Quantification of uncertainty in reference evapotranspiration climate change signals in Belgium

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ABSTRACT

Projections of evapotranspiration form the basis of future runoff and water availability assessment in a climate change context. The scarcity of data or insufficiency of time/funds compels the application of simple reference evapotranspiration (ET_o) methods requiring less meteorological inputs for ET_o projections which adds uncertainty to the projected changes. This study investigates the bias in ET_o climate change signals derived from seven simple temperature- and radiation-based methods (Blaney–Criddle, Hargreaves–Samani, Schendel, Makkink, Turc, Jensen–Haise, Tabari) compared with that from the standard Penman–Monteith FAO 56 method on the basis of 12 general circulation model (GCM) outputs from the Coupled Model Intercomparison Project Phase 5 for central Belgium for four future greenhouse gas scenarios (RCP2.6, RCP4.5, RCP6.0, RCP8.5). The results show the lack of conformity on the amount of ET_o changes between the simple and standard methods, with biases of over 100% for some simple methods. The uncertainty affiliated with ET_o methods for monthly ET_o changes is smaller but of comparable magnitude to GCM uncertainty, which is usually the major source of uncertainty, and larger for daily extreme ET_o changes. This emphasizes the imperative of addressing the uncertainty associated with ET_o methods for quantifying the hydrological response to climate change.

Key words | Belgium, climate change signal, Penman–Monteith approach, reference evapotranspiration, simple methods, uncertainty analysis

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INTRODUCTION

Evapotranspiration (ET) is a main flux term in the water cycle and an important process in the climate system, thereby playing a key role in water and energy balance. It is also vital for climate change impact studies, drought prediction and monitoring, agricultural water requirement planning and effective management of water resources. Specifically for hydrology, reference ET (ET_o) is a necessary component for computing actual ET for a watershed as a function of soil moisture deficit and a key input parameter for hydrological water-balance models (Bergström *et al.* 2001; Obeysekera 2013; Tabari & Hosseinzadeh Talaee 2014; Meng *et al.* 2016). ET_o is, moreover, used to assess the hydrological impact of climate change at catchment scales (Taye *et al.* 2011; Ntegeka *et al.* 2014; Vansteenkiste *et al.* 2014; Rudd & Kay 2016).

Climate change is one of the most critical global problems of our time (IPCC 2007), which may influence watershed hydrology and water availability by changing the patterns of precipitation and ET (King *et al.* 2015). Future changes in ET rate together with changes in precipitation patterns will affect runoff and water balance and consequently water infrastructure design (Prudhomme & Williamson 2013; Mohor *et al.* 2015; Koedyk & Kingston 2016).

There are numerous methods to estimate ET_o based on meteorological data ranging from simple temperature

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(e.g., Hargreaves–Samani: Hargreaves & Samani 1985) or radiation (e.g., Jensen–Haise: Jensen & Haise 1963) based methods to complex Penman family methods (e.g., Penman: Penman 1948; Kimberly–Penman: Wright 1982). Among them, the Penman–Monteith FAO 56 (PMF-56) method was strongly recommended by the United Nations Food and Agriculture Organizations (FAO) and the American Society of Civil Engineers (ASCE) as a standard method for ET_o estimation (Allen *et al.* 1998; ASCE-EWRI 2005), because the PMF-56 method incorporates most of the meteorological variables controlling the ET process. Nevertheless, to simplify the process of ET_o estimation due to limited time and/or budget and in some cases because of unavailability of the full meteorological data required for the standard PMF-56 method, simple, empirical equations have been used in many climate change studies for this purpose (e.g., Immerzeel *et al.* 2012; Bastola 2013; Lu *et al.* 2013; Capell *et al.* 2013; Kopytkovskiy *et al.* 2015). The simple equations relate ET_o to an easily measured process variable such as temperature and do not consider the effect of 'advective' variables (i.e., wind speed and vapor pressure) (Donohue *et al.* 2010). However, ET_o is primarily a function of four key weather variables of radiation, wind speed, humidity (or vapor pressure), air temperature and these variables must be considered for a better understanding of ET_o changes under climate change conditions (McVicar *et al.* 2012). The ET_o changes projected by simple approaches may differ substantially from those by the standard method that may add uncertainty to derived climate change signals (CCS) and future water balance projections (Kingston *et al.* 2009; Bae *et al.* 2011; McAfee 2013; Thompson *et al.* 2014; Wang *et al.* 2015). Therefore, the existence of potential systematic bias or uncertainty in the derivation of ET_o CCS by using simple ET_o methods needs to be considered. The uncertainty in ET_o CCS by simple methods is, however, largely unknown. This research gap is addressed in this paper. More specifically, the bias in ET_o CCS obtained from seven simple methods (Blaney–Criddle, Hargreaves–Samani, Schendel, Makkink, Turc, Jensen–Haise, Tabari) compared with those from the PMF-56 method as a benchmark is investigated under different time resolutions, i.e., seasonal, monthly and daily.

DATA

The general circulation model-Coupled Model Intercomparison Project Phase 5 (GCM-CMIP5) ensemble considered for this study consists of 12 GCMs (listed in Table S1 with their respective resolution; Table S1 is available with the online version of this paper). All the meteorological data needed for ET_o estimation by the PMF-56 method (which include those needed for seven simple methods) were obtained from 264 CMIP5 GCM runs (44 runs for each of six meteorological variables including maximum, minimum, and mean temperature, radiation, wind speed, and humidity). In fact, all the GCMs providing the complete set of meteorological inputs for ET_o estimation were selected. Although some authors recommend 50-year periods (Bonell & Bruijnzeel 2005), in this study the period 1961–1990 was applied as the control period. This period is recommended by WMO (2007) and commonly applied in climate change studies. The period 2071–2100 was considered as the scenario period. Four 21st century scenarios for future greenhouse gas concentrations including RCP2.6, RCP4.5, RCP6.0, and RCP8.5 were considered, where RCP8.5 represents the highest concentrations and RCP2.6 corresponds to the lowest concentrations (Moss *et al.* 2010). The analyses were done for the GCM grid cell covering central Belgium.

METHODOLOGY

After extracting all the meteorological data from the GCMs, ET_o is calculated by different methods, that are briefly explained in the next section. Daily ET_o values are averaged to obtain monthly ET_o. Afterwards, CCS are derived for both daily and monthly ET_o as the difference between the values for the scenario period (2071–2100) and those for the control period (1961–1990). The changes in daily ET_o are shown by means of box-and-whisker plots for summer and winter seasons. The calculation of these results involves the following steps:

1. For each ET_o model, separate the ET_o results for summer (JJA: June, July, August) and winter (DJF: December, January, February) seasons.

2. Calculate CCS as the difference between the ET_o values for the scenario (ET_{o_S}) and control (ET_{o_C}) periods of each GCM out of the total 12 GCMs:

$$CCS\ (g) = ET_{o_S}(g) - ET_{o_C}(g) \quad g = 1, 2, 3, \ldots, 12 \tag{1}$$

3. Combine CCS of all GCMs.
4. Calculate climate change signals in percent ($PCCS\ (com)$) by dividing the combined signals obtained from step 3 ($CCS(com)$) over the median of all GCMs' ET_o values for the control period ($Med_C(com)$):

$$PCCS\ (com) = \frac{CCS(com)}{Med_C(com)} \tag{2}$$

5. Compute 5%, 25%, 50%, 75%, and 95% percentiles of the signals (%) and show the results in a box-and-whisker plot.

High, mean, and low climate scenarios for monthly or daily ET_o change are later defined as 95%, 50%, and 5% quantiles of the relative changes. For the monthly ET_o, the changes are considered as such; for the daily ET_o, the changes are considered as changes in the quantiles (percentiles). As the changes in high ET rates are of vital importance for drought monitoring and agricultural water planning and management, the changes in high daily ET_o quantiles (percentiles) are also investigated.

Once the ET_o changes for different methods are computed, the uncertainty associated with ET_o methods is quantified and compared with other uncertainties sources (i.e., GCMs and RCPs). For the uncertainty comparison purpose, it is important to have an equal number of model runs from each scenario to avoid merging model and scenario uncertainty. The GCMs (seven GCMs) providing simulations for RCP2.6 and RCP8.5 are selected for the uncertainty analysis, because only two GCMs have the outputs for all four scenarios. The RCP2.6 and RCP8.5 scenarios are selected to cover the full range of projected concentrations. To determine the uncertainty in ET_o methods, the median of the ET_o changes across all GCMs (Med_{CCS}) is first calculated for each RCP and each ET_o method:

$$Med_{CCS} = Median\ (CCS_1, CCS_2, \ldots, CCS_m) \tag{3}$$

where CCS refers to the climate change signal and m the number of GCMs (in our case, m = 12). The two medians related to the two RCPs are then averaged for each ET_o method:

$$M = \frac{Med_{CCS}\ (RCP2.6) + Med_{CCS}\ (RCP8.5)}{2} \tag{4}$$

Finally, the variance in the average ET_o change across the eight ET_o models (seven simple models plus the PMF-56 method) is computed:

$$Var\ (M) = \frac{\sum_{i=1}^{n} (M_i - \bar{M})}{n - 1} \tag{5}$$

where n is the number of ET_o methods (in our case, n = 8). In a similar way, the uncertainties related to GCMs and RCPs are quantified.

ET_o methods

In this study, the ET_o CCS derived from the PMF-56 method are compared with the ones from three temperature-based (i.e., Blaney–Criddle, Hargreaves–Samani and Schendel) and four radiation-based (i.e., Makkink, Turc, Jensen–Haise, and Tabari) methods.

PMF-56

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \dfrac{900}{T_a + 273} U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \tag{6}$$

where ET_o is the reference evapotranspiration (mm day^{-1}), R_n the net radiation (MJ m^{-2} day^{-1}), G the soil heat flux (MJ m^{-2} day^{-1}), γ the psychrometric constant (kPa °C^{-1}), e_s the saturation vapor pressure (kPa), e_a the actual vapor pressure (kPa), Δ the slope of the saturation vapor pressure–temperature curve (kPa °C^{-1}), T_a the average daily air temperature (°C), and U_2 the mean daily wind speed at 2 m (m s^{-1}) (Allen *et al.* 1998).

Blaney–Criddle (Blaney & Criddle 1950)

$$ET_o = a + b[P(0.46T_a + 8.13)] \quad (7)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), P the mean annual percentage of daytime hours that can be obtained from Doorenbos & Pruitt (1977), and a and b the parameters of the equation. The a and b coefficients are computed using regression equations developed by Allen & Pruitt (1991).

Hargreaves–Samani (Hargreaves & Samani 1985)

$$ET_o = 0.0023R_a(T_a + 17.8)\sqrt{T_{\max} - T_{\min}} \quad (8)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), R_a the water equivalent of extraterrestrial radiation (mm day^{-1}), T_a the mean air temperature (°C), $T_{\max}$ the daily maximum temperature (°C), and $T_{\min}$ the daily minimum temperature (°C). R_a is estimated for each day of the year by:

$$R_a = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin\omega_s] \quad (9)$$

where R_a is the water equivalent of extraterrestrial radiation (MJ m^{-2} day^{-1}), G_{sc} the solar constant equal to 0.0820 MJ m^{-2} day^{-1}, d_r the relative distance between the Earth and the Sun, ω_s the sunset hour angle (rad), ϕ the latitude (rad), and δ the solar declination angle (rad). The coefficient of 0.408 is used for converting MJ m^{-2} day^{-1} into mm day^{-1}.

Schendel (Schendel 1967)

$$ET_o = 16.\frac{T_a}{RH} \quad (10)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), T_a the mean air temperature (°C), and RH the relative humidity (%).

Jensen–Haise (Jensen & Haise 1963)

$$ET_o = \frac{C_T(T_a - T_x) \times R_s}{\lambda} \quad (11)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), λ the latent heat of vaporization (cal gr^{-1}), R_s the solar radiation (mm day^{-1}), C_T a temperature constant equal to 0.025, and $T_x = -3$ when T_a is in degrees Celsius. These coefficients are considered to be constant for a given area.

Makkink (Makkink 1957)

$$ET_o = 0.61\frac{\Delta}{\Delta + \gamma}\frac{R_S}{\lambda} - 0.12 \quad (12)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), R_s the solar radiation (MJ m^{-2} day^{-1}), γ the psychrometric constant (kPa °C^{-1}), Δ the slope of the saturation vapor pressure–temperature curve (kPa °C^{-1}), and λ the latent heat of vaporization (MJ kg^{-1}).

Turc (Turc 1961)

$$ET_o = a_T 0.013\frac{T_a}{T_a + 15}\frac{23.8856R_S + 50}{\lambda} \quad (13)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), T_a the mean air temperature (°C), R_s the solar radiation (MJ m^{-2} day^{-1}), and λ the latent heat of vaporization (MJ kg^{-1}). The coefficient a_T is a humidity-based value which is equal to 1 for the mean daily relative humidity (RH_{mean}) greater than or equal to 50%. Otherwise, it is calculated from the following equation:

$$a_T = 1 + \frac{50 - RH_{\mathrm{mean}}}{70} \quad (14)$$

Tabari (Tabari *et al.* 2013)

Tabari *et al.* (2013) developed a model for $\mathrm{ET_o}$ estimation for humid regions, with $\mathrm{ET_o}$ equal to zero under freezing conditions ($T_a < 0$ °C):

$$ET_o = -0.642 + 0.174R_s + 0.0353T_a \quad (15)$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day^{-1}), R_s the solar radiation (MJ m^{-2} day^{-1}), and T_a the mean air temperature (°C).

RESULTS

Future changes in monthly ET_o based on the PMF-56 method and the seven simple methods are shown in Figure 1. As can be seen, simple methods both overestimate and underestimate the changes in monthly ET_o compared with PMF-56 ET_o. For instance, monthly ET_o changes are underestimated by the Hargreaves–Samani method and overestimated by the Blaney–Criddle method. For estimating the deviation of the simple method results from the standard method (PMF-56) results, the ranges of high, mean, and low climate change scenarios by the simple methods are computed (Figure 2). In general, the high scenario is overestimated by the simple methods in winter (DJF), while in summer (JJA) both overestimations and underestimations are found. The overestimation of the changes in winter is generally more obvious for temperature-based methods than for the radiation-based methods. The difference between the deviation of the temperature- and radiation-based methods for the summer season is larger for the mean scenario, at which the radiation-based methods mostly overestimate the ET_o changes for summer but the temperature-based methods underestimate them. For the low scenario, the deviation of simple methods is not noticeable.

Bias in the mean scenario of seasonal ET_o calculated based on the simple ET_o methods is presented in Table 1. As the results indicate, the performance of the simple methods changes seasonally. The Hargreaves–Samani, Makkink, and Tabari methods underestimate the mean scenario and the rest of the methods overestimate it. In winter, the best performance in estimation of the mean scenario for seasonal ET_o is produced by the Hargreaves–Samani, Tabari and Jensen–Haise methods, while the Makkink and Tabari methods perform the best in spring. The mean scenario for summer ET_o is underestimated by most of the simple methods, among which Turc and Schendel show the smallest biases. For autumn, the Tabari and Makkink methods more closely reproduce the PMF-56-driven scenario. Overall, among all the simple methods, Schendel has the worst performance in estimation of monthly and seasonal ET_o changes.

Next to the bias analysis of the simple method results for monthly and seasonal ET_o changes, the analysis is also performed for daily ET_o changes (Figure 3). By considering the mean scenario of the PMF-56 method as reference, the simple ET_o methods totally overestimate the changes in daily ET_o in winter and mostly underestimate these during summer. The range of daily ET_o changes in winter by all the simple methods except the Hargreaves–Samani method is wider than that of the PMF-56 method. In contrast, the range of the simple methods for summer is more or less the same as that of the standard method. The mean climate scenario for daily ET_o percentiles for winter and method. In contrast, the range of the simple methods for summer is more or less summer seasons based on different ET_o methods is shown in Figure 4. The deviation of the simple method results from the reference is evident for different percentiles. The poor performance of the Schendel method for the winter season makes it an unsuitable choice for ET_o climate change studies in the region. For the summer season, the Jensen–Haise method shows a remarkable overestimation for all ET_o percentiles.

A closer look at the changes in the high ET_o extremes (Figures S1 and S2, available with the online version of this paper) reveals that the ET_o methods (standard and simple methods) agree on the direction of the changes (ET_o increase) in the extremes for both winter and summer seasons, but disagree on the magnitude of the changes. For winter, extreme ET_o increase by the PMF-56 method is less than 1 mm/day, while it goes as high as 1.5 mm/day for the temperature-based methods of Blaney–Criddle and Schendel (Figure S1). The uncertainty is larger for summer when the range of ET_o increase (0–3 mm/day) by the reference method is highly overestimated by some simple methods, e.g., 0–12 mm/day for Schendel and 0–5 mm/day for Blaney–Criddle. Some other simple methods such as Makkink and Tabari show a narrower increase range for summer ET_o extremes (Figure S2). The mean scenario extracted from the results of the Turc and Hargreaves–Samani methods for summer has the lowest bias, while the Hargreaves–Samani and Makkink methods show the lowest bias for the winter season (Figure 5). For the high scenario, the lowest bias for winter (summer) is obtained from the Turc and Jensen–Haise methods (Jensen–Haise and Hargreaves–Samani methods).

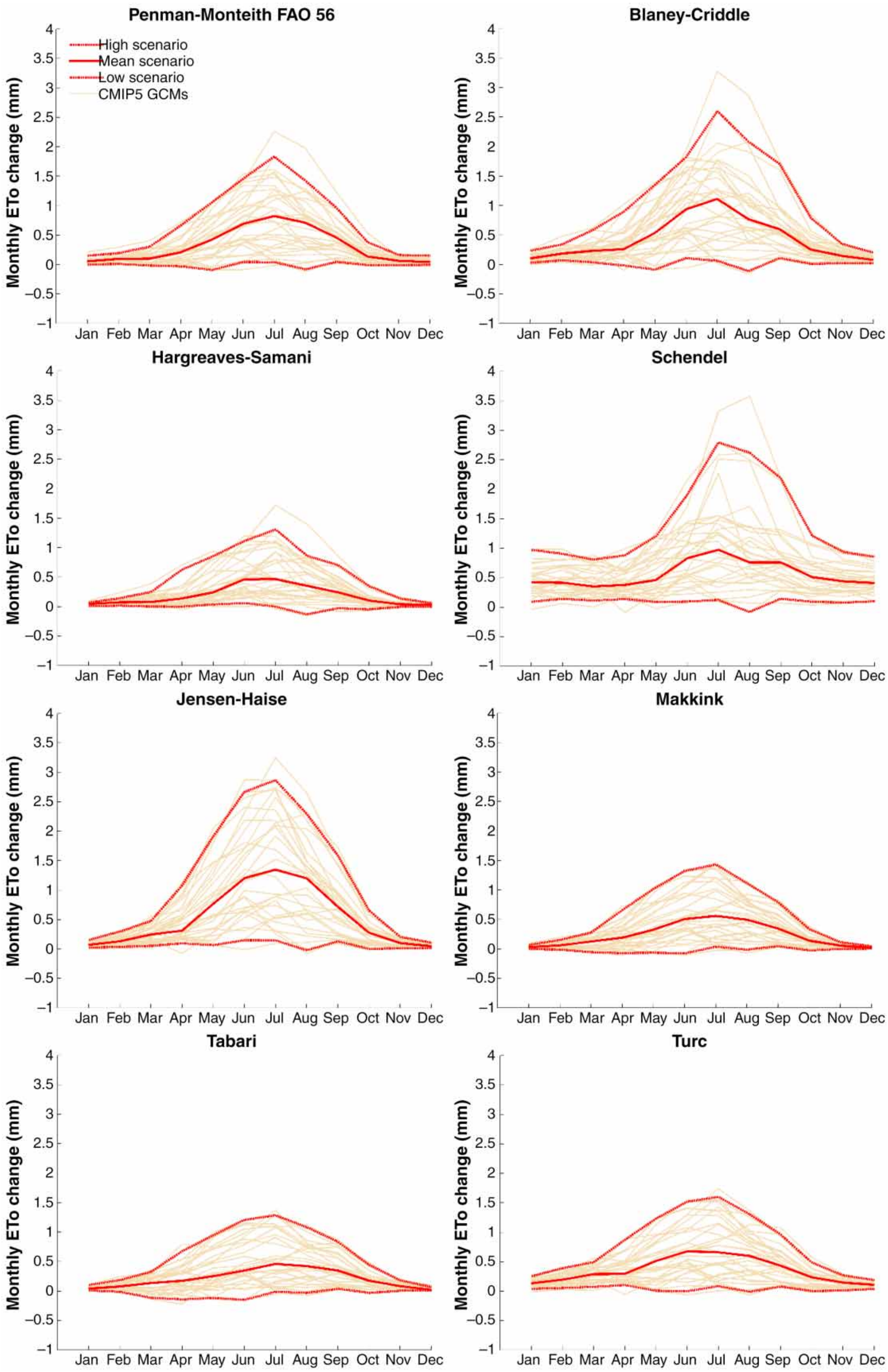

Figure 1 | Change in mean monthly ET_o calculated based on control (1961–1990) and scenario (2071–2100) CMIP5 GCM runs using all RCP scenarios, highlighting high, mean, and low climate scenarios.

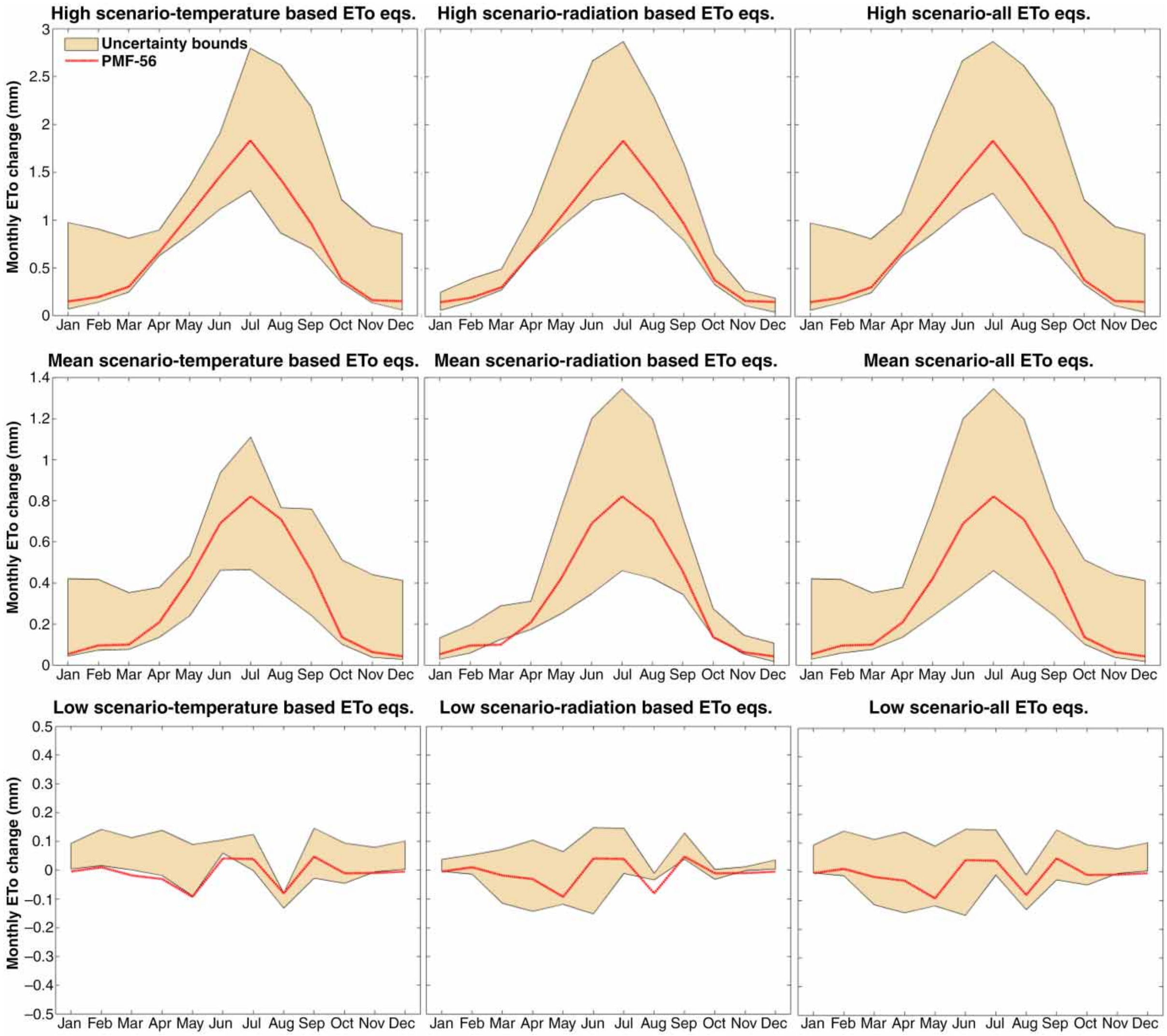

Figure 2 | Range of high, mean, and low climate change scenarios for mean monthly ET_o derived from the simple ET_o methods compared to the scenarios from the PMF-56 method (temperature-based equations: Blaney–Criddle, Hargreaves–Samani, and Schendel; radiation-based equations: Makkink, Turc, Jensen–Haise, and Tabari).

Table 1 | Bias (%) in the mean climate change scenario of seasonal ET_o calculated based on the simple ET_o methods compared to the PMF-56 method

ET_o method	Winter	Spring	Summer	Autumn
Blaney–Criddle	87.21	39.85	26.54	51.38
Hargreaves–Samani	−23.95	−37.83	−42.42	−41.72
Schendel	548.01	63.48	15.40	161.69
Makkink	−44.22	−12.52	−29.79	−17.62
Turc	126.03	50.09	−12.93	24.14
Jensen–Haise	28.29	80.97	68.60	66.59
Tabari	−28.04	−23.30	−44.59	−7.21

DISCUSSION

The results obtained indicate that the ET_o change signals projected by the simple methods broadly follow the pattern of those by the PMF-56 method. However, the magnitude of the changes differs substantially between the simple and standard method. The main reason for such difference is the inclusion of more meteorological variables controlling the ET process in the PMF-56 method. Moreover, simple ET_o approaches with the same meteorological

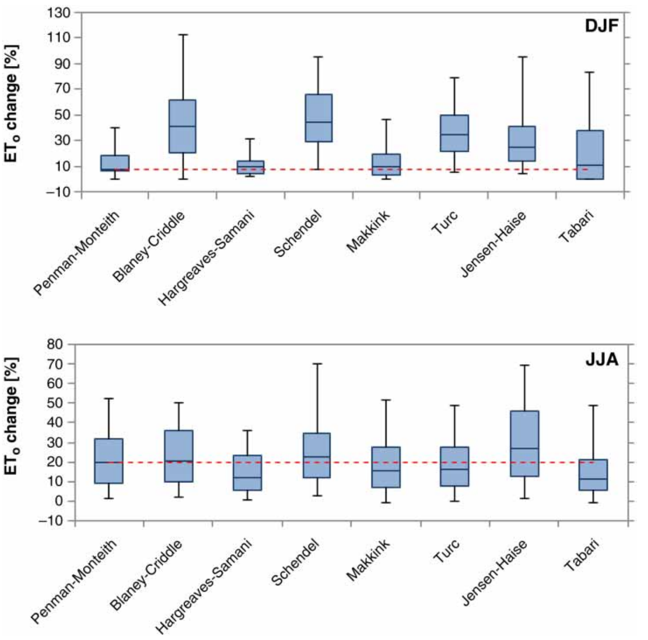

Figure 3 | Change in daily ET_o computed by different methods for winter and summer seasons (median of daily ET_o changes from the PMF-56 method is marked with dashed line).

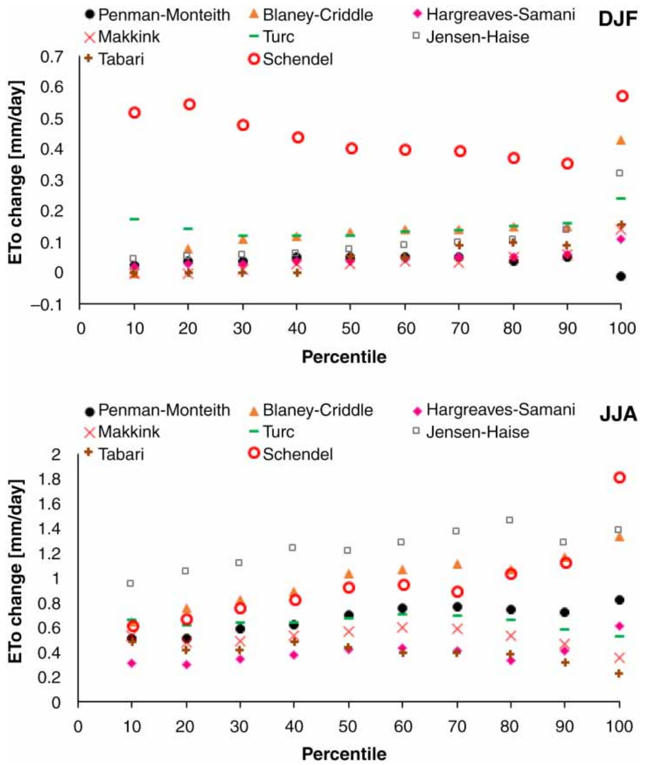

Figure 4 | Mean climate change scenario for daily ET_o percentiles based on different ET_o methods for winter and summer seasons (mean scenario is defined based on the median of the relative changes in ET_o percentiles ranging between 10% and 100%).

inputs present different CCS. This difference stems from the difference in empirical formulation for each approach and the difference in climatic regions for which they were originally developed. Let us consider the drawback of the Hargreaves–Samani method as the most widely used simple approach in hydrological impact studies of climate change. First of all, the Hargreaves–Samani method uses extraterrestrial radiation rather than solar radiation, implying the use of maximum possible radiation and neglecting atmospheric transmissivity. The existence of high moisture content in the atmosphere in humid regions influences transmissivity or sky clearness and leads to an increase of the attenuation of solar radiation at the surface (Fontenot 2004). The other important variable in humid regions is atmospheric moisture, which is not considered in the Hargreaves–Samani method. Atmospheric moisture (directly correlated with vapor pressure) has an indirect relationship with ET, and in fact, ET decreases as atmospheric moisture increases (McKenney & Rosenberg 1993; Tabari 2010; Moratiel *et al.* 2010). These two important factors result in bias in the estimates of the Hargreaves–Samani method. The calibration of the method to local conditions may decrease this bias (Tabari & Hosseinzadeh Talaee 2011).

The findings show that choosing an alternative method to the PMF-56 method with less data demand is difficult. The performance of the simple methods varies remarkably by time scale and season. Taking the mean scenario into account, the Hargreaves–Samani, Makkink, Turc and Tabari methods are the best choices for seasonal and monthly ET_o climate change studies in winter, spring, summer, and autumn, respectively, while the Turc, Jensen–Haise and Hargreaves–Samani methods perform best for investigation of the changes in high ET_o percentiles. This suggests using different simple methods for different time scales and seasons in the absence of full meteorological data for the PMF-56 method application.

In order to investigate the importance of the uncertainty associated with ET_o methods, it is compared with GCM uncertainty which is considered as the main source of

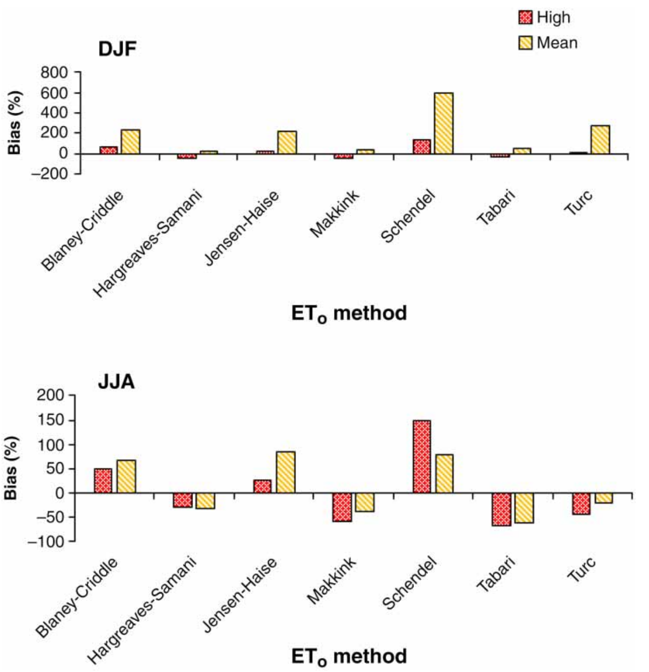

Figure 5 | Bias in daily summer and winter ET$_o$ percentiles (>90%) with respect to present-day climate for the simple ET$_o$ methods.

uncertainty in climate change studies (Wilby & Harris 2006; Kay *et al.* 2009; Chen *et al.* 2011; Exbrayat *et al.* 2014) and also that of future greenhouse gas scenarios (RCP). For the monthly ET$_o$ change and also taking the full range of daily ET$_o$ change into consideration, the uncertainty in GCMs is larger than that in the ET$_o$ methods and RCPs (Table 2). For both mentioned cases, the ET$_o$ uncertainty is of comparable magnitude to the GCM uncertainty. As for the changes in high daily ET$_o$ percentiles, the uncertainty related to the ET$_o$ methods is the dominant source of uncertainty for both summer and winter seasons, while RCP has the lowest contribution to the total uncertainty in ET$_o$ changes.

Table 2 | Comparison of the total variance decomposition related to the uncertainty in GCMs, RCPs, and ET$_o$ methods

Uncertainty source	Monthly ET$_o$ changes	Daily ET$_o$ percentile changes (full range of percentiles)	Daily ET$_o$ percentile changes (>90%) DJF	JJA
GCMs	44	39	25	36
RCPs	28	27	21	23
ET$_o$ methods	28	34	54	42

Generally, the uncertainty analysis shows that the uncertainty in ET$_o$ methods is noticeable for all the cases considered. This shows the importance of addressing the uncertainty associated with ET$_o$ methods next to that in GCMs and future greenhouse gas scenarios as is traditionally done.

CONCLUSIONS AND RECOMMENDATIONS

In this study, the difference between the ET$_o$ CCS derived from the standard PMF-56 method and those from seven simple methods (Blaney–Criddle, Hargreaves–Samani, Schendel, Makkink, Turc, Jensen–Haise, Tabari) was investigated. The meteorological data required for ET$_o$ estimation by the methods were obtained from 12 CMIP5 GCMs for control (1961–1990) and scenario (2071–2100) periods. The results show that the standard and the simple methods generally agree on ET$_o$ increase for all time scales, but disagree on the magnitude of the increase. Biases of over 100% are found for CCS extracted from some simple methods such as Turc and Schendel.

A comparison between the uncertainties related to ET$_o$ methods and GCMs shows that the uncertainty associated with ET$_o$ methods is of comparable magnitude to GCM uncertainty as the main source of uncertainty, suggesting that the uncertainty in the choice of ET$_o$ methods must not be neglected in such studies. Use of further advanced methods for ET$_o$ estimation, which is a function of time scale and season (as the results of this study show), may reduce the uncertainty associated with ET$_o$ methods. Comparing the ET$_o$ uncertainty with the other sources of uncertainty, such as GCM boundary conditions, was impossible in this study because of the limited number of GCM runs providing all meteorological inputs for the ET$_o$ methods. This type of comparison can be made for precipitation as another important input for hydrological modeling in future studies. The uncertainty related to the choice of a downscaling method was not addressed in this study. Thus, further work is needed to assess the degree to which the choice of the statistical method to transfer the climate change signal to the hydrological model inputs, i.e., the downscaling method, contributes to the total uncertainty.

Moreover, the effect of the different sources of uncertainties affiliated with precipitation and ET_o may be explored for hydrological impact projections.

To conclude, considering the large bias of the simple ET_o methods, a fully physically based formulation of ET_o like the PMF-56 method is recommended for projecting ET CCS. This, moreover, requires that the climate modeling centers produce and provide model outputs for all meteorological variables governing the evaporative process. In the case of data unavailability, the simple methods must be used with caution. The bias in the results of the simple methods depends on the time scale and season, as is shown in this study for central Belgium. This bias obviously may differ for other regions of the world.

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