Climatological time series for the KfC project
High-Quality
Climate Projections (Theme 6 WP3)

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Alexander Bakker

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<tr>
<td><strong>Project</strong></td>
<td>Knowledge for Climate (KfC), Theme 6: High-Quality Climate Projections, Work Package 3</td>
</tr>
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<td><strong>Authors</strong></td>
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1. Introduction

After the publication of the KNMI’06 climate change scenarios for the Netherlands (Van den Hurk et al. 2006), it took several years before the impacts of these KNMI’06 scenarios were estimated. One of the reasons for this was the lack of climatological time series that could be used directly in models to simulate, for instance, hydrological, ecological and agricultural impacts. The data requirements vary with sector and case study and tailoring of the climatological data appears necessary. For instance, river management is typically interested in basin-scale extreme precipitation and agriculture in local extreme rainfall during certain periods of the growing season. Yet, there are also many similarities between the hydrological, agricultural and ecological data requirements: They need information, directly or indirectly, on rainfall (extremes and drought), temperature (mean, minimum and maximum), wind, humidity and radiation (directly or for the estimation of evapotranspiration), often on a daily time resolution.

Climate change itself is not of most interest to society, but the impacts in several sectors are. Therefore, in the Knowledge for Climate (KfC) project “High-Quality Climate Projections” (Theme 6) a Work Package (WP3) was included on “Scenario development for climate change impact”. The central research question of this WP3 was: “How to couple climate projections to impact assessment models and how can uncertainty in the impact assessment be incorporated in such a way that it can effectively be used by the adaptation climate community?”

This report presents a set of time series that largely match the KNMI’14 climate change scenarios (KNMI 2014; van den Hurk et al. 2014), constructed to enable early impact assessments before the official publication of the KNMI’14 climate scenarios. In this way, the time between the publication of the climate scenarios and estimates of related impacts can be reduced and at the same time this may promote the coherence in data use between different sectors.

The data requirements were discussed with the partners in WP3 (climate variables, spatial and temporal resolution, area to be covered, etc.) and are discussed in chapter 2. After determining the requirements for the common dataset, methods were developed to generate the dataset. The future time series are obtained by transformation (chapter 3) of the reference time series. This is often referred to as perturbation or delta method. Some climate variables are derived with the help of the other transformed time series (e.g. potential evapotranspiration, relative humidity).
2. Reference time series

Two 30-year (1981-2010) reference datasets have been constructed to enable early impact assessments (Klerk et al. 2015, e.g.). The first dataset (Rhine-Meuse dataset) provides daily data for the entire Rhine and Meuse catchment and the entire surface of the Netherlands at a $0.25^\circ \times 0.25^\circ$ regular grid similar to the E-OBS grid (see figure 2.1). Table 2.1 presents the variables that were derived.

Table 2.1: Rhine-Meuse dataset: required variables, as discussed with the partners from WP3 in Theme 6, Knowledge for Climate research programme

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>Units</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>daily mean temperature</td>
<td>$T_g$</td>
<td>$^\circ$C</td>
<td>E-OBS v7.0</td>
</tr>
<tr>
<td>daily minimum temperature</td>
<td>$T_n$</td>
<td>$^\circ$C</td>
<td></td>
</tr>
<tr>
<td>daily maximum temperature</td>
<td>$T_x$</td>
<td>$^\circ$C</td>
<td></td>
</tr>
<tr>
<td>daily precipitation amount</td>
<td>$P$</td>
<td>[mm]</td>
<td></td>
</tr>
<tr>
<td>daily mean sea level pressure</td>
<td>$slp$</td>
<td>[hPa]</td>
<td></td>
</tr>
<tr>
<td>daily downward short wave surface radiation</td>
<td>$R_s$</td>
<td>[kJ m$^{-2}$]</td>
<td>ERA-Interim</td>
</tr>
<tr>
<td>daily Net long wave surface radiation</td>
<td>$R_l$</td>
<td>[kJ m$^{-2}$]</td>
<td></td>
</tr>
<tr>
<td>daily maximum relative humidity</td>
<td>$R_Hx$</td>
<td>[%]</td>
<td></td>
</tr>
<tr>
<td>daily minimum relative humidity</td>
<td>$R_Hn$</td>
<td>[%]</td>
<td></td>
</tr>
<tr>
<td>daily mean wind speed at 10m</td>
<td>$w_{10}$</td>
<td>[ms$^{-1}$]</td>
<td></td>
</tr>
<tr>
<td>daily mean wind direction (from which blowing)</td>
<td>$w_{dir}$</td>
<td>[degrees]</td>
<td></td>
</tr>
<tr>
<td>daily mean atmospheric transmittance</td>
<td>$k_t$</td>
<td>[-]</td>
<td>$R_s$</td>
</tr>
<tr>
<td>daily mean relative humidity</td>
<td>$R_H$</td>
<td>[%]</td>
<td>$R_{Hn}, R_{Hx}$</td>
</tr>
<tr>
<td>daily reference crop evapotranspiration</td>
<td>$e_{vmk}$</td>
<td>[mm]</td>
<td>$R_s, T_g$</td>
</tr>
<tr>
<td>(according to Makkink)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>daily mean vapour pressure</td>
<td>$e_a$</td>
<td>[kPa]</td>
<td>$R_{Hn}, R_{Hx}, T_x, T_n$</td>
</tr>
<tr>
<td>early morning vapour pressure</td>
<td>$e_{a,6h}$</td>
<td>[kPa]</td>
<td>$R_{Hx}, T_n$</td>
</tr>
</tbody>
</table>

The second reference dataset (North sea dataset) has been constructed to model storm surges (Klerk et al. 2015). It provides 3-hourly instantaneous ‘forecasts’ from the ERA-Interim Reanalysis (Berrisford et al. 2011) (full resolution) for a region extending from $43.5^\circ$ to $60^\circ$ latitude and from $-15^\circ$ to $15^\circ$ longitude. The dataset covers the entire North sea and includes the following variables (Table 2.2):
Table 2.2: North sea dataset, as discussed with the partners from WP3 in Theme 6, Knowledge for Climate research programme

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>Units</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-component (eastward direction) of daily mean wind at 10m</td>
<td>u10</td>
<td>[ms$^{-1}$]</td>
<td>ERA-Interim</td>
</tr>
<tr>
<td>V-component (northward direction) of daily mean wind at 10m</td>
<td>v10</td>
<td>[ms$^{-1}$]</td>
<td></td>
</tr>
<tr>
<td>Sea level pressure</td>
<td>slp</td>
<td>[hPa]</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.1: Applied grid for land datasets (filled small boxes), where the colours refer to height with respect to mean sea level. The boxes with grey lines, other than the longitude/latitude lines show the ERA-Interim grid from which many data were derived. Blue bounded boxes refer to sea cells.

2.1 E-OBS

Where possible daily time series were subtracted from the European daily high-resolution observational gridded dataset E-OBS version 7.0 (Haylock et al. 2008; Van den Besselaar et al. 2011) because of its high quality, rigorous documentation and general and easy availability. Temperature ($Tg$, $Tn$ and $Tx$), precipitation ($P$) and sea level pressure ($slp$) have been obtained directly from this dataset.

2.2 ERA-Interim

E-OBS does not provide all necessary variables (see table 2.1) and neither it provides time series above sea at sub-daily temporal resolution necessary for assessments of storm surges (see table 2.2 Klerk et al. 2015). These data have been derived from the courser spatial, but finer temporal resolution ERA-Interim Reanalysis (Berrisford et al. 2011), if available. First daily values are estimated from the sub-daily ‘forecasts’ and ‘analyses’. Second, these daily data are regridded
to the E-OBS grid by a nearest neighbour interpolation from ERA-Interim land cells only.

**Daily downward short wave** \((R_s)\) and **net long wave radiation** \((R_l)\) have been obtained by summing two 12-hour accumulated 'forecasts'.

**Daily minimum** \((R_{H\text{n}})\) and **maximum** \((R_{H\text{x}})\) **relative humidity** have been obtained by selecting the minimum and maximum instantaneous 'forecasts' per day.

**Daily mean wind speed** \((w_{10})\) and **wind direction from which blowing** \((w_{\text{dir}})\) have been derived from 6-hourly analyses of the U- and V-component of the 10m wind \((u_{10} \text{ and } v_{10})\), see table 2.1. For \(w_{\text{dir}}\), first, the daily mean \(u_{10}\) and \(v_{10}\) are estimated by equation 2.1.

\[
X_{\text{day}} = \frac{X(0)/2 + X(6) + X(12) + X(18) + X(24)/2}{4}\tag{2.1}
\]

where \(X\) is the particular variable of interest \((u_{10} \text{ or } v_{10})\) and the argument refers to the time of the particular day of interest in hours UT \((0 = 0:00\text{UT} \text{ and } 24 = 0:00\text{UT next day})\). After obtaining daily mean \(u_{10}\) and \(v_{10}\), the direction is subsequently estimated from the two-argument arctangent of the two components (equation 2.2).

\[
w_{\text{dir}} = \text{atan2}(-u_{10}, -v_{10})\frac{360}{2\pi} = 270 - \left(\text{atan2}(v_{10}, u_{10})\frac{360}{2\pi}\right)\tag{2.2}
\]

For the estimation of daily mean \(w_{10}\), first the 6-hourly values are calculated and subsequently the daily means are derived.

### 2.3 Remaining derived variables

Finally, the remaining variables necessary for the impact modelling or for the time series transformation are derived from the above mentioned data.

**Atmospheric transmittance** \((kt)\)\(^1\) is the quotient of \(R_s\) and the downward short wave radiation at the top of atmosphere \((\text{Angot radiation}, R_A)\).

\[
kt = \frac{R_s}{R_A}\tag{2.3}
\]

Daily mean \(R_A \text{ [kJ m}^{-2}\text{]}\) depends on day number \(J\) and latitude \(\phi \text{ [rad]}\) and can be estimated by the following equation (Allen et al. 1998)

\(^1kt\) was originally preferred over \(R_s\) because it is more homogeneous in time. Yet, final results appear insensitive for the choice of variable and the official transformation program. Bakker (2015b) therefore applied a transformation of \(R_s\).
\[ R_A = 1000 \frac{24 \cdot 60}{\pi} G_{sc} d_r [\omega_s \sin(\phi) \sin(\delta) + \sin(\omega_s) \cos(\phi) \cos(\delta)] \]  

(2.4)

in which \( G_{sc} \) is the solar constant (0.0820 MJ m\(^{-2}\) min\(^{-1}\)), \( d_r \) the inverse relative distance Earth-Sun (equation 2.5), \( \delta \) the solar declination [rad] (2.6) and \( \omega_s \) the sunset hour angle [rad] (equation 2.7)

\[
d_r = 1 + 0.033 \cos\left(\frac{2\pi}{365} J\right) \tag{2.5}
\]

\[
\delta = 0.409 \sin\left(\frac{2\pi}{365} J - 1.39\right) \tag{2.6}
\]

\[
\omega_s = \arccos(-\tan(\phi) \tan(\delta)) \tag{2.7}
\]

**Vapour pressure** Daily mean vapour pressure \((e_a)\) and early morning vapour pressure \((e_a6h)\) depend on temperature and relative humidity

\[
e_a = e_s(T)n \frac{RH_x}{100} + e_s(T)x \frac{RH_n}{100} \div 2 \tag{2.8}
\]

\[
e_a = e_s(T)n \frac{RH_x}{100} \tag{2.9}
\]

where the saturation vapour pressure \(e_s\) depends on temperature (Allen et al. 1998)

\[
e_s(T) = 6.108 \exp\left(\frac{17.27T}{T + 237.3}\right) \tag{2.10}
\]

**Reference crop evapotranspiration** \((ev_{mk})\) The reference crop evapotranspiration is calculated by means of the Makkink equation (KNMI 2006)

\[
ev_{mk} = R_s \frac{1000 \cdot 0.65 \cdot \delta_s(Tg)}{\delta_s(Tg) + \gamma(Tg)) \cdot \rho \cdot \lambda(Tg)} \tag{2.11}
\]

where \( \rho \) is the mass density of water (1000 kg m\(^{-3}\)), \( \delta_s(Tg) \) the gradient (equation 2.13) of the saturation vapour pressure [hPa °C\(^{-1}\)] according to equation 2.12, \( \gamma(Tg) \) the psychrometer-constant [hPa °C\(^{-1}\)] (equation 2.14) and \( \lambda(Tg) \) the latent heat [J/kg] (equation 2.15).

\[
e_s(Tg) = 6.107 \cdot 10^{7.5 \frac{Tg-237.3}{237.3+Tg}} \tag{2.12}
\]

\[
\delta_s(Tg) = \frac{7.5 \cdot 237.3}{(237.3+Tg)^2} \ln(10)e_s(Tg) \tag{2.13}
\]

\[
\gamma(Tg) = 0.646 + 0.0006Tg \tag{2.14}
\]

\[
\lambda Tg = 1000(2501 - 2.38Tg) \tag{2.15}
\]
3. Future time series

Future time series are obtained by transformation of the reference data (often referred to as *perturbation* or *delta* method) or they are derived with the help of *transformed* time series of other climate variables (see table 3.1). Sea level pressure *slp*, net long wave radiation *Rl* and wind direction *wdir* are not transformed because of a small (projected) change with respect to the natural variability and in the case of wind direction also because of the non-trivial interpretation of the changes.¹

Table 3.1: Future variables derived for impact modelling

<table>
<thead>
<tr>
<th>Variable</th>
<th>method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tg</td>
<td>linear quantile scaling</td>
</tr>
<tr>
<td>Tn</td>
<td>linear quantile scaling</td>
</tr>
<tr>
<td>Tx</td>
<td>linear quantile scaling</td>
</tr>
<tr>
<td>P</td>
<td>wet-day correction + power-law transformation</td>
</tr>
<tr>
<td>kt</td>
<td>linear transformation</td>
</tr>
<tr>
<td>RHx</td>
<td>linear transformation</td>
</tr>
<tr>
<td>RHn</td>
<td>linear transformation</td>
</tr>
<tr>
<td>w10</td>
<td>power-law transformation</td>
</tr>
<tr>
<td>Rs</td>
<td>$(kt)$</td>
</tr>
<tr>
<td>RH</td>
<td>$(RH_n, RH_x)$</td>
</tr>
<tr>
<td>evmk</td>
<td>$(Rs, T_g)$</td>
</tr>
<tr>
<td>ea</td>
<td>$(RH_n, RH_x, Tx, Tn)$</td>
</tr>
<tr>
<td>ea6h</td>
<td>$(RH_x, Tn)$</td>
</tr>
<tr>
<td>wdir</td>
<td>NO TRANSFORMATION</td>
</tr>
<tr>
<td>slp</td>
<td>NO TRANSFORMATION</td>
</tr>
<tr>
<td>Rl</td>
<td>NO TRANSFORMATION</td>
</tr>
</tbody>
</table>

3.1 General transformation framework

The reference time series are transformed by applying a certain change (or "delta") to daily values. For every grid cell 12 sets (one set per calendar month) of change factors were derived from an ensemble of eight samples per climate scenario, resampled from eight climate model simulations.

¹In case of biased climate model output, projected relative or absolute changes in frequencies of different wind directions can never be ‘applied’ to observed frequencies in an internally consistent way. This is also the case, but to a lesser extent, for other variables (see discussion on wet and dry days in Bakker 2015a, section 2.6).
The applied resampling method is a preliminary version of the resampling that was used for the KNMI’14 climate change scenarios for the Netherlands (Van den Hurk et al. 2014). The climate model output is available at a rotated grid of about $0.25^\circ \times 0.25^\circ$. The change factors have been translated to the regular grid (figure 2.1) by a nearest neighbour interpolation.

*Note that, the transformations are performed for each grid cell and for twelve calendar months independently, but that the equations in the following do not specifically refer to the calendar month and grid cell.*

*Note that none of the presented transformation procedures exactly matches the final transformation tool (Bakker 2015b, see also “Toelichting transformatieprogramma” on www.klimaatscenarios.nl/toekomstig_weer/transformatie/index.html.). The main reasons for this are that

- the presented datasets cover a much larger area than the KNMI’14 climate change scenarios
- the change factors vary with grid cell rather than using universal deltas for the entire area of interest like in KNMI’14
- there were reasons to include higher quantiles in KNMI’14

Indirectly derived variables

For some variables *deltas* are not available. In this case, future time series are derived with the help of *transformed* time series of other climate variables by applying equations 2.3 to 2.15.

### 3.2 Precipitation

Future precipitation ($P_f$) time series are obtained by a two-step transformation of the reference precipitation ($P$) such that the wet-day frequency $F$ and the $55^{th}$ and $95^{th}$ percentile ($P_{55}$ and $P_{95}$) of the original wet-day amounts are perturbed by the relative changes $\Delta F$, $\Delta P_{55}$ and $\Delta P_{95}$.

\[
\begin{align*}
F_f &= (1 + \Delta F)F \\
\text{P}_{55}^f &= (1 + \Delta P_{55})\text{P}_{55} \\
\text{P}_{95}^f &= (1 + \Delta P_{95})\text{P}_{95}
\end{align*}
\]  

\text{(3.1)}

First the wet-day frequency $F$ is adjusted and second a power-law transformation is applied to transform the wet-day amounts. Wet days are defined as days with 0.1 mm or more precipitation. Note that the applied percentiles are slightly different from the statistics used for the official transformation program (Bakker 2015b). $P_{55}$ is on average close to the wet-day mean, but its use makes the estimation of the coefficients much more efficient. $P_{95}$ is used rather than $P_{99}$ because the monthly $P_{99}$ cannot be robustly estimated for individual grid cells.
**wet-day frequency** In the case that the wet-day frequency decreases ($\Delta F < 0$), the following wet-day adjustment is applied

$$P^* = \max(P - c, 0)$$

(3.2)

where $P^*$ is the wet-day adjusted precipitation and $c$ is the correction constant that is chosen such that $-\Delta F$ of the wet days are 'dried' or 'set to zero'.

Occasionally, for some grid cells in some calendar months, a positive $\Delta F$ is projected, but this is usually smaller than 5%. The transformation does not account for these projected increases in the wet-day frequency.

**wet-day amounts** The second step applies a power-law to $P^*$ such that the $55^{th}$ and $95^{th}$ percentile ($P_{55}$ and $P_{95}$) of the original wet-day amounts $P$ are perturbed by $\Delta P_{55}$ and $\Delta P_{95}$

$$P_f = a (P^*)^b$$

(3.3)

Note that this equation is applied to all percentiles, which is different from the procedure followed by the Transformation Program KNMI14 (Bakker 2015b).

The constants $a$ and $b$ are obtained as follows

$$b = \frac{\log(P_{95}/P_{55})}{\log(P_f_{95}/P_f_{55})}$$

(3.4)

$$a = \frac{P_f_{95}}{(P^*_{95})^b} = \frac{P_f_{55}}{(P^*_{55})^b}$$

(3.5)

### 3.3 Temperature

Future mean, minimum and maximum temperature ($T_{gf}$, $T_{nf}$ and $T_{xf}$) are derived by transformation of reference temperature ($T_g$, $T_n$ and $T_x$) such that the $5^{th}$, $50^{th}$ and $95^{th}$ percentile ($T_{05}$, $T_{50}$ and $T_{95}$) are perturbed by the absolute changes $\Delta T_{05}$, $\Delta T_{50}$ and $\Delta T_{95}$

$$T_{05}^f = T_{05} + \Delta T_{05}$$

$$T_{50}^f = T_{50} + \Delta T_{50}$$

$$T_{95}^f = T_{95} + \Delta T_{95}$$

(3.6)

where $T$ refers to $T_g$, $T_n$ or $T_x$.

This is done by a linear transformation after which the mutual consistencies between $T_g$, $T_n$ and $T_x$ are checked and corrected for.
\[ T^f = \begin{cases} T_{50}^f + a1(T - T_{50}) & \text{if } T \geq T_{50} \\ T_{50}^f + a2(T - T_{50}) & \text{if } T < T_{50} \end{cases} \] (3.7)

where the \( a1 \) and \( a2 \) coefficients are estimated for every grid cell, calendar month and variable independently

\[ a1 = \frac{T_{95}^f - T_{50}^f}{T_{95} - T_{50}} \] (3.8)

\[ a2 = \frac{T_{05}^f - T_{50}^f}{T_{05} - T_{50}} \] (3.9)

### 3.4 Relative humidity and atmospheric transmittance

Daily minimum and maximum relative humidity and atmospheric transmittance are transformed such that the averages \( RH_{n_{av}}, RH_{x_{av}} \) and \( kt_{av} \) are perturbed by the relative changes \( \Delta RH_{n_{av}}, \Delta RH_{x_{av}} \) and \( \Delta kt_{av} \)

\[ X^f_{av} = (1 + \Delta X_{av})X_{av} \] (3.10)

where \( X \) refers to \( RH_n, RH_x \) or \( kt \)

This is done by a simple linear scaling that prevents the values to exceed a certain upper threshold \( X_{max} \)

\[ X^f = \min(\alpha \cdot X, X_{max}) \] (3.11)

where the coefficient \( \alpha \) is iteratively estimated and \( X_{max} \) is set 100% for \( RH_n \) and \( RH_x \) and 0.7 for \( kt \). A maximum value of 0.7 for \( kt \) is caused by a typo in the program and it would have been better if this value was set to 0.75 (Allen et al. 1998). Clear-sky radiation is therefore slightly underestimated.

### 3.5 Wind speed

For future wind speed \( w10^f \) the same power-law transformation as used for wet-day precipitation amounts (see equations 3.3, 3.4 and 3.5) is applied to perturb the 50th and 95th percentile \( w10_{50} \) and \( w10_{95} \) of the reference wind speed \( w10 \) by the relative changes \( \Delta w10_{50} \) and \( \Delta w10_{95} \)

\[ w10^f_{50} = (1 + \Delta w10_{50})w10_{50} \]

\[ w10^f_{95} = (1 + \Delta w10_{95})w10_{95} \] (3.12)
North sea dataset

The North sea dataset provides 3-hourly data for the U- and V-component of the wind. Before transforming, this is aggregated to daily wind speed by applying the procedure as described in section 2.2. After transformation, for each day the relative change is determined and applied to the 3-hourly u- and v-components of the particular day.
References


Noije, G. J. van Oldenborgh, F. Selten, P. Siebesma, A. Sterl, H. de Vries, M. van Weele, R.
de Winter, and G.-J. Zadelhoff (2014). *KNMI'14: Climate Change scenarios for the 21st Cen-