Uncertainties in modelling of climate change impact in future: An example of onion thrips (Thrips Tabaci Lindeman) in Slovenia

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Abstract
Uncertainties related to the climate impact studies are reviewed on the case of onion thrips in Slovenia. Paper illustrates cumulative uncertainty introduced by future emission scenarios, general circulation models, downscaling procedures, weather generators and impact (degree-day) models as common tools in climate impact studies. The result of cumulative uncertainty is a wide range of expected warming in Slovenia in the 21st century. An expected increase of air temperature, relative to 1990, is between 1.5 and 7 °C till the end of present century. Due to heterogeneity of the present climate conditions in Slovenia, quite uniform air temperature increase on the entire area will have different impact on the change of cumulative degree-days (DD) and related number of generations of onion thrips per year (Ngen) in different regions. An example of Ljubljana and Bilje shows that larger increase of DD and related Ngen is expected for regions with warmer climate. As a result, more damage will probably be caused in areas that are already strongly exposed to the problem of onion thrips. Harmfulness of the pest in the areas, where it is not a serious threat at present, will also increase. However, we have to be fully aware of a large amount of uncertainty related to studies of climate change impact while interpreting their results.

1. Introduction
Chaotic nature of climate system (Lorenz, 1967) does not enable the predictability of climate years ahead. However, a long-term systematic change in boundary conditions (e.g. change in atmospheric composition) may influence the climate statistics, and the resulting long-term climatic response to such change may still be estimated (Benestad, 2003). The problem of unpredictability remains in the assumptions about future change in boundary conditions. Different assumptions for socio-economic development and consequent emissions and concentrations of greenhouse gases and sulphate aerosols in the atmosphere introduce uncertainty at the very beginning of any future climate change study (Fig. 1). Further assumptions about the impact of changes in atmospheric composition on global, regional or even local climate enlarge the cumulative uncertainty in quantitative climate change estimates. Due to the uncertainty, projections of climate
change are usually related to the term scenarios \(^2\) and not to the term projection. The scope of this paper is to illustrate different sources of uncertainty in local future climate change scenarios. The later are commonly based on climate simulations with general circulation models and local projections of their results with empirical downscaling (e.g. Bums and Dehn, 2000). Additional uncertainty that arise from the estimation of climate change impact is further discussed in the paper.

Insects are the most diverse class of organisms on Earth. As insects have many detrimental effects on humans and natural ecosystems, both directly and indirectly, it is not surprising that considerable thought has already been given to the impacts that the global environmental change may have on them (Harrington et al., 2001). Our paper is focused on a temperature change impact, as the temperature is the key environmental driver of insects' development (e.g. Edelson and Magaro, 1988; Harrington et al., 2001). Temperature is also the climate variable for which there is most confidence in its change in the future (Houghton et al., 2005). Through the temperature change, the climate change will strongly affect the insects' physiology, phenology and spatial distribution (Harrington et al., 2001). The problem of cumulative uncertainty in local climate change impact studies is illustrated in this paper on the example of insect pest onion thrips (Thrips tabaci Lindeman) in Slovenia, although the general principles may be applied more widely.

\[^2\] A plausible and often simplified description of how the future may develop, based on a coherent and internally consistent set of assumptions about driving forces and key relationships. Scenarios may be derived from projections, but are often based on additional information from other sources, sometimes combined with a narrative storyline (Houghton et al., 2001).

2. Data

2.1. Large-scale near-ground air temperature and sea-level pressure

Average monthly near-ground air temperature (\(T\)) and sea-level pressure (\(p\)) were used as predictors in empirical downscaling. Reanalysis of \(T\) and \(p\) from a common project of the US National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) (Kistler et al., 2001) were used as observed predictor values \(^3\) for the period 1951–2002. Horizontal resolution of gridded \(T\) reanalysis is approximately \(1.9^\circ \times 1.9^\circ\) and of \(p\), \(2.5^\circ \times 2.5^\circ\). Modeled \(T\) and \(p\) values were obtained from the results of simulations \(^4\) with four GCM (Table 1):

- Australian coupled GCM CSIRO/Mk2 developed by the Commonwealth Scientific and Industrial Research Organization;
- UK coupled GCM UKMO/HadCM3 developed by the Hadley Centre of United Kingdom Meteorological Office;
- USA coupled GCM DOE/NCAR/PCM developed as a common project of the National Center for Atmospheric Research and Department of Energy;
- German coupled GCM MPI-DE/MACAM4-OPFC3 developed as a common project of the Max Planck Institut für Meteorologie and the Deutsches Klimarechenzentrum.

For the simulation of future climate, GCM are forced by emission scenarios. The Intergovernmental Panel on Climate Change (IPCC) developed a wide range of possible future emission scenarios (SRES) (Nakićenović et al., 2000; Houghton et al., 2000). We used the results of GCM simulations based on the two marker SRES A2 and B2. We used the results of GCM simulations based on these two marker SRES. Due to the methodology used for empirical downscaling, observed and modeled \(T\) and \(p\) were interpolated in a common grid of \(2.5^\circ \times 2.5^\circ\) by a simple bi-linear interpolation method (Press et al., 2001). Interpolated predictor values across the area extending from \(35^\circ N\) to \(65^\circ N\) and from \(10^\circ W\) to \(30^\circ E\) (Fig. 2) were used as input in empirical models (EM). This area was chosen as a compromise between the skillful scale of GCM (Grimm and MacCracken, 1995) and the quality of EM, which usually decreases with enlargement of predictor area (Benestad, 2002).

2.2. Global temperature

Estimated future changes of global air temperature, based on simulations with simple climate model (Rahmstorf et al., 2000), were used to derive ratios of climate system responses to different SRES. Such ratios are needed for scaling the GCM simulation results and empirical downscaling estimates based on


Table 1 – General circulation models whose results were used in our study: model label, period for which the model output were used, the approximate horizontal resolution of data, and some references for the models and/or simulations

<table>
<thead>
<tr>
<th>Model</th>
<th>Period</th>
<th>Resolution</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO/Mk2</td>
<td>1951–2100</td>
<td>5.6° × 3.2°</td>
<td>Gordon and O’Farrel (1997)</td>
</tr>
<tr>
<td>UKMO/HadCM3</td>
<td>1951–2099</td>
<td>3.8° × 2.5°</td>
<td>Pope et al. (2000), Gordon et al. (2000)</td>
</tr>
<tr>
<td>DOE-NCAR/PCM</td>
<td>1961–2099</td>
<td>2.8° × 2.8°</td>
<td>Washington et al. (2000)</td>
</tr>
<tr>
<td>MPI-ESM/ECHAM4-OPYC3</td>
<td>1951–2100</td>
<td>2.8° × 2.8°</td>
<td>Roeckner et al. (1996), Stendel et al. (2000)</td>
</tr>
</tbody>
</table>

The A2 and B2 marker SRES to the other SRES (A1T, A1F, A1B and B1). The global warming estimates are available from the IPCC Data Distribution Centre as changes relative to 1765. For our purpose, the changes for selected four GCM were recalculated relative to a reference year 1990 and were used for the estimation of the ratios.

2.3. Local near-ground air temperature

Near-ground air temperature at locations Ljubljana (λ_g = 14.52° E, φ_g = 46.07° N, z_g = 299 m, climate = temperate continental) and Bilje (λ_g = 13.63° E, φ_g = 45.90° N, z_g = 55 m, climate = sub-Mediterranean) was used as predictand. Mean daily values were used to derive daily temperature generator, and to estimate cumulative degree-days (DD). Average monthly values (y) were used as predictand data in empirical downscaling. Local temperatures were measured and quality checked by the Environmental Agency of the Republic of Slovenia. Some long-term statistics of predictand data are presented in Table 2.

2.4. Monitoring of onion thrips (T. tabaci Lindeman)

Onion thrips (T. tabaci Lindeman, Thysanoptera, Thripidae) is a polyphagous pest, which causes serious damage on different vegetables and ornamentals all over the world (Murai, 2000). It is especially important as a pest on Alliaceae plants like onion (Allium cepa L.) and leek (Allium porrum L.) (McKenzie et al., 1993; Theunissen and Schelling, 1998), as also on Brassicaceae plants like cabbage (Brassica oleracea L.) (Shelton et al., 1998). The monitoring of onion thrips was performed in an onion field in Ljubljana and a leek field in Bilje in years 1999 and 2000 using light-blue sticky boards, which are widely used for the monitoring of thrips population (Brødsgaard, 1989; Tidu et al., 2003). The first boards were set in April 1999. Four light-blue sticky boards were placed on random locations in the field and were changed with new ones approximately twice a month.
3. Methods

Empirical downscaling was used to relate the variability of \( T \) and \( p \) fields across western and central Europe to the variability of \( y \) at locations Ljubljana and Bilje. Observed and modeled \( T \) and \( p \) values were standardized prior to their use in EM to avoid some systematic errors in GCM results (Schubert, 1998).

As the trends in time series can affect the variability measures (Giorgi, 2002), linear trends were removed for estimation of standard deviations that were used in a standardization procedure. The standardization was performed separately for every single grid point. Long-term standard deviations and averages based on values for the years up to 1990 were used in the standardization procedure (Bergant and Kajfež-Bogataj, 2005). To avoid inflated correlation coefficients and related undesirable effects in the calibration of EM (Benedat et al., 2002), EM were developed and used separately for every single month. Developed EM were used for projecting standardized but not detrended GCM results for \( y \) to the local \( y \) values.

Pattern-scaling technique was used to adjust the local projections, based on results of GCM simulations forced by A2 and B2 marker SRES, also to other marker SRES. Projected \( y \) values for all marker SRES were used in a daily temperature generator to generate synthetic daily air temperature values for the estimation of cumulative degree-days.

3.1. Empirical downscaling

For the empirical downscaling of \( p \) and \( T \) GCM results to \( y \), three different but similar regression techniques were used to develop EM and illustrate the potential dependence of downscaling results on selected method. Predictors’ values were joined in a common matrix \( X \), where the columns of matrix \( X \) are the time series of standardized \( p \) and \( T \) for each grid point. Regression models are used to relate predictors’ variability to local air temperatures \( y \) that are joined in time series vector \( y \). A mathematical description of developed EM can be written as

\[
S = XW, \quad \hat{y} = Sb. \tag{1}
\]

The left part of the Eq. (1) presents the extraction of important features from predictors’ variability and the right part presents the regression model used for downscaling. The time series of important features (columns of matrix \( S \)) are extracted from predictors’ time series with the help of the weight matrix \( W \). Determination of this matrix from observed data depends on the selection of method.

In the first method, common principal component analysis (Rutherford et al., 1992; Benedat et al., 2002) was used for feature extraction - determination of \( W \) matrix, and stepwise regression (e.g. Wilks, 1995) for feature selection – determination of regression vector \( b \). The first few principal components, together explaining 95% of predictor variability, were used in stepwise regression. The method is usually addressed as principal component regression (PCR).

In the second and the third method, the feature extraction and selection were performed simultaneously. In the second method, two-dimensional partial least squares regression (2PLS) (Bro, 1998; Helland, 2001) was used for development of EM, and in the third method three-dimensional version of partial least squares regression (3PLS) (Bro, 1998; Jong de, 1998; Bergant and Kajfež-Bogataj, 2005) was used. Regression models were developed and used separately for every single month in the year.

The leave-one-out cross-validation (LOOCV) (e.g. Wilks, 1995) was used to select the optimal number of features in EM. To estimate the LOOCV mean square error of prediction (MSEP), we exclude from all \( i \) observation a single one and use the remaining \( i-1 \) to develop an EM. This EM is used afterwards to estimate excluded predictand value on the base of corresponding predictor values. The procedure is repeated for the entire set of observations. The corresponding MSEP can be written as

\[
\text{MSEP} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \tag{2}
\]

where \( y_i \) present the \( i \)th observation of predictand and \( \hat{y}_i \) its LOOCV estimate. The inclusion of additional feature in EM

### Table 2 – Long-term averages (top), standard deviations (middle) and autocorrelation coefficients (bottom) of observed local daily near-ground air temperature for individual months in the period 1951–2002

<table>
<thead>
<tr>
<th>Location</th>
<th>January</th>
<th>February</th>
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<th>April</th>
<th>May</th>
<th>June</th>
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<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljubljana</td>
<td>6.5</td>
<td>6.4</td>
<td>6.2</td>
<td>5.9</td>
<td>5.6</td>
<td>6.2</td>
<td>6.2</td>
<td>6.3</td>
<td>6.9</td>
<td>7.1</td>
<td>7.2</td>
<td>6.9</td>
</tr>
<tr>
<td>Bilje</td>
<td>2.9</td>
<td>4.1</td>
<td>7.5</td>
<td>11.2</td>
<td>16.1</td>
<td>19.5</td>
<td>21.7</td>
<td>21.1</td>
<td>16.8</td>
<td>12.5</td>
<td>7.7</td>
<td>3.1</td>
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Long-term standard deviations of daily air temperature:

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<th>Location</th>
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<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljubljana</td>
<td>1.4</td>
<td>1.6</td>
<td>1.8</td>
<td>2.0</td>
<td>1.9</td>
<td>1.8</td>
<td>1.8</td>
<td>1.9</td>
<td>1.9</td>
<td>2.1</td>
<td>2.4</td>
<td>2.5</td>
</tr>
<tr>
<td>Bilje</td>
<td>2.5</td>
<td>2.5</td>
<td>2.0</td>
<td>3.9</td>
<td>4.1</td>
<td>4.9</td>
<td>5.6</td>
<td>5.1</td>
<td>4.0</td>
<td>3.1</td>
<td>2.4</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Autocorrelation coefficients of daily air temperature:

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<th>Location</th>
<th>January</th>
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<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljubljana</td>
<td>0.6</td>
<td>0.4</td>
<td>0.8</td>
<td>1.0</td>
<td>1.4</td>
<td>1.8</td>
<td>2.2</td>
<td>2.4</td>
<td>2.5</td>
<td>2.7</td>
<td>2.9</td>
<td>3.1</td>
</tr>
<tr>
<td>Bilje</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
<td>0.3</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Until the end of the year 2000. The average daily catch from all four boards (\( N_{day} \)) was used as a measure of population extension.
is usually terminated when the ratio of MSEP_{new}/MSEP_{previous} becomes greater than one. As such a criteria could lead to the over-fitting due to the sampling variability, an adjusted ratio of MSEP_{new}/MSEP_{previous}, where \( c < 1 \), should be applied (Li et al., 2002). In our case, we used a value of \( c = 0.97 \), since higher values led to an over-fitting in few cases. The prediction performance of EM is quantified in the paper by the Pearson’s correlation coefficient (\( \rho \)) (e.g. Wilks, 1995) between observation (\( y \)) and LOOCV estimates (\( \tilde{y} \)), and the closeness of the model fit by the Pearson’s correlation coefficient (\( r \)) between observation (\( y \)) and final model estimates (\( \hat{y} \)), based on the EM developed on all available observations.

3.2. Pattern-scaling

The core of the pattern scaling method is the assumption that there is a linear relationship between regional or local climate and the amount of global warming (Mitchell, 2003). In this manner, we can estimate the local response of the climate variable, in our case local air temperature, to selected SRES (\( \Delta T_{\text{sel}} \)) knowing the local response to the reference SRES (\( \Delta T_{\text{ref}} \)) and the global warming under the selected (\( \Delta T_{\text{sel}} \)) and reference SRES (\( \Delta T_{\text{ref}} \)). In our case, when using the GCM results for SRES A2 and B2, the estimates for other SRES on local level can be calculated as:

\[
\Delta T_{\text{ref}} = \frac{\Delta T_{\text{sel}}}{\Delta T_{\text{ref}}} \Delta T_{\text{ref}}
\]

SRES A2 was used as a reference for SRES A1(F, T, B), and SRES B2 for SRES B1. This is in accordance to Mitchell (2003) recommendations, that pattern scaling should be performed from a scenario with greater increases in radiative forcing. All the differences (\( \Delta y \)) were calculated relative to the year 1990. The approach was evaluated comparing the available GCM simulation results for air temperature averaged across the selected predictor area (\( \Delta T_{\text{sel}} \)), based on SRES A2 and B2. It can be seen in Fig. 3 that the temporal behaviour of air temperature results of GCM simulations using (a) SRES B2 directly, and (b) SRES B2 scaled from SRES A2, is similar, indicating that the use of pattern scaling approach is reasonable. The ratios used for scaling the results of empirical downscaling based on SRES A2 and B2 to other marker SRES (A1T, A1B, A1F and B1) are shown in Fig. 4.

3.3. Noise addition

Since no reasonable EM explains all the temporal variability of \( y \), the downscaled estimates for observed values (\( \hat{y} \)) have smaller variance than the real values (\( \text{var}(\hat{y}) < \text{var}(y) \)) (Storch von, 1999). Temporal variability of \( y \) is only partially controlled by the large-scale dynamics described in \( X \), and the unexplained part can be treated as a noise. If we somehow describe this noise and add it to the \( \hat{y} \) values, such randomized values exhibits similar temporal variability as observed values. In our case, the noise was treated as white noise with values normally distributed according to zero mean and variance of differences between observations (\( y \)) and their

![Fig. 3 – The ratio between global warming relative to 1990 related to the SRES B2 and A2 (upper plot) and comparison of GCM simulated (model) and pattern scaled changes (estimate) of average annual air temperature averaged across selected predictor area (bottom four subplots).](image-url)
Fig. 4 – The ratio between global warming relative to 1990 related to the SRES A1F and A2 (upper left), A1B and A2 (upper right), A1T and A2 (bottom left), and B1 and B2 (bottom right) used for pattern scaling.

downscaled estimates ($\hat{y}$) vary $y$. The noise was added to the downscaled $y$ values for the future before using them in daily temperature generator. The assumption was made that the behaviour of noise will not change in the future.

3.4. Daily temperature generator

A simple stochastic temperature generator (Wilks and Wilby, 1999), describing average daily temperature as a first order autoregressive process (AR(1)), was used to relate the monthly and the daily statistics of local near-ground air temperature (Yu et al., 2002):

$$y_d = \alpha (\bar{y} - y) + s \sqrt{1 - \rho^2} \varepsilon_d$$

(4)

In the Eq. (4), $y_d$ presents daily air temperature on $d$th day in selected month, $\bar{y}$ the average monthly value of $y_d$ and $s$ its standard deviation in this month, $\alpha$ the autocorrelation coefficient of $y_d$ for selected month of the year and $\varepsilon_d$ a standardized Gaussian random number. Synthetic $y_d$ can be generated using Eq. (4) on empirical downsampling results for $y$ and assuming that the autocorrelation of $y_d$, the weak linear relationship between $s$ and $y$ ($\varepsilon = s\alpha + \rho$; $\rho$: estimate of $s$, $\alpha$, $\rho$: linear model parameters), and the noise contribution to the $s$ and $y$ will remain the same in future. Derived $y_d$ values can be used for the estimation of degree-days, as a measure of pest developmental rate.

3.5. Degree-day model

A common approach to the prediction of development dynamics and migrations of insects in relationship to weather conditions is the use of degree-day models (e.g. Bryant et al., 1998).

Different approaches can be used for the calculation of degree-days (Bolton et al., 1999). In our case, the sum of positive differences between mean daily air temperature and threshold temperature ($y_d - y_{base}$) so called effective temperatures, was used for the estimation of cumulative DD in the period of $D$ days. In our case, annual cumulative DD were calculated ($D = 365$):

$$DD = \begin{cases} 
\sum_{d=1}^{D} (y_d - y_{base}) & \text{for } y_d > y_{base} \\
0 & \text{for } y_d \leq y_{base}
\end{cases}$$

(5)

The number of onion thrips generations per year ($N_{gen}$) were estimated dividing the annual cumulative degree-days by the sum of effective temperatures (ST) needed for development of onion thrips from the stage of an egg to the mature female ($N_{gen} = DD/ST$).

4. Results with discussion

The basic source of uncertainty that cannot be avoided from the very beginning of climate change scenario development are the assumptions about future socio-economic development and related emissions of greenhouse gasses and sulphur dioxide. As a measure of uncertainty related to the future emissions, a wide range of SRES suggested by IPCC can be used. Different GCM respond slightly different to the same SRES and resulting concentrations of greenhouse gasses and sulphate aerosols. Such climate model shortcomings are another source of uncertainty and are mainly related to a crude description of unresolved processes using statistical
parameterisation schemes (Benestad, 2002). To illustrate the uncertainty related to the future SRES and climate model shortcomings, we present the results of simulations with selected four GCM using marker SRES A2 and B2, additionally scaled also to marker SRES A1T, A1B and B1, and averaged across the selected predictor area. In Fig. 5 we can see, that the resultant increase of air temperature by the end of 21st century is between 1.5 and 5.5 °C relative to the 1990 value, with an average value of around 3.5 °C. A more detailed estimate of the time evolution of expected temperature change can be seen in Fig. 5.

GCM are able to simulate reliably the most important features of the global climate in a large-scale (Zorita and von Storch, 1999), but not on a regional or even a local scale, mostly due to the low horizontal resolution and limited description of sub-grid processes (Grotch and MacCracken, 1991). Despite these limitations, their results can be linked to regional climate characteristics, if the regional climate is affected by large-scale features (Benestad et al., 2002). Different approaches to downscaling, dynamical (e.g. Giorgi and Mearns, 1999) and empirical (e.g. Storch von et al., 2000), are commonly used to bridge the gap between large-scale and local-scale, and the selection of method and predictors could influence the results, especially due to the problem of the extrapolation. As it is expected that air temperature will change significantly in the future, its values will probably exceed the range of values used for EM development. We have no guaranty that the EM will still be valid within the new range of values ($T; p; y$), which is another source of uncertainty. We tested three similar regression techniques (PCR, 2PLS and 3PLS) as empirical downscaling methods. The quality of developed EM is presented in Table 3 for all three methods in terms of $q$ and $r$ correlation coefficients. High values of $q$ and $r$, comparable between all three methods, give some confidence in developed EM. As the extrapolated values using the three methods for projecting the results of HADCM3 forced by SRES A2 scenario are almost the same (Fig. 6), we can conclude that the local estimates based on each of the method can be treated with similar confidence, and that the use of different methods in our case does not contribute significantly to the uncertainty of final results despite their use for the extrapolation.

For further calculations, we used only 3PLS based local projections of GCM results. The time evolution of estimated range of annual air temperature in second half of the 20th and the entire 21st century at locations Ljubljana and Bilje is presented in Fig. 7 together with the observed values in the past.

<table>
<thead>
<tr>
<th>Location</th>
<th>PCR</th>
<th>2PLS</th>
<th>3PLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljubljana</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>88</td>
<td>54</td>
<td>40</td>
</tr>
<tr>
<td>February</td>
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<td>58</td>
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<tr>
<td>November</td>
<td>86</td>
<td>51</td>
<td>38</td>
</tr>
</tbody>
</table>

Results for models using PCR, 2PLS and 3PLS method are presented.
Fig. 6 – Empirical downscaling estimates of local annual air temperature ($y$) in Ljubljana (left) and Bilje (right) based on results of future climate simulation with HADCM3 model forced by SRES A2 and local projections with 3PLS, 2PLS and PCR method.

The estimated change of $y$ by the end of the 21st century is between 1.5 and 7 $^\circ$C, with an average about 4 $^\circ$C relative to 1990 value. The wide range of estimated change indicates the uncertainty in local temperature projections. For the past, in case of Ljubljana, the observations are within the range of modeled values, but in case of Bilje, a decrease of temperature before 1980 is not captured.

Development of insects is often related to the weather conditions with degree-day models. Different DD models for onion thrips in literature (Edelson and Magaro, 1988; Murai, 2000; Stacey and Fellowes, 2002) indicate that either the pest is capable of local adaptation, or the estimation of DD model parameters is not trivial. On the base of available observations for the years 1999 and 2000 (Fig. 8) it is hard to distinguish, which $y_{base}$ and corresponding ST is more appropriate to relate the onion thrips development with daily temperature conditions in Slovenia. As two of the models for onion thrips development, from the stage of the egg to the mature female—capable of oviposition, are very similar (Edelson and Magaro, 1988: $y_{base} = 11.5 $ $^\circ$C, ST = 228.2 $^\circ$C; Murai, 2000: $y_{base} = 10.8 $ $^\circ$C, ST = 232.6 $^\circ$C), and as the first one was also used in European region (Rijn van et al., 1995), model proposed by Edelson and Magaro (1988), developed under variable temperature conditions, seems to be an appropriate choice. The model corresponds to the Charnov and Gillooly (2003) $10^\circ$C rule establishing that the lower threshold temperature ($y_{base}$) is about $10^\circ$C below the mean developmental temperature for ectotherms in nature. Edelson and Magaro (1988) report a linear increase of developmental rate for the temperatures between 17.5 and 27.5 $^\circ$C, and Murai (2000) for the temperatures between 15 and 30 $^\circ$C (mean developmental temperature is 22.5 $^\circ$C in both cases). In contrary, the $10^\circ$C rule does not confirm Stacey and Fellowes (2002) $y_{base} = 5.9 $ $^\circ$C, ST = 260.8 $^\circ$C, based on the assumption of linear increase of developmental rate for temperatures between 12 and 28 $^\circ$C (mean developmental temperature is 20 $^\circ$C). To be sure, that a proper DD model was chosen, a laboratory experiment under constant and variable temperature conditions, studying the development of onion thrips caught on the area of Slovenia, should be performed.

The problem is also that the pest on the field is exposed to the temperatures different to those obtained by meteorological measurements that are commonly used in DD calculation. The lack of studies and data about the adaptation capability of onion thrips in changed environmental conditions is another important source of uncertainty in estimation of climate change impact on harmfulness of this pest. Neglecting an important impact of food availability (Milne and Walter, 1998; Murai, 2000; Stacey and Fellowes, 2002), and also possible impact of other abiotic factors beside temperature (irradiance,
humidity, precipitation, etc.), on development of onion thrips additionally contributes to the uncertainty. The main reason for a large difference in onion thrips population extension at both locations in years 1999 and 2000 (Fig. 8) could be beside the difference in air temperature also the difference in precipitation (Norris et al., 2002). Year 1999 was a wet year and precipitation influenced the survival of onion thrips and so reduced the population. On the other hand, year 2000 was a dry year with more favorable conditions for onion thrips development. Less intensive population of onion thrips in 2000 in Bilje than in Ljubljana, despite higher average air temperatures, could be related to the differences in host plants (onion in Ljubljana and leek in Bilje) and related differences in quality of food. Quality of food influences different aspects of herbivore insects’ population dynamics (Underwood, 2004) and so also the population dynamics of Thrips species (Oparaocha and Okigbo, 2003).

For the estimation of DD the air temperature data at least in daily time scale are needed. The gap between monthly scale of downscaled estimates and daily scale of needed data was bridged with simple temperature generators in our case. This is another source of uncertainty, since the parameters of such
The number of generations ($N_{\text{gen}}$) of onion thrips per season, which can develop in specific temperature conditions, can be estimated by using proper DD model. Expected temperature increase will prolong the period with favorable conditions for onion thrips development and probably lead to more generations per year. The later could result in larger populations of onion thrips, causing more harm to cultivated plants. This will only happen in case of coincidence between host plants and favorable conditions for the pest. A similar increase of air temperature expected on the entire area of Slovenia will have quite a different impact on the change of cumulative DD and related $N_{\text{gen}}$ due to different present climate conditions. An example of Ljubljana and Bilje (Fig. 9), using all three described DD models, shows that larger increase of DD and related $N_{\text{gen}}$ is expected for Bilje, with warmer sub-Mediterranean climate, than for Ljubljana, with temperate continental climate. At location Ljubljana present values of $N_{\text{gen}}$ are from 3 to 7 and the increase by the end of the 21st century could be from 1 to 6 (mean increase about 3), the new values of $N_{\text{gen}}$ are expected to be between 4 and 13. For location Bilje present values of $N_{\text{gen}}$ are from 4 to 7 (Murai even 9) and increase could be from 2 to 9 (mean increase about 4), predicted values of $N_{\text{gen}}$ by the end of the 21st century from 6 to 16. More damage will probably be caused in warmer areas that are already strongly exposed to the problem of onion thrips, but the harmfulness of the pest in the areas, where it is not a serious threat at present, will also increase. On the other hand, some studies (Murai, 2000) show that higher temperature could shorten the longevity of onion thrips, which could mitigate to some extend the increase of population due to higher $N_{\text{gen}}$. However, we have to be aware, that all our quantitative estimates of climate change and its impact on onion thrips are burdened with all described uncertainties that have to be considered during the interpretation of results.
5. Conclusions
A review of uncertainties of present climate change impact studies is illustrated in the paper on the example of onion thrips. A lot of assumptions have to be made in impact studies that all contribute to the uncertainty in final results. Some of them will probably be reduced in the future by gaining new knowledge about climate system response to the changes in the atmospheric composition, and by response of climate dependent processes and activities to climate variability. Better description of model physics and better horizontal resolution of GCM will reduce the importance of downscaling approaches and the uncertainties related to that, and will probably also reduce the inter-model differences. More reliable estimates of the climate systems response to the changed boundary conditions will be available even on a regional or local level. Different laboratory and field experiments will deepen the knowledge about response and adaptation capability of different organisms to the changed environmental conditions. But still at least the problem of reasonable estimation of climate boundary conditions change in the future will always remain as a basic source of the uncertainty in any climate change impact study.

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REFERENCES
Murai, T., 2000. Effect of temperature on development and reproduction of the onion thrips, Thrips tabaci Lindeman
ecological modelling 194 (2006) 244–255


