Meteorological Interpolation based on Surface Homogenized Data Basis

(MISH v1.02)

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The present version MISHv1.02 is a continued development of the first version MISHv1.01. The new parts built in the interpolation subsystem of MISH procedure are as follows:

- Data series complementing that is missing value interpolation, completion for monthly or daily station data series.

- Interpolation, gridding of monthly or daily station data series for given predictand locations. In case of gridding the predictand locations are the nodes of a relatively dense grid.

The potential interpolation area was also increased. At the present version the maximum number of the rows of the half minutes grid that covers the interpolation area is 600 instead of the earlier 400 ones. This means area with 150 000-300 000 km² in Europe.
The MISH method for the spatial interpolation of surface meteorological elements was developed at the Hungarian Meteorological Service. This is a meteorological system not only in respect of the aim but in respect of the tools as well. It means that using all the valuable meteorological information – climate and supplementary model or background information – is intended. For that purpose developing an adequate mathematical background was also necessary of course.

In the practice many kinds of interpolation methods exist therefore the question is the difference between them. According to the interpolation problem the unknown predictand value is estimated by use of the known predictor values. The type of the adequate interpolation formula depends on the probability distribution of the meteorological elements! Additive formula is appropriate for normal distribution (e.g. temperature) while some multiplicative formula can be applied for quasi lognormal distribution (e.g. precipitation). The expected interpolation error depends on certain interpolation parameters as for example the weighting factors. The optimum interpolation parameters minimize the expected interpolation error and these parameters are certain known functions of different climate statistical parameters e.g. expectations, deviations and correlations. Consequently the modelling of the climate statistical parameters is a key issue to the interpolation of meteorological elements.

The various geostatistical kriging methods applied in GIS are also based on the above mathematical theory. However these methods use only a single realization in time for modelling of the necessary statistical parameters that is neglecting the long data series which series form a sample in time and space alike. The long data series is such a speciality of the meteorology that makes possible to model efficiently the climate statistical parameters in question!

The MISH method has been developed according to the above basic principles. The main steps of the interpolation procedure are as follows.

- To model the climate statistical parameters by using long homogenized data series.
- To calculate the modelled optimum interpolation parameters which are certain known functions of the modelled climate statistical parameters.
- To substitute the modelled optimum interpolation parameters and the predictor values into the interpolation formula.

The software MISH consists of two units that are the modelling and the interpolation systems. The interpolation system can be operated on the results of the modelling system.

Modelling System for climate statistical (deterministic and stochastic) parameters:
- Based on long homogenized monthly series and supplementary model variables. The deterministic model variables may be as height, topography, distance from the sea etc..
- Benchmark study, cross-validation test for representativity.
- Modelling procedure must be executed only once before the interpolation applications!

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 values and many years’ means can be interpolated.
- Few predictors are also sufficient for the interpolation and no problem if the greater part of daily precipitation predictors is equal to 0.
- The representativity values are modelled too.
- Capability for application of supplementary background information (stochastic variables) e.g. satellite, radar, forecast data.
I. MATHEMATICAL BACKGROUND

1. INTRODUCTION

The MISH method was developed at the Hungarian Meteorological Service for the spatial interpolation of surface meteorological elements. This is a meteorological system not only in respect of the aim but in respect of the tools as well. It means that using all the valuable meteorological information – e.g. climate and possible background information – is required. For that purpose an adequate mathematical background is also necessary of course.

2. SURFACE METEOROLOGICAL INFORMATION

The two basic types of information for the surface meteorological values are data measured at the observation stations and certain background information given at the nodes of a relatively dense grid. Fig. 1. is an illustration of the different kinds of utilized information.

Figure 1. Types of information for the surface meteorological values

The long data series can be considered as a sample in space and time for the climate and this sample implies valuable information for the interpolation as well.

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3. SPATIAL INTERPOLATION METHODS

In practice many kinds of interpolation methods exist therefore the question is the difference between them. According to the interpolation problem the unknown predictand $Z(s_i, t)$ is estimated by use of the known predictors $Z(s_i, t)$ \((i = 1, ..., M)\) where the location vectors $s_i$ are the elements of the given space domain $D$ and $t$ is the time. The type of the adequate interpolation formula depends on the probability distribution of the meteorological element.

### 3.1 Additive Interpolation Formula

Assuming normal distribution (e.g. temperature) the additive formula is adequate, that is, the estimate may be written as

$$
\hat{Z}(s_0, t) = w_0 + \sum_{i=1}^{M} w_i \cdot Z(s_i, t) \quad \text{where} \quad \sum_{i=1}^{M} w_i = 1, \ w_i \geq 0 \quad (i = 1, ..., M), \quad (1)
$$

and $w_0, \ w_i \ (i = 1, ..., M)$ are the interpolation parameters.

#### Root Mean Square Interpolation Error and Representativity:

$$
ERR(s_0) = \sqrt{\mathbb{E}\left( \left( Z(s_0, t) - \hat{Z}(s_0, t) \right)^2 \right)}, \quad REP(s_0) = 1 - \frac{ERR(s_0)}{D(s_0)},
$$

where $\mathbb{E}$ is the expectation and $D(s_0)$ is the standard deviation of the predictand.

The local statistical parameters (expectations, standard deviations) and the stochastic connections (correlations), which are climate statistical parameters in meteorology, uniquely determine the optimum interpolation parameters that minimize the interpolation error. The various geostatistical kriging methods applied in GIS are also based on the above theory. However, these methods use only a single realisation in time for modelling statistical parameters and neglect the long data series which form a sample in time and space as well, while the sample makes it possible to model the climate statistical parameters in question.

### 3.2 Multiplicative Interpolation Formula

Assuming quasi-lognormal distribution (e.g. precipitation sum) the multiplicative formula is adequate, that is, the estimate may be written as

$$
\hat{Z}(s_0, t) = \vartheta \cdot \left( \prod_{q_i Z(s_i, t) \geq \theta} \left( \frac{q_i \cdot Z(s_i, t)}{\theta} \right)^{w_i} \right) \cdot \left( \sum_{q_i Z(s_i, t) \geq \theta}^{M} w_j + \sum_{q_i Z(s_i, t) < \theta} w_j \left( \frac{q_i \cdot Z(s_i, t)}{\theta} \right) \right)
$$

where $\vartheta > 0, \ q_i > 0, \ \sum_{i=1}^{M} w_i = 1$ and $w_i \geq 0 \quad (i = 1, ..., M)$,

and $q_i, \ w_i \ (i = 1, ..., M)$ are the interpolation parameters.

Similarly to the additive case above the optimum interpolation parameters are uniquely determined by certain climate statistical parameters such as some local statistical parameters and stochastic connections.
4. POSSIBLE CONNECTION OF DIFFERENT TOPICS AND SYSTEMS

As we have seen modelling of the climate statistical parameters is a key issue to the interpolation of meteorological elements and that modelling can be based on the long data series. Before detailing the problem of modelling and interpolation we present a block diagram to illustrate the possible connection between various important meteorological topics.

Figure 2. Connection of topics and systems
5. SPATIAL INTERPOLATION WITH OPTIMUM PARAMETERS

If we want to obtain appropriate modeled interpolation parameters first we have to examine the optimum interpolation parameters, which can be written as certain functions of the climate statistical parameters. In this paper only the interpolation by additive formula (chapter 3.1) is detailed.

**Notation:**

- \( Z(s_0,t) \): predictand, \( Z(s_i,t) \) \((i = 1, \ldots, M)\): predictors
- \( ERR(s_0) \): root mean square interpolation error
- \( E(s) \): expectation, \( D(s) \): standard deviation, \( r(s_i,s_j) \): correlation

where location vectors \( s \) are the elements of the given space domain \( D \).

**Optimum Interpolation Error and Representativity:**

- \( ERR_{op}(s_0) = \text{minimum} \ ERR(s_0) \), \( REP_{op}(s_0) = 1 - \frac{ERR_{op}(s_0)}{D(s_0)} \)

**The Structure of the Optimum Interpolation Parameters:**

The minimum error can be obtained by the optimum interpolation parameters. The optimum constant \( w_0 \) depends on the differences \( E(s_i) - E(s_j) \) \((i = 1, \ldots, M)\), furthermore the optimum weighing factors \( w_i \) \((i = 1, \ldots, M)\) as well as the optimum representativity \( REP_{op}(s_0) \) depend on the ratios \( D(s_i)/D(s_j) \) \((i = 1, \ldots, M)\) and the correlations \( r(s_i,s_j) \) \((i, j = 0, \ldots, M)\). Thus the optimum interpolation parameters and the optimum representativity depend only on the correlation structure and the spatial variability of local statistical parameters. Therefore the monthly interpolation parameters are applicable for the interpolation of daily values too.

**Remark:** It can be proved that \( w_0 = \sum_{i=1}^{M} w_i (E(s_0) - E(s_i)) \) and the vector of nonzero weighing factors is \( w = \left( C_{pr}^{-1} 1 \right) + \left( C_{pr}^{-1} 1 \right) c_{0,pr} \), where \( c_{0,pr} \) and \( C_{pr} \) are the proper predictand-predictors covariance vector and predictors-predictors covariance matrix respectively and vector \( 1 \) is identically one.

6. SPATIAL MODELLING OF CLIMATE PARAMETERS

6.1 Known Climate Statistical Parameters for Modelling

The long data series can be used to model the climate statistical parameters. If the stations \( s_j \) \((j = 1, \ldots, N)\) \((s \in D)\) have long monthly series then the local parameters \( E(s_j), D(s_j) \) \((j = 1, \ldots, N)\) as well as the correlations \( r(s_{j_1},s_{j_2}) \) \((j_1, j_2 = 1, \ldots, N)\) can be estimated statistically. Consequently these parameters are essentially known and provide a lot of information for modelling. It is again to be
remarked that the geostatistical methods applied in GIS neglect the long data series which leads to a loss of information.

6.2 Neighbourhood Modelling of Climate Statistical Parameters
The known climate statistical parameters can be used for modelling the correlation structure as well as the spatial variability of local statistical parameters. The basic principle of the neighbourhood modelling is as follows. Let \( P(s), Q(s), \tilde{r}_s(s_i, s_j) \) \((s, s_0, s_1, s_2 \in D)\) be certain model functions depending on different model variables with the following properties:
(a) \( P(s_1) - P(s_2) \approx E(s_1) - E(s_2) \), if \( \|s_1 - s_2\| < d_0 \)
(b) \( \frac{Q(s_1)}{Q(s_2)} \approx \frac{D(s_1)}{D(s_2)} \), if \( \|s_1 - s_2\| < d_0 \)
(c) \( \tilde{r}_s(s_1, s_2) = r(s_1, s_2) \), if \( \|s_1 - s_0\| < d_0 \) and \( \|s_1 - s_2\| < d_0 \)

The model variables may be height, topography (e.g. AURELHY principal components), distance from the sea etc..

7. SPATIAL INTERPOLATION WITH MODELLED PARAMETERS
According to the chapters 5., 6.2 both the modelled weighting factors \( \tilde{w} = [\tilde{w}_1, \ldots, \tilde{w}_M]^T \) and the modelled optimum representativity \( REP_{OP}^{mod}(s_0) \) can be derived from the values of \( \frac{Q(s_i)}{Q(s)} \) \((i = 1, \ldots, M)\), \( \tilde{r}_s(s_i, s_j) \) \((i, j = 0, \ldots, M)\). Hence, Interpolation with Modelled Parameters:
\( \tilde{z}(s_0, t) = \tilde{w}_0 + \sum_{i=1}^{M} \tilde{w}_i z(s_i, t) = \sum_{i=1}^{M} \tilde{w}_i (P(s_i) - P(s_0)) + \sum_{i=1}^{M} \tilde{w}_i E(s_i, t) \). Furthermore, Representativity of the Interpolation with Modelled Parameters:
\( REP_{MP}(s_0) = 1 - \frac{ERR_{MP}(s_0)}{D(s_0)} \), where \( ERR_{MP}(s_0) \) is the root mean square interpolation error obtained by the modelled parameters.
To model the local statistical parameters we can follow a similar approach, that is, Modelling of Monthly Expectation (using additive interpolation):
\( E^{mod}(s_0) = \sum_{k=1}^{K} \tilde{w}_k (P(s_0) - P(s_{jk})) + \sum_{k=1}^{K} \tilde{w}_k E(s_{rk}) \)
Modelling of Monthly Standard Deviation (using multiplicative interpolation):
\( D^{mod}(s_0) = \prod_{k=1}^{K} \left( \frac{Q(s_0)}{Q(s_{jk})} \right)^{\tilde{w}_k} D(s_{rk}) \)
Examples in Hungary
Hungary: 0.5’x0.5’ resolution, approx. 300 000 grid points.

Example 1
Monthly mean temperature: 57 stations with long homogenized data series (1971-2000). One model for each grid point taking into account the nearest 10 stations. Examination of approx. 600 combinations of stations.

Figure 3. Modelled expectation of monthly mean temperature in September

Figure 4. Modelled standard deviation of monthly mean temperature in September

Figure 5. Interpolation of daily mean temperature on 29 September 2004 based on 100 observations
**Example 2**
Monthly precipitation sum: 500 stations with long homogenized data series (1971-2000). One model for each grid point taking into account the nearest 30 stations. Examination of approx. 18 000 combinations of stations.

![Figure 6. Modelled expectation of monthly precipitation sum in July](image)

![Figure 7. Modelled standard deviation of monthly precipitation sum in July](image)

![Figure 8. Interpolation of daily precipitation sum on 27 July 2004 based on 103 observations](image)
8. BENCHMARK STUDY TO TEST THE MODELLING RESULTS

The cross-validation test is a possibility to evaluate the interpolation methods. That is interpolation between the station data series and examination of the root mean square interpolation errors $ERR(S_j)$ or the representativity $REP(S_j)$ ($j = 1, ..., N$).

In our case the interpolation with modelled parameters has been compared to the interpolation with optimum parameters. In Figures 9, 10 we show the mean monthly representativity values that were calculated for both the monthly mean temperature (based on 57 stations) and the monthly precipitation sum (based on 500 stations). For temperature the additive formula (chapter 3.1) while for precipitation the multiplicative formula (chapter 3.2) was applied. For the temperature the inverse distance method which has also an additive interpolation formula was applied too. The notations of the various representativity values are, $REP_{op}$: interpolation with optimum parameters, $REP_{mp}$: interpolation with modelled parameters, $REP_{inv}$: inverse distance method.

Figure 9. Mean monthly representativity values for monthly mean temperature, 57 stations

Figure 10. Mean monthly representativity values for monthly precipitation sum, 500 stations
9. MODELLING OF REPRESENTATIVITY $\textit{REP}_{MP}$

We can also develop an interpolation procedure for modelling the interpolation error or the representativity. Let $\textit{REP}_{\text{OP}}^{\text{mod}}(s_0)$, $\textit{REP}_{\text{OP}}^{\text{mod}}(S_j)$ ($j = 1, ..., N$) be the modelled optimum representativity values according to chapter 7, where $s_0$ is the predictand location, and $S_j$ ($j = 1, ..., N$) are the former station locations. Moreover the representativity values $\textit{REP}_{MP}(S_j)$ ($j = 1, ..., N$) are known as a result of the benchmark study (see chapter 8). Then the representativity of the interpolation with modelled parameters can be interpolated as

$$\textit{REP}_{MP}^{\text{mod}}(s_0) = 1 - \prod_{k=1}^{K} \left( 1 - \frac{\textit{REP}_{MP}^{\text{mod}}(S_k)}{\textit{REP}_{\text{OP}}^{\text{mod}}(S_k)} \right) \cdot \left( 1 - \textit{REP}_{\text{OP}}^{\text{mod}}(s_0) \right)$$

The strength of representativity depends on the predictand-predictors system as well as the quality of modelling. Figures 11,12 are an illustration where the grid points are the predictand locations.

![Figure 11. Modelled representativity values $\textit{REP}_{MP}^{\text{mod}}$ for mean temperature in September, the former 100 observing stations are the predictor locations](image1)

![Figure 12. Modelled representativity values $\textit{REP}_{MP}^{\text{mod}}$ for precipitation sum in July, the former 103 observing stations are the predictor locations](image2)
10. INTERPOLATION WITH BACKGROUND INFORMATION

The background information e.g. forecast, satellite, radar data (see Fig. 1) can be efficiently used to decrease the interpolation error. In this paper only the interpolation based on additive model or normal distribution is presented. Let us assume that \( Z(s_j, t) \) \( (j = 1, \ldots, N) \) are the data measured at the observation stations, \( Z(s_0, t) \) is the predictand and \( Z(s_i, t) \) \( (i = 1, \ldots, M) \) are the predictors where the location vectors \( s \) are the elements of the given space domain \( D \). Furthermore let \( G(s, t) \) \( (s \in D) \) be some background information given on a dense grid. The linear model of conditional expectation of \( Z(s, t) \), given \( G(s, t) \), is

\[
E(Z(s, t) | G(s, t)) = E(s) + \gamma_0 + \gamma_1 \cdot (G(s, t) - E(s)), \quad (s \in D)
\]

where \( E(s) \) is the expectation in space (chapter 5.). The unknown regression parameters \( \gamma_0, \gamma_1 \) and the correlation \( R = \text{corr}(Z(s, t), G(s, t)) \) can be estimated taking into account the given \( Z(s_j, t), G(s_j, t) \) \( (j = 1, \ldots, N) \) and the modelled expectations \( E_{\text{mod}}(s_j) \) \( (j = 1, \ldots, N) \) formulated in chapter 7. According to chapter 7 again the interpolation without background information can be written as

\[
\hat{Z}(s_0, t) = \hat{w}_0 + \sum_{j=1}^{M} \hat{w}_{ji} \cdot Z(s_j, t)
\]

Applying the same interpolation formula for the background information, we have

\[
\hat{G}(s_0, t) = \hat{w}_0 + \sum_{i=1}^{M} \hat{w}_{ji} \cdot G(s_j, t)
\]

Finally, the formulas in case of using background information are as follows:

**Interpolation:**

\[
\hat{Z}_G(s_0, t) = \hat{Z}(s_0, t) + \gamma_1 \cdot \left( G(s_0, t) - \hat{G}(s_0, t) \right)
\]

**Representativity:**

\[
\text{REP}_{G, MP}^\text{mod}(s_0) = \text{REP}_{MP}^\text{mod}(s_0) + \left( 1 - \text{REP}_{MP}^\text{mod}(s_0) \right) \cdot \left( 1 - \sqrt{1 - R^2} \right)
\]

Figure 13 shows an example. The similarity to Figure 5 is a consequence of the weakness of the correlation.
11. SOFTWARE: MISHv1.01

We summarize briefly the most important facts about the developed software MISH. Essentially the system consists of two units that are the modelling and the interpolation systems. The interpolation system can be operated on the results of the modelling subsystem.

(a) Modelling Subsystem
(1) Based on long homogenized monthly series.
(2) Benchmark study for interpolation errors or representativity.
(3) Modelling procedure must be executed only once before the interpolation applications.

(b) Interpolation System
(1) Additive (e.g. temperature) or multiplicative (e.g. precipitation) model and interpolation formula can be used depending on the climate elements.
(2) Daily, monthly values and many years’ means can be interpolated.
(3) Few predictors are also sufficient for the interpolation.
(4) No problem if the greater part of daily precipitation predictors is zero.
(5) Interpolation error (or rather the representativity) can be modelled too.
(6) Capability for application of background information such as satellite, radar, forecast data.

12. CONCLUSION

To clarify the problem of spatial interpolation in meteorology we have to compare the statistical climatology to the geostatistics in respect of methodology. The statistical climatology based on sample in time is bound to be more powerful than the geostatistics based on only one realisation in time. In meteorology the preference of the geostatistical methods – applied also in GIS – over the statistical climatology leads to a loss of information. Nevertheless appropriate spatial modelling parts must be incorporated into statistical climatology. For that purpose an adequate mathematical background is also necessary of course.
II. THE PROGRAM SYSTEM MISH

II.1 GENERAL COMMENTS

The software MISH consists of two units that are the modelling and the interpolation systems. The interpolation system can be operated on the results of the modelling system!

A, Modelling System

– For monthly climate statistical parameters:
  deterministic parameters (e.g. expectations), stochastic parameters (e.g. correlations)
– Based on long homogenized monthly series and supplementary model variables.
  The statistical parameters can be modelled per month on the basis of the monthly series.
  The deterministic model variables may be as height, topography, distance from the sea etc.
– Additive (e.g. temperature) or multiplicative (e.g. precipitation) model can be used depending on the climate elements.
– Benchmark study, cross-validation test for expected interpolation error or representativity.
– Modelling procedure must be executed only once before the interpolation applications!
– The statistical parameters modelled for a month can be used for the interpolation of arbitrary daily and monthly values within the month!

1. Coordinate system: spherical coordinates in decimal degrees ($\varphi', \lambda'$)

2. To cover the interpolation area with a (rectangle) Grid in decimal degrees ($\varphi', \lambda'$).
   Cell size: equidistant dense scale, scale is the same in decimal degrees ($\varphi', \lambda'$);
   0.5’x0.5’ resolution is suggested (0.5’≈ 0.0083333333’!)
   The Grid as a matrix: maximum number of rows: 600, maximum number of columns: 900
   (e.g. 0.5’x0.5’ resolution, 600 rows, 900 columns: 150 000-300 000 km$^2$ in Europe).

3. Height data for the Grid (A,2). The height is always model variable.

4. Observation stations with long (homogenized) monthly series within the interpolation area (covered by the Grid (A,2)). Modelling of the statistical parameters for a month is based on the monthly series. However the modelled monthly statistical parameters can be used also to interpolate daily values within the month!
   Minimum number of the stations: 10; maximum number of the stations: 500.
   Representative station network is suggested.
   Minimum length of the series: 20; maximum length of the series: 50.
   Length 30-50 is suggested taking into account the temporal representativity as well as the possible climate change.

5. Other model variables besides the height for the Grid (A,2). The model variables are deterministic variables, e.g. topography, distance from the sea.
   Minimum number of model variables besides the height: 0; maximum number of model variables besides the height: 19.
B. Interpolation System

- The interpolation system can be operated on the results of the modelling system!
- Modelling procedure must be executed only once before the interpolation applications!
- Daily, monthly values and many years’ means can be interpolated. The statistical parameters modelled for a month can be used for the interpolation of arbitrary daily and monthly values within the month!
- Additive (e.g., temperature) or multiplicative (e.g., precipitation) model and interpolation formula can be used depending on the climate elements.
- Few predictors are also sufficient for the interpolation and no problem if the greater part of daily precipitation predictors is equal to 0.
- The representativity values are modelled too.
- Capability for application of supplementary background information (stochastic variable) e.g. satellite, radar, forecast data.

1. Observations within the interpolation area (covered by the Grid (A,2)) can be daily and monthly values or many years’ means.
   Minimum number of observations: 1; maximum number of observations: 1000.

2. Interpolation:
   a. For given predictand locations (minimum: 1, maximum: 1000) with detailed Results.
      Predictand locations: spherical coordinates in decimal degrees $(\varphi^*, \lambda^*)$
   b. For the Grid (A,2), to obtain Map.

3. Background Information for a relatively dense grid covered by the Grid (A,2).
   Background Information Grid: in decimal degrees $(\varphi^*, \lambda^*)$. Cell size: equidistant scale (at our example: 0.15 $\lambda^*$, 0.1 $\varphi^*$); matrix form: maximum number of rows: 600, maximum number of columns: 900. In case of having Background Information the minimum number of observations is 10. The Background Information is appropriate stochastic variable such as satellite, radar or forecast data.

**Remark**

The modelling and the interpolation systems can be applied directly for interpolation of annual values and many years’ annual means as well. In this case the modelling of statistical parameters is based on long homogenized annual series.

**The new parts of Interpolation System in Version MISHv1.02**

- Missing value interpolation, completion for monthly or daily station data series.
  (max. number of series: 500; max. length of series for a given month: 4000)
- Interpolation, gridding of monthly or daily station data series for given predictand locations. In case of gridding the predictand locations are the nodes of a relatively dense grid. (max. number of series: 500; max. length of series for a given month: 4000; max. number of predictand locations, gridpoints: 5000)

These new parts can be also operated on the results of the modelling system! The statistical parameters modelled for a month can be used for arbitrary daily and monthly series values separated for the month!
II.2 THE STRUCTURE OF PROGRAM SYSTEM

Main Directory MISHv1.02:
- MISHMANUAL.PDF
- Subdirectory EXAMPLE
- Directory MISH:
  - Subdirectory MODEL:
    - Modelling Program and I/O Files of MISH
    - Subdirectory MODPARINTER
      (Parameter Files for subdirectory INTERPOL)
    - Subdirectory MODELSUB
      (Executive subroutines for MODEL.BAT, do not run them)
  - Subdirectory INTERPOL:
    - Interpolation Program and I/O Files of INTERPOL
    - Subdirectory MODPARINTER
      (Parameter Files of subdirectory INTERPOL)
    - Subdirectory INTERSUB
      (Executive subroutines for INTERPAR.BAT, INTERPRED.BAT, INTERGRID.BAT, do not run them)
  - Subdirectory MISHMISS
    - Program and I/O Files of MISHMISS
    - Subdirectory MISSSUB
      (Executive subroutines, do not run them)
  - Subdirectory MISHINTERSER
    - Program and I/O Files of MISHINTERSER
    - Subdirectory INTERSERSUB
      (Executive subroutines, do not run them)
I. Modelling in Subdirectory MODEL
MODEL.BAT: Modelling Procedure. Modelled Statistical Parameters for Interpolation are obtained in Subdirectory MODEL\MODPARINTER.
(To save the Modelled Statistical Parameters is suggested.)

II. Interpolation in Subdirectory INTERPOL
The appropriate monthly Modelled Statistical Parameters for Interpolation must be included by Subdirectory INTERPOL\MODPARINTER.
(Modelled Statistical Parameters must be copied in.)
1. INTERPAR.BAT:
Parametrization and Examination of Observations and Background Information.
2. The further steps can be used optionally
INTERPRED.BAT: Interpolation for given Predictand Locations.
INTERGRID.BAT: Interpolation for the Grid.
Attention: The INTERPAR.BAT must be repeated before the interpolation if the Files of Observations or Background Information are changed!

III. Data Complementing in Subdirectory INTERPOL\MISHMISS
The appropriate monthly Modelled Statistical Parameters must be included by Subdirectory INTERPOL\MODPARINTER. (Modelled Statistical Parameters must be copied in.)
MISHMISS.BAT: Missing Values Completion of Station Data Series.

IV. Interpolation of Series (Gridding) in Subdirectory INTERPOL\MISHINTERSER
The appropriate monthly Modelled Statistical Parameters must be included by Subdirectory INTERPOL\MODPARINTER. (Modelled Statistical Parameters must be copied in.)
MISHINTERSER.BAT: Interpolation of Station Data Series for given Predictand Locations.
Gridding: the locations are the nodes of a relatively dense grid.
The MODELLING PROGRAM and I/O FILES of Subdirectory MODEL

1. Executive Batch File in Directory MODEL
MODEL.BAT: Modelling Procedure

1.1 Subroutines of MODEL.BAT (in MODEL\MODELSUB):
PAR.EXE: Parametrization
STATISTICS.EXE: Estimation of statistical parameters of the data series
COMBIN.EXE: Selection of station combinations for neighbourhood modelling
STOCHMODEL.EXE: Modelling of stochastic parameters
DETMODEL.EXE: Modelling of deterministic parameters
BENCHMARK.EXE: Evaluation of modelling, cross-validation test
MODELGRID.EXE: Modelling results for the grid

2. Input Files and Input Data in Directory MODEL
(See the Data Files of Subdirectory EXAMPLE)

DATASERIES.DAT:
Monthly data series for a given month.
Format of DATASERIES.DAT (max. number of series: 500, suggested length of series: 30):
row 1: indexes or numbers of stations (obligatory!)
column 1: dates or serial indexes
column i+1: series i.

FILAMBDAHST.DAT: Spherical coordinates \( \varphi^*, \lambda^* \) and heights for the stations

HEIGHTGRID.DAT: Determination of the grid (\( \varphi^*, \lambda^* \)); heights for the grid

MODVARIST.DAT: Model variables for the stations

MODVARIGRID.DAT: Model variables for the grid determined by HEIGHTGRID.DAT

Question on the screen
Model?: (a)dditive (e.g temperature) or (m)ultiplicative (e.g. precipitation)

3. Output and Result Files

3.1 Result Files 1 written in Subdirectory MODEL\MODPARINTER
(See: Input Files of Directory INTERPOL)
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR,
INTPAR1.PAR, HEIGHT.PAR(=HEIGHTGRID.DAT)

3.2 Result Files 2 in Directory MODEL
DETMODSTAT.RES: Statistical results of modelling deterministic parameters
BENCHMARK.RES: Benchmark study, evaluation of modelling
MEANGRID.RES: Long term means interpolated for the grid determined by
HEIGHTGRID.DAT

4. Parameter Files
TRANS.PAR, MHTR.PAR, STAT1.PAR, TOPOG.PAR, TAVOLSAG.PAR,
MAPCOMB.PAR, REFCOMB.PAR, REFSPECTCOMB.PAR, STAT2ST.PAR,
STAT2.PAR, VARST.PAR, VAR.PAR, REPST.PAR
The INTERPOLATION PROGRAM and I/O FILES of Subdirectory INTERPOL

1. Executive Batch Files in Subdirectory INTERPOL
INTERPAR.BAT: Parametrization and Examination of the Background Information
INTERPRED.BAT: Interpolation for given Predictand Locations
INTERGRID.BAT: Interpolation for the grid determined by HEIGHT.PAR

2. Input Files and Input Data

2.1 Input Files 1 in Subdirectory INTERPOL\MODPARINTER
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, INTPAR1.PAR, HEIGHT.PAR
See: Result Files of Directory MODEL
Attention: Subdirectory MODPARINTER must include the necessary Parameter Files!
(Modelled Statistical Parameters must be copied in Subdirectory MODPARINTER.)

2.2 Input Files 2 in Subdirectory INTERPOL
(See the Data Files of Subdirectory EXAMPLE)
OBSERVED.DAT: Observations and coordinates (min. number: 1; max. number: 1000)
BACKINFGRID.DAT: Background Information for a grid inside the grid determined by
HEIGHT.PAR
PREDTANDFILA.DAT: Predictand coordinates (min. number: 1; max. number: 1000)
(Input of INTERPRED.BAT)

3. Output and Result Files in Subdirectory INTERPOL
INTERPAR.RES: Output of INTERPAR.BAT (if we have Background Information)
INTERPRED1.RES: Output of INTERPRED.BAT (detailed Results)
INTERPRED2.RES: Output of INTERPRED.BAT (less detailed Results)
INTERGRID1.RES: Output of INTERGRID.BAT (Interpolation without Background
Information)
INTERGRID2.RES: Output of INTERGRID.BAT (Interpolation with Background
Information)

4. Parameter Files
BACKINFH.PAR, BACKINFM.PAR, OBSERVED1.PAR, INTPAR2.PAR, MODPAR.PAR
The PROGRAM and I/O FILES of Subdirectory INTERPOL\MISHMISS

1. Executive Batch File in Directory MISHMISS

MISHMISS.BAT: Data Complementing Procedure

Subroutines of MISHMISS.BAT (in MISHMISS\MISSSUB):
INTERPAR3.EXE: Parametrization
INTERMISS.EXE: Data Complementing Subroutine

2. Input Files and Input Data

2.1 Input Files 1 in Subdirectory INTERPOL\MODPARINTER
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR,
INTPAR1.PAR, HEIGHT.PAR
See: Result Files of Directory MODEL
Attention: Subdirectory MODPARINTER must include the necessary Parameter Files!
(Modelled Statistical Parameters must be copied in Subdirectory MODPARINTER.)

2.2 Input Files 2 in Subdirectory MISHMISS
(See the Data Files of Subdirectory EXAMPLE)

OBSSERIES.DAT:
Observed station data series with missing values.
Format of OBSSERIES.DAT (max. number of series: 500; max. length of series: 4000):
row 1: indexes or numbers of stations (obligatory!)
column 1: dates or serial indexes
column i+1: series i.
Mark of Missing Values: 9999

OBSFILA.DAT: Coordinates of Stations

3. Output and Result File in Subdirectory MISHMISS

OBSSERIES.RES: Complemented station data series

4. Parameter Files
MODPAR.PAR, MISS1.PAR, MISS2.PAR
The PROGRAM and I/O FILES of Subdirectory INTERPOL\MISHINTERSER

1. Executive Batch File in Directory MISHINTERSER

MISHINTERSER.BAT: Series Interpolation Procedure

Subroutines of MISHINTERSER.BAT (in MISHINTERSER\INTERSERSUB):
INTERPAR4.EXE: Parametrization
INTERSER.EXE: Series Interpolation Subroutine

2. Input Files and Input Data

2.1 Input Files 1 in Subdirectory INTERPOL\MODPARINTER
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, INTPAR1.PAR, HEIGHT.PAR
See: Result Files of Directory MODEL
Attention: Subdirectory MODPARINTER must include the necessary Parameter Files!
(Modelled Statistical Parameters must be copied in Subdirectory MODPARINTER.)

2.2 Input Files 2 in Subdirectory MISHINTERSER
(See the Data Files of Subdirectory EXAMPLE)

OBSSERIES.DAT: Observed station data series.
Format of OBSSERIES.DAT (max. number of series: 500; max. length of series: 4000):
  row 1: indexes or numbers of stations (obligatory!)
  column 1: dates or serial indexes
  column i+1: series i.

OBSFILA.DAT: Coordinates of Stations
PREDTANDFILA.DAT: Coordinates of Predictand Locations (max. number: 5000)
  Gridding: the locations are the nodes of a relatively dense grid.

3. Output and Result Files in Subdirectory MISHINTERSER

INTERSERIES.RES: Interpolated (Gridded) Series
INTERSERSTAT.RES: Statistical Results for the Predictand Locations

4. Parameter Files
MODPAR.PAR, OBSSER.PAR
III. EXAMPLE FOR APPLICATION OF MISH SYSTEM

Interpolation Area: Transdanubia (the western part from Danube in Hungary)
Modelled Elements: (Monthly, daily) mean temperature in September and (monthly, daily) precipitation sum in November.
Interpolated Elements: Daily mean temperature for a day in September and daily precipitation sum for a day in November.
Missing Values Completion of Station Data Series: Monthly mean temperature series in September and monthly precipitation sum series in November.
Gridding: Monthly mean temperature series in September and monthly precipitation sum series in November.

III.1 EXAMPLE FOR TEMPERATURE

III.1.1 MODELLING PART (Directory MODEL)

Input Data Files
(See the Data Files Format in Subdirectory EXAMPLE\HUNTEMP\DATA\MODEL)
DATASERIES.DAT: Series of monthly mean temperature in September; 30 stations and 30 years. (Not genuine data.)
FILAMBDAHST.DAT: spherical coordinates in decimal degrees $\phi^\circ, \lambda^\circ$ and heights for the stations
HEIGHTGRID.DAT: grid (0.5’x0.5’ resolution) covering Transdanubia; heights for the grid
MODVARIST.DAT: 15 model variables (AURELHY principal components) besides the height for the stations
MODVARIGRID.DAT: the model variables for the grid determined by HEIGHTGRID.DAT
MODEL (answer to the question on the screen): (a)dditive
Output and Result Files

Result Files 1: Modelled Climate Statistical Parameters for September
written in Subdirectory MODEL\MODPARI\INTER:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR,
INTPAR1.PAR
(See: Input Files of Directory INTERPOL)

Result Files 2 (written in Directory MODEL) are the following:

MODELLING OF DETERMINISTIC PART (linear regression)

FINAL RESULT:
number of model variables: 6  correlation: 0.921  percentage: 61.1%
model variables and coefficients:
    h 5 9 10 12 14
-0.0033 0.0284 0.0482 0.0324 -0.0924 -0.0274

(percentage=(1-RMSE/(Standard Deviation))*100%)

DETAILED RESULTS:

number of variables: 1  correlation: 0.814  percentage: 41.9%
h -0.004

number of variables: 2  correlation: 0.879  percentage: 52.4%
h 12
-0.004 -0.079

number of variables: 3  correlation: 0.901  percentage: 56.6%
h 10 12
-0.004 0.042 -0.081

number of variables: 4  correlation: 0.907  percentage: 57.9%
h 3 10 12
-0.004 -0.011 0.047 -0.084

number of variables: 5  correlation: 0.919  percentage: 60.6%
h 5 9 10 12
-0.004 0.024 0.045 0.040 -0.079

number of variables: 6  correlation: 0.921  percentage: 61.1%
h 5 9 10 12 14
-0.003 0.028 0.048 0.032 -0.092 -0.027

number of variables: 7  correlation: 0.926  percentage: 62.1%
h 4 5 9 10 12 14
-0.004 -0.027 0.038 0.061 0.041 -0.086 -0.038

number of variables: 8  correlation: 0.929  percentage: 63.1%
h 1 4 5 9 10 12 15
-0.003 0.009 -0.033 0.036 0.045 0.041 -0.059 0.096

Figure 2. Statistical results of modelling deterministic parameters
(DETMODSTAT.RES)
BENCHMARK STUDY: cross-validation test, interpolation between the stations

REPRESENTATIVITY VALUES (REP) FOR THE STATIONS
REP=1-RMSE/(Standard Deviation)
REPop: interpolation with optimum parameters
REPmp: interpolation with modelled parameters

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<th>REPmp</th>
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</table>

Figure 2. Benchmark study, evaluation of modelling (BENCHMARK.RES)

Figure 3. Modelled expectation (or interpolated many years’ mean) of monthly mean temperature in September (MEANGRID.RES)
III.1.2 INTERPOLATION PART (Directory INTERPOL)

**Input Files and Input Data**
(See the Data Files Format in Subdirectory EXAMPLE\HUNTEMP\DATA\INTERPOL)

**Input Files 1: Modelled Climate Statistical Parameters for September**
in Subdirectory INTERPOL\MODPARINTER:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR,
INTPAR1.PAR
(See: Output Files of Directory MODEL)

**Input Data Files 2 (in Directory INTERPOL)**
OBSERVED.DAT: 49 daily mean temperature observations for a day in September and the observing locations (coordinates $\phi$, $\lambda$)
BACKINGGRID.DAT: Forecast data as Background Information for a grid (6°x9’ resolution) inside the grid (0.5°x0.5’ resolution) determined by HEIGHT.PAR
PREDTANDFILA.DAT: 121 predictand coordinates $\phi$, $\lambda$ (Input of INTERPRED.BAT)

**Result Files (written in Directory INTERPOL) are the following**

EXAMINATION OF BACKGROUND INFORMATION
Correlation: 0.300
Constant: -0.354
Coefficient: 0.571
Interpolated Background Information for the Observing Locations:

Figure 4. Correlation and regression analysis between observations and background information (forecast data) (INTERPAR.RES)

Number of Predictands: 121

Predictand 64: 17.600000 47.400000

Predictor Indexes: 12 13 10 30 16 11 14
Weighting Factors: 0.204 0.065 0.199 0.178 0.114 0.129 0.110
Interpolation without Background Information:
Predictand Value: 14.77
Representativity: 0.814
Interpolation with Background Information:
Predictand Value: 14.74
Representativity: 0.822

Figure 5. Detailed result of interpolation for the given predictand locations (INTERPRED1.RES)
Figure 6. Interpolation without background information for the grid (0.5’x0.5’ resolution) determined by HEIGHT.PAR (INTERGRID1.RES)

Figure 7. Interpolation with background information (forecast data) for the grid (0.5’x0.5’ resolution) determined by HEIGHT.PAR (INTERGRID2.RES)
III.1.3 DATA SERIES COMPLEMENTING (Subdirectory INTERPOL\MISHMISS)

**Input Files and Input Data** (See the Data Files Format in Subdirectory EXAMPLE\HUNTEMP\DATA\INTERPOL\MISHMISS)

**Input Files 1: Modelled Climate Statistical Parameters for September**
in Subdirectory INTERPOL\MODPARINTER:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR, INTPAR1.PAR (See: Output Files of Directory MODEL)

**Input Data Files 2 (in Subdirectory INTERPOL\MISHMISS)**
OBSSERIES.DAT: Monthly mean temperature series in September with missing values; 30 stations and 29 years. Mark of missing values: 9999.00
OBSFILA.DAT: spherical coordinates in decimal degrees $\varphi^*, \lambda^*$ for the stations

**Result File (written in Subdirectory INTERPOL\MISHMISS) is the following:**
OBSSERIES.RES: The complemented data series
(See in Subdirectory EXAMPLE\HUNTEMP\RESULTS\INTERPOL\MISHMISS)

---

III.1.4 INTERPOLATION OF SERIES, GRIDDING (Subdirectory INTERPOL\MISHINTERSER)

**Input Files and Input Data** (See the Data Files Format in Subdirectory EXAMPLE\HUNTEMP\DATA\INTERPOL\MISHINTERSER)

**Input Files 1: Modelled Climate Statistical Parameters for September**
in Subdirectory INTERPOL\MODPARINTER:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR, INTPAR1.PAR (See: Output Files of Directory MODEL)

**Input Data Files 2 (in Subdirectory INTERPOL\MISHINTERSER)**
OBSSERIES.DAT: Monthly mean temperature series in September without missing values; 30 stations and 29 years
OBSFILA.DAT: spherical coordinates in decimal degrees $\varphi^*, \lambda^*$ for the stations
PREDTANDFILA.DAT: spherical coordinates in decimal degrees $\varphi^*, \lambda^*$ of 768 grid points, 0.1 $\lambda$ x 0.1 $\varphi$ resolution.
(Gridding: the grid points are the predictand locations)

**Result Files (written in Subdirectory INTERPOL\MISHINTERSER) are the following:**
INTERSERIES.RES: Interpolated (Gridded) Series for the 768 grid points
INTERSERSTAT.RES: Statistical Results of the Interpolation for the 768 grid points
(See in Subdirectory EXAMPLE\HUNTEMP\RESULTS\INTERPOL\MISHINTERSER)
III.2 EXAMPLE FOR PRECIPITATION

III.2.1 MODELLING PART (Directory MODEL)

**Input Data Files**

(See the Data Files Format in Subdirectory EXAMPLE\HUNPREC \DATA\MODEL)

DATASERIES.DAT: Series of monthly precipitation sum in November; 117 stations and 30 years. (Not genuine data.)

FILAMBDAHST.DAT: spherical coordinates in decimal degrees $\varphi^\circ, \lambda^\circ$ and heights for the stations

HEIGHTGRID.DAT: grid (0.5˚x0.5˚ resolution) covering Transdanubia; heights for the grid

MODVARIST.DAT: 15 model variables (AURELHY principal components) besides the height for the stations

MODVARIGRID.DAT: the model variables for the grid determined by HEIGHTGRID.DAT

MODEL (answer to the question on the screen): (m)ultiplicative

**Output and Result Files**

Result Files 1: Modelled Climate Statistical Parameters for November

written in Subdirectory MODEL\MODPARINTER:

ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR, INTPAR1.PAR

(See: Input Files of Directory INTERPOL)

Result Files 2 (written in Directory MODEL) are the following:

MODELLING OF DETERMINISTIC PART (linear regression)

Multiplicative model: logarithmic values are used

FINAL RESULT:

number of model variables: 5 correlation: 0.530 percentage: 15.2%

model variables and coefficients:

\[
\begin{array}{cccc}
  h & 3 & 5 & 6 & 9 \\
  0.0004 & 0.0018 & -0.0023 & -0.0031 & 0.0066 \\
\end{array}
\]

(percentage=(1-RMSE/(Standard Deviation))*100%)

DETAILED RESULTS:

number of variables: 1 correlation: 0.391 percentage: 8.0%

\[
\begin{array}{c}
  h \\
  0.001 \\
\end{array}
\]

number of variables: 2 correlation: 0.449 percentage: 10.7%

\[
\begin{array}{c}
  h \\
  0.001 & 0.006 \\
\end{array}
\]

number of variables: 3 correlation: 0.494 percentage: 13.1%

\[
\begin{array}{c}
  h \\
  0.000 & 0.002 & 0.007 \\
\end{array}
\]

number of variables: 4 correlation: 0.521 percentage: 14.7%

\[
\begin{array}{c}
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  0.000 & 0.002 & -0.003 & 0.007 \\
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\]

number of variables: 5 correlation: 0.530 percentage: 15.2%

\[
\begin{array}{c}
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  0.000 & 0.002 & -0.002 & -0.003 & 0.007 \\
\end{array}
\]

number of variables: 6 correlation: 0.534 percentage: 15.4%

\[
\begin{array}{c}
  h \\
  0.000 & 0.002 & -0.002 & -0.003 & 0.007 \\
\end{array}
\]

Figure 8. Statistical results of modelling deterministic parameters (DETMODSTAT.RES)
BENCHMARK STUDY: cross-validation test, interpolation between the stations

REPRESENTATIVITY VALUES (REP) FOR THE STATIONS
REP=1-RMSE/(Standard Deviation)
REPop: interpolation with optimum parameters
REPmp: interpolation with modelled parameters

REPRESENTATIVITY VALUES FOR THE STATIONS

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</table>

Figure 9. Benchmark study, evaluation of modelling (BENCHMARK.RES)

Figure 10. Modelled expectation (or interpolated many years’ mean) of monthly precipitation sum in November (MEANGRID.RES)
III.2.2 INTERPOLATION PART (Directory INTERPOL)

**Input Files and Input Data**
(See the Data Files Format in Subdirectory EXAMPLE\HUNPREC \DATA\INTERPOL)

**Input Files 1: Modelled Climate Statistical Parameters for November**
in Subdirectory INTERPOL\MODPARINTER:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR, INTPAR1.PAR
(See: Output Files of Directory MODEL)

**Input Data Files 2 (in Directory INTERPOL)**
OBSERVED.DAT: 43 daily precipitation sum observations for a day in November
and the observing locations (coordinates $\varphi^o, \lambda^o$)
BACKINFGRID.DAT: No
PREDTANDFILA.DAT: 121 predictand coordinates $\varphi^o, \lambda^o$ (Input of INTERPRED.BAT )

**Result Files (written in Directory INTERPOL) are the following**

Number of Predictands: 121

Predictand 64: 17.600000 47.400000

  Predictor Indexes : 10 8 27 25 9 11 13
  Weighting Factors: 0.422 0.199 0.080 0.191 0.058 0.002 0.048
  Interpolation:
  Predictand Value: 24.40
  Representativity: 0.663

Figure 11. Detailed result of interpolation for the given predictand locations
(INTERPRED1.RES)

Figure 12. Interpolation without background information for the grid (0.5’x0.5’
resolution) determined by HEIGHT.PAR (INTERGRID1.RES)
III.2.3 DATA SERIES COMPLEMENTING (Subdirectory INTERPOL\MISHMISS)

**Input Files and Input Data** (See the Data Files Format in Subdirectory EXAMPLE\HUNPREC\DATA\INTERPOL\MISHMISS)

**Input Files 1: Modelled Climate Statistical Parameters for November**
in Subdirectory INTERPOL\MODPARI:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR,
INTPAR1.PAR (See: Output Files of Directory MODEL)

**Input Data Files 2 (in Subdirectory INTERPOL\MISHMISS)**
OBSSERIES.DAT: Monthly precipitation sum series in November with missing values; 117 stations and 30 years. Mark of missing values: 9999.00
OBSFILA.DAT: spherical coordinates in decimal degrees $\phi^\circ, \lambda^\circ$ for the stations

**Result File (written in Subdirectory INTERPOL\MISHMISS) is the following:**
OBSSERIES.RES: The complemented data series
(See in Subdirectory EXAMPLE\HUNPREC\RESULTS\INTERPOL\MISHMISS)

---

III.2.4 INTERPOLATION OF SERIES, GRIDDING PART (Subdirectory INTERPOL\MISHINTERSER)

**Input Files and Input Data** (See the Data Files Format in Subdirectory EXAMPLE\HUNPREC\DATA\INTERPOL\MISHINTERSER)

**Input Files 1: Modelled Climate Statistical Parameters for November**
in Subdirectory INTERPOL\MODPARI:
ALF.PAR, BET.PAR, GAM.PAR, MED.PAR, DEL.PAR, POTPRED.PAR, HEIGHT.PAR,
INTPAR1.PAR (See: Output Files of Directory MODEL)

**Input Data Files 2 (in Subdirectory INTERPOL\MISHINTERSER)**
OBSSERIES.DAT: Monthly precipitation sum series in November without missing values; 117 stations and 30 years
OBSFILA.DAT: spherical coordinates in decimal degrees $\phi^\circ, \lambda^\circ$ for the stations
PREDTANDFILA.DAT: spherical coordinates in decimal degrees $\phi^\circ, \lambda^\circ$ of 768 grid points, $0.1^\circ x 0.1^\circ$ resolution.
(Gridding: the grid points are the predictand locations)

**Result Files (written in Subdirectory INTERPOL\MISHINTERSER) are the following:**
INTERSERIES.RES: Interpolated (Gridded) Series for the 768 grid points
INTERSERSTAT.RES: Statistical Results of the Interpolation for the 768 grid points
(See in Subdirectory EXAMPLE\HUNPREC\RESULTS\INTERPOL\MISHINTERSER)
References


Bihari, Z., Szentimrey, T., Lakatos, M., Szalai, S., 2007: „Verification of radar precipitation measurements with interpolated surface data”, Advances in Geosciences (submitted)


Szentimrey, T., Bihari, Z., Szalai, S., 2005: „Meteorological Interpolation based on Surface Homogenized Data Basis (MISH)”, European Geosciences Union, General Assembly 2005, Vienna, Austria, 24 - 29 April 2005

Szentimrey, T., Bihari, Z., Szalai, S., 2005: „Limitations of the present GIS methods in respect of meteorological purposes”, 5th Annual Meeting of the European Meteorological Society (EMS)/7th ECAM; Utrecht, Netherlands, 12-16 September 2005

Szentimrey, T., Bihari, Z., 2006: „MISH (Meteorological Interpolation based on Surface Homogenized Data Basis)”, COST Action 719 Final Report, The use of GIS in climatology and meteorology, Edited by Ole Einar Tveito, Martin Wegehenkel, Frans van der Wel and Hartwig Dobesch, 2006, pp. 54-56


Tveito, O., E., Schöner, W., 2002: „Applications of spatial interpolation of climatological an meteorological elements by the use of geographical information systems (GIS)”, Report no. 1/WG2 Spatialisation/ COST-719, DNMI report 28/02 KLIMA, Oslo, Norway