CarpatClim Maximum temperature, 1961-2010



Tx E (°C)

$$\hat{E}(\mathbf{s}_j) = \frac{1}{n} \sum_{t=1}^{n} Z(\mathbf{s}_j, t) \quad (j = 1, ..., N) - \text{temporal mean at location } \mathbf{s}_j$$

 $\widehat{D}(s_j)$ and the difference between the two CarpatClim Maximum temperature, 1961-2010



The difference is less than 0.01°C

$$\hat{D}^{2}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} \left(Z(\mathbf{s}_{j}, t) - \hat{E}(\mathbf{s}_{j}) \right)^{2} \quad (j = 1, ..., N) - \text{temporal variance at location } \mathbf{s}_{j}$$

Monthly RMSE for the year



Monthly MSESS for the year



Monthly series: **Z**(**y**, **m**)(y: year, m: month)

$$V(Z(m)) = \frac{1}{n_y} \sum_{y=1}^{n_y} \left(Z(y,m) - \frac{1}{n_y} \sum_{y=1}^{n_y} Z(y,m) \right)^2$$
$$V(Z) = \frac{1}{12} \sum_{m=1}^{12} V(Z(m))$$
$$MSE\left(Z_{1,2}(m)\right) = \frac{1}{n_y} \sum_{y=1}^{n_y} (Z_1(y,m) - Z_2(y,m))^2$$
$$MSE(Z_{1,2}) = \frac{1}{12} \sum_{m=1}^{12} MSE\left(Z_{1,2}(m)\right)$$

Monthly RMSE for the year:

$$RMSE(Z_{1,2}) = \sqrt{MSE(Z_{1,2})}$$

$$MSESS(Z_{1,2}) = 1 - MSE(Z_{1,2})/V(Z_2)$$

Maximum temperature

ANOVA results for precipitation

Spatial mean series of annual precipitation sum for the period 1961-2010

Spatial standard deviation series of annual precipitation sum for the period 1961-2010



Total mean: 700.96 Total variance: 39178.73 CarpatClim gridBOX

Spatial variance of temporal means: 23225.56 Spatial mean of temporal variances: 15953.17 Temporal variance of spatial means: 8293.03 Temporal mean of spatial variances: 30885.27



Total mean: 701.21 Total variance: 40565.66 CarpatClim gridpoint

Spatial variance of temporal means: 24571.22 Spatial mean of temporal variances: 15994.44 Temporal variance of spatial means: 8294.19 Temporal mean of spatial variances: 32271.01







 \widehat{E} (s_j) and the difference between the two CarpatClim (precipitation) 1961-2010

 $\hat{E}(\mathbf{s}_j) = \frac{1}{n} \sum_{t=1}^n Z(\mathbf{s}_j, t) \quad (j = 1, ..., N) - \text{temporal mean at location } \mathbf{s}_j$





 $\widehat{D}(s_j)$ and the difference between the two CarpatClim, precipitation 1961-2010

 $\hat{D}^{2}(\mathbf{s}_{j}) = \frac{1}{n} \sum_{t=1}^{n} \left(Z(\mathbf{s}_{j}, t) - \hat{E}(\mathbf{s}_{j}) \right)^{2} \quad (j = 1, ..., N) - \text{temporal variance at location } \mathbf{s}_{j}$



Precipitation

Monthly RMSE for the year 1961-2010



Monthly MSESS for the year 1961-2010

CarpatClim has two versions:

- -gridpoint database (climate studies)
- -box average database (climate modelling)

Climate studies: extremes Climate modelling: smoothed data

There is a difference between the two CarpatClim where the surface is more complex: in the mountains, in the valleys, slopes and other surface forms.



Thank you for your attention!



