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# A method for investigating the relative importance of three components in overall uncertainty of climate projections

Running head: A method to study relative importance of climate change uncertainties

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**Abstract:** Climate model response (M) and greenhouse gas emissions (S) uncertainties are consistently estimated as spreads of multi-model and multi-scenario climate change projections. In comparison, there has been less agreement in estimating internal climate variability (V). Recently, an initial condition ensemble (ICE) of a climate model has been developed to study V. This ICE is simulated by running a climate model using an identical climate forcing but different initial conditions. Inter-member differences of an initial condition ensemble manifestly represent V. However, ICE has been barely used to investigate relative importance of climate change uncertainties. Accordingly, this study proposes a method of using ICEs, without assuming V as constant, for investigating the relative importance of climate change uncertainties and its temporal-spatial variation. Prior to investigating temporal-spatial variation in China, V estimated using ICE was compared to that using multi-model individual time series at national scale. Results show that V using ICE is qualitatively similar to that using multi-model individual time series for temperature. However, V is not constant for average and extreme precipitations. V and M dominate before 2050s especially for precipitation, while S is dominant in the late 21st century especially for temperature. Mean temperature change is projected to be 30%-70% greater than its uncertainty until 2050s, while uncertainty becomes 10%-40% greater than the change in the late 21st century. Precipitation change uncertainty overwhelms its change by 70%-150% throughout 21st century. Cold regions (e.g.

northern China, Qinghai-Tibetan Plateau) tend to have greater projected temperature change uncertainties. In dry regions (e.g. northwest China), all three uncertainties tend to be great for changes in average and extreme precipitations. Overall, this study emphasizes the importance of considering climate change uncertainty in impact studies, especially taking into account that V is irreducible in the future. Using ICEs without assumption of constant V is an appropriate approach to study climate change uncertainty.

**Key words:** Climate change, Uncertainty, Internal climate variability, Global climate model, Greenhouse gases emissions scenario, China

# 1. Introduction

Climate change will affect human economic societies and natural ecologic systems at various temporal and spatial scales, with its impacts lasting for the whole 21st century (IPCC, 2014). For the assessment of climate change impacts, future climate projections are needed, which are usually provided by global climate models (GCMs) (e.g. Solomon et al., 2007). However, the climate projections usually come into being along with great, multi-source climate change uncertainties. Specifically, the cascade of climate change uncertainties goes from assumptions about future greenhouse gas (GHG) emission scenarios, GCM simulations, impact models, and local impacts (i.e. what those scenarios mean for real climate adaptation decisions on a local scale) (Wilby and Dessai, 2010).

The process from GHG emissions to GCM simulation mainly consists of three sources of climate change uncertainties (Cox and Stephenson, 2007; Mearns, 2010; Dobler et al., 2012). Economic activities in future human society and relevant policies for climate change are unknown (Nakicenovic et al., 2000), so there is uncertainty in future GHG and aerosols emissions. Sets of assumptions for future GHG emissions, such as Special Report on Emission Scenarios (SRESs) in IPCC Fourth Assessment Report (Nakicenovic and Swart, 2000) and Representative Concentration Pathways (RCPs) in IPCC Fifth Assessment Report (Meinshausen et al, 2011), are given to represent this uncertainty, which can be termed as scenario uncertainty. GCMs are used to produce future climate projections. However, due to limitations of knowledge of physical processes in real climate system and imperfect implementation of the limited knowledge, GCMs vary in model structure and model parameterization. Therefore, different GCMs give different responses even to a same future scenario forcing. This uncertainty can be defined as model response uncertainty (IPCC, 2013). There is also an inherent source of climate change uncertainty in the chaotic nature of real climate system, usually termed as internal climate variability. It exists as natural fluctuations superimposed on a steady climate equilibrium state in pre-industrial time or superimposed on an anthropogenic climate change trend in industrial time. Internal climate variability is due to internal forcing such as natural processes within atmosphere and ocean, and their interactions in real climate system.

However, not all sources of climate change uncertainties are equally important. The relative importance will depend on factors like spatial and temporal scales, and climate variables of interest. Previous studies have shown that model response uncertainty plays a significant role throughout the 21st century (e.g. Hawkins and Sutton, 2009, 2011; Terray and Boé, 2013; Little et al., 2015), while scenario uncertainty gradually becomes the most important source in the late 21st century, especially for temperature (e.g. Stott and Kettleborough, 2002; Hawkins and Sutton, 2009; Yip et al., 2011). Internal climate variability contributes greatly to climate change uncertainty in near future particularly for precipitation (e.g. Hawkins and Sutton, 2011; Trenberth, 2012; Hingray and Said, 2014; Fatichi et al., 2016).

The importance of the climate change uncertainties can also be assessed by comparing them to climate change signals. A fractional uncertainty defined as a ratio of climate change uncertainty to mean climate change has been used recently (e.g. Cox and Stephenson, 2007; Hawkins and Sutton, 2009, 2011). The numerator of fractional uncertainty can be identified with total climate change uncertainty or with each specific component of climate change uncertainty. Knutti et al. (2008) have also studied fractional uncertainty for temperature using various probabilistic methods. In addition, signal-to-noise ratio is also commonly used. Signal is defined to be mean climate change while noise is climate change uncertainty (e.g. Christensen et al., 2007; Hawkins and Sutton, 2009, 2011, 2012; Santer et al., 2011; Deser et al., 2014). For example, Giorgi and Bi (2009) defined a signal-to-noise ratio as the ratio of mean precipitation change to a combination of internal precipitation variability and model response uncertainty.

The three components of climate change uncertainty need to be estimated. Several methods have been proposed to partition climate change uncertainties in literatures. For example, Cox and Stephenson (2007) estimated climate change uncertainties based on a simple linear modeling of climate sensitivity and radiative forcing for temperature. Most of other studies (e.g. Hawkins and Sutton, 2009, 2011; Blázquez and Nuñez, 2013; Booth et al., 2013) divided climate projections into climate change trends and residuals. They defined model response uncertainty as an inter-model variance of trends averaged over multiple scenarios, and defined scenario uncertainty as an inter-scenario variance of trends averaged over multiple models. They defined the mean variance of residuals over multiple models and multiple scenarios as internal climate variability. This method was first proposed by Hawkins and Sutton (2009, 2011) and is arguably the best available for dealing with climate change uncertainty. In this method, three components of climate change uncertainties are considered as additively independent and internal climate variability was estimated as a constant value. This analysis of variance method (Storch and Zwiers, 2001) was also used in some other studies (e.g. Räisänen, 2001; Yip et al., 2011; Pelt et al., 2014; Little et al., 2015) to decompose model response uncertainty to a scenario-dependent model response uncertainty and a scenario-independent model response uncertainty. Essentially, this method is similar to the method of Hawkins and Sutton (2009, 2011). However, these studies estimated internal climate variability as a multi-scenario and multi-model mean of variances over several runs for a climate model. In this way, internal climate variability estimated was not constant over time.

To our knowledge, estimation methods for model response uncertainty and scenario uncertainty are identical in most studies (e.g. Giorgi and Bi, 2009; Hawkins and Sutton, 2009, 2011; Yip et al., 2011). In addition, model response uncertainty and scenario uncertainty are generally judged to be potentially reducible in the literature (e.g. Cox and Stephenson, 2007; Hawkins and Sutton, 2009, 2011; Deser et al., 2012a; Fischer et al., 2013). However, internal climate variability is irreducible as it is an inherent property of a climate system (e.g. Hawkins and Sutton, 2012; Deser et al., 2012a; Fischer et al., 2013; Maraun, 2013; Fatichi et al., 2016). In addition, there has been less agreement in terms of estimating internal climate variability. There are different assumptions in definition and methods in the estimation of internal climate variability. For example, Hawkins and Sutton (2009, 2011) estimated internal climate variability as the decadal variability over each climate projection and assumed it to be constant with time. Conversely, Yip et al. (2011) defined internal climate variability as a variance of two runs which is not constant.

In real climate system, internal climate variability is relatively steady but actually not constant (Solomon et al., 2007). In fact, there are initial condition ensembles in particular for studying the role of internal climate variability in future climate change (e.g. Hu and Deser, 2013; Kang et al., 2013; Lu et al., 2014; Kay et al., 2015; Fasullo and Nerem, 2016). The members in this ensemble are produced within the same climate model under identical emissions scenario, but using different initial conditions. In other words, only internal variability within the climate system gives rise to inter-member differences. Therefore, inter-member differences can be used to estimate internal climate variability which is not constant over time. In recent literatures, internal climate variability is usually investigated using initial condition ensembles (Selten et al., 2004; IPCC, 2014; Chen et al., 2015, 2016) and defined as inter-member differences (Deser et al., 2012b; Deser et al., 2014; Zhuan et al., 2018). Previous studies (e.g. Seager et al., 2011; Chen and Brissette, 2018) have shown that initial condition ensembles are capable of capturing observed patterns of internal variability for temperature and precipitation. However, far fewer studies involve in using initial condition ensembles to investigate the relative importance of climate change uncertainties derived from different sources, especially for climate extremes.

Accordingly, this study proposes a method of using initial condition ensembles (ICEs) to estimate internal climate variability for investigating the relative importance of multi-source climate change uncertainties (i.e. internal climate variability, model response uncertainty and scenario uncertainty) and its temporal-spatial variation over the 21st century using China as a case study. Uncertainties of climate model responses and emission scenarios are estimated based on multi-model and multi-scenario ensembles, respectively. Since the relative importance of multi-source climate change uncertainties depends on climate variables of interest and on whether the mean climate or extremes are considered, this study investigates average temperature and precipitation as well as extreme precipitation. Prior to looking at the temporal-spatial variation in the importance of each uncertainty, internal climate variability estimated using ICE method is compared with that estimated using multi-model individual time series at the national scale.

## 2. Data

This study used climate simulations (precipitation and temperature) obtained from 20 GCMs (table 1) in the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Taylor et al., 2012). These climate simulations are driven under historical forcing in 1981-2005 and under three different Representative Concentration Pathways (RCPs 2.6, 4.5 and 8.5) forcing in 2006-2100 (Moss et al., 2010). These three RCP scenarios were chosen for that they correspond to the lowest, medium and the highest anthropogenic forcings for the 21st century, respectively. Although RCP 4.5 and RCP 6.0 both are medium scenarios, only one of them is chosen and RCP 4.5 is probably more often used. For ICEs, a 40-member ensemble under RCP8.5 from the Community Earth System

Model version1 (CESM1) and a 10-member ensemble under RCP8.5 from the Commonwealth Scientific and Industrial Research Organization Mark version 3.6.0 (CSIRO-Mk3.6.0) are used. Totally, climate simulations from 20 GCMs, a 40-member ensemble from CESM1 and a 10-member ensemble from CSIRO-Mk3.6.0 over 1981-2100 were used. Model climate data were all uniformly interpolated to 1°×1° longitude-latitude resolution in the study area, mainland China.

This study also used observed climate data for climate model weighting calculations. Observed climate data include maximum, minimum temperatures and precipitation over 1961-2010 in China, from one 0.5°×0.5° grid dataset of Chinese surface daily precipitation and daily temperature. The dataset is derived from 2472 national meteorological stations and provided by the China Meteorological Data Service Center (http://data.cma.cn/data/cdcindex/cid/00f8a0e6c590ac15.html).

Appendix figure A1 presents national mean climate changes estimated by 20 GCMs under RCP2.6, 4.5, 8.5 for the 1961-2100 period. Observed average temperature and precipitation changes are with the range of model simulations before 2005 (historical forcing), while observed extreme precipitation changes vary around model simulations. Annual mean temperature is projected to increase 4-8°C under RCP8.5, 1.7-4°C under RCP4.5 and 0-2.5°C under RCP2.6 at the end of the 21st century. Annual precipitation is projected to change from -6-35% under RCP8.5, -8-20% under RCP4.5 and -8-18% under RCP2.6. Annual extreme precipitation is projected to change 10-40% under RCP8.5, 0-25% under RCP4.5 and -4-20% under RCP2.6. The estimated climate changes in China are consistent with global climate change (IPCC, 2014). Climate changes under RCP2.6, 4.5, 8.5 (averaged over 20 climate models) of grids nationwide are also provided as appendix figures A2-A4 for three future periods (the 2nd, 6th, 10th decades of the 21st century).

# 3. Methodology

To study the relative importance of multi-source climate change uncertainties, each source (i.e. internal climate variability, model response uncertainty and scenario uncertainty) of total climate change uncertainty needs to be estimated. Internal climate variability is estimated using both the method of multi-model individual time series of Hawkins and Sutton (2009, 2011) and the initial condition ensemble method proposed in this study. Model response uncertainty and scenario uncertainty are respectively estimated using multi-model and multi-scenario ensembles following the method of Hawkins and Sutton (2009, 2011). For mean temperature, precipitation and maximum daily precipitation at annual and seasonal (i.e. summer: June, July and August; winter: December, January and February) scales, the estimation has been done for national mean climate as well as climate in 1°×1° grids nationwide in China.

## 3.1 Estimation of multi-source climate change uncertainties

Internal climate variability manifests itself at various temporal scales including inter-annual variability to multi-decadal variability. This study focused only on decadal variability, which is one of the key components of internal climate variability. In order to study internal decadal variability and the other two climate change uncertainties at decadal scale, precipitation and temperature time series over 1981-2100 period are divided into 111 time periods using a 10-year moving window running from the first to the last year in a one-year increment. Climate data are averaged over each one of the 111 time periods. Thus, one hundred and eleven values are obtained for each climate projection. This time period division is conducted prior to estimating three components of climate change uncertainty.

In order to separate climate change signal and climate noise (i.e. manifestation of internal climate variability), a trend fitting is adopted. The 111 values of each simulation from 20 GCMs ($N_m=20$) are fitted with a fourth-order polynomial using an ordinary least squares method (e.g. Hawkins and Sutton, 2009, 2011). Therefore, each simulation $X$ is separated into three components: the reference climate $r$ (i.e. the mean of the fitted trend over reference period (1981-2010)), the climate change signal $x$ (i.e. the fitted trend relative to the reference climate $r$), the climate noise $\xi$ (i.e. the residual from the fitted trend). For precipitation, $x$, $\xi$ are relative changes to the reference climate $r$, while they are absolute changes for temperature.

$$X_{(m,s,t)} = x_{(m,s,t)} + r_{(m,s)} + \xi_{(m,s,t)}, \tag{1}$$

where, subscript $m$ means for each GCM and $s$ means for each RCP scenario. For trend fitting, subscript $t$ refers to the 111 time periods over 1981-2100 as trend fitting covers the reference period (i.e. 1981-2010). While for uncertainty estimations, subscript $t$ refers to 86 time periods over 2006-2100, as future climate scenarios start at 2006.

**Internal climate variability**

The method of Hawkins and Sutton (2009, 2011) (hereafter, HS0911) assumes that internal climate variability ($V_{HS0911}$) is constant over time. Internal climate variability is manifested as the climate noise. For each GCM, climate noises under all three scenarios are pooled together to create one time series of climate noise. A second-order origin moment of the climate noise is calculated over the whole time series. Then, the mean of second-order origin moments over multiple models is defined as internal climate variability. The calculation can be written as

$$V_{HS0911} = \frac{1}{N_m} \sum_m \left[ E_{s,t} \left[ \xi_{(m,s,t)}{}^2 \right] \right]. \tag{2}$$

where, E denotes mathematical expectation for this and following equations.

**Climate model uncertainty**

Climate model uncertainty is manifested as the spread of climate change signals projected by all GCMs under one future scenario and can be estimated as the variance of these climate change signals. A variance (i.e. second-order central moment) of climate change signals from all GCMs under one RCP scenario is first calculated. Then, a multi-scenario ($N_s$=3) mean of three variances is defined to be an estimate of model response uncertainty (M) (Hawkins and Sutton, 2009, 2011). The calculation can be written as

$$M_{(t)} = \frac{1}{N_s} \sum_s \left[ E_m \left[ \left[ x_{(m,s,t)} - E_m \left[ x_{(\mathrm{m,s,t})} \right] \right]^2 \right] \right]. \tag{3}$$

**Scenario uncertainty**

Scenario uncertainty is manifested as the spread of climate change signals projected by the same GCM under all future scenarios and can be estimated as the variance of these climate change signals. A multi-model mean of climate change signals under one RCP scenario is first calculated. Then, scenario uncertainty (S) is then defined as a variance of three multi-model means (Hawkins and Sutton, 2009, 2011). The calculation can be written as

$$S_{(t)} = E_s\left[\left[\left[\frac{1}{N_m}\sum_m x_{(m,s,t)}\right] - E_s\left[\frac{1}{N_m}\sum_m x_{(m,s,t)}\right]\right]^2\right]. \tag{4}$$

For equations (2)-(4), a simple model weighting method (e.g. Hawkins and Sutton, 2009, 2011) is used to give weights to different climate models. This method gives weights to GCMs for each climate variable. The weight of each GCM is calculated according to its performance in simulating observed national-mean precipitation or temperature for the 2001-2010 period. The summation of all GCMs' weights is equal to one. The weight of each GCM is presented in Table A1.

### 3.2 Initial condition ensemble method

An initial condition ensemble method (hereafter, ICE) is used in particular for the estimation of internal climate variability. The ICE method uses a 40-member ensemble from CESM1. Development of this 40-member ensemble is intended to investigate internal climate variability in climate change impacts (e.g. Kay et al., 2015; Fasullo and Nerem, 2016). Until now, it is one of the initial condition ensembles with the most members. The results of other initial condition ensembles, e.g. a 10-member ensemble of CSIRO-Mk3.6.0, were also calculated and presented in the limitation discussion section 4.4. This ICE method defines the difference among the 40 members as internal climate variability (e.g. Chen et al., 2011, 2016; Deser et al., 2012b; Kang et al., 2013; IPCC, 2014; Kay et al., 2015; Fasullo and Nerem, 2016), which is not assumed to be constant with time.

Prior to estimating internal climate variability using the ICE method, the same time period division and a similar trend fitting procedure are applied to the 40 members. Specifically, one hundred and eleven mean values are first calculated over 111 time periods for each of 40 members. Since all members are generated under the same climate forcing, they are supposed to have an identical climate change trend. A fourth-order polynomial is used to fit the 40-member ensemble mean to get only one trend. Then, the trend of the ensemble mean is removed from each of the 40 members. In this way, each member projection $Y_i$ $(i = 1, 2, \ldots, 40)$ can be written as

$$Y_{(i,t)} = y_{(t)} + r + \xi_{(i,t)} \,, \tag{5}$$

where reference climate $r$ is estimated as the fitted trend of ensemble mean averaged over reference period (1981-2010), $y$ refers to the climate change signal for this specific model, $\xi_i$ $(i = 1, 2, \ldots, 40)$ refer to climate noises for 40 members (for precipitation, $y$, $\xi$ are relative changes to the reference climate; for temperature, they are absolute changes). A second-order origin moment of climate noises of 40 members is defined as internal climate variability ($V_{ICE}$). The calculation can be written as

$$V_{ICE(t)} = E_i\left[\xi_{(i,t)}{}^2\right]. \tag{6}$$

### 3.3 Estimation of total climate change uncertainty

Similar to most of other studies (e.g. Papoulis, 1991; Hawkins and Sutton, 2009, 2011), the three sources of uncertainty are treated independently (i.e. interactions between them are not considered). Thus, the variance for total uncertainty (T) can be defined as the sum of internal climate variability ($V_{HS0911}$ or $V_{ICE}$), climate model uncertainty (M) and scenario uncertainty (S). When considering the standard deviation for total uncertainty, it can be defined as the sum of scaled standard deviations of V, M and S, following the method of Hawkins and Sutton (2011). The scaling factor can be calculated as the ratio of the sum of standard deviations of V, M and S, to the standard deviation of total uncertainty.

### 3.4 Relative importance of climate change uncertainties in climate change

When studying the relative importance of climate change uncertainty in climate change, two ratios between climate change and its uncertainty, and a superposition of climate change uncertainty on climate change were considered.

These two ratios include fractional uncertainty and signal-to-noise ratio (S/N). Fractional uncertainty (90% confidence level) is a ratio of climate change uncertainty to mean climate change (e.g. Cox and Stephenson, 2007; Knutti et al., 2008; Hawkins and Sutton, 2009, 2011). The climate change uncertainty (i.e. standard deviation) can be each one of three uncertainty components or the total uncertainty (IPCC, 2013). Mean climate change is estimated as the mean of climate change signals over all GCMs and all RCP scenarios. For example, the fractional uncertainty for the total uncertainty is a ratio of 1.645 standard deviations (5-95% range) of total uncertainty to mean climate change. The signal-to-noise ratio (S/N) is the reciprocal of the fractional uncertainty for the total uncertainty (Christensen et al., 2007). It is usually used to represent the robustness or reliability of climate projections (e.g. Christensen et al., 2007; Hawkins and Sutton, 2011; IPCC, 2014).

A superposition method is used to indicate possible future climate change. Specifically, three components of climate change uncertainty (i.e. ±1.645 times of the scaled standard deviations in section 3.3) are superimposed onto the mean climate change in turn. Thus, the width of total uncertainty is ±1.645 standard deviations (5-95% range). In this way, different climate change uncertainty regions are given. The climate change uncertainty regions provide insight into what could happen in the single climate projection that will occur in the real world. The boundaries of regions are defined following the superposition method used by Hawkins and Sutton (2011).

# 4. Results and discussion

## 4.1 Contribution of climate change uncertainties

Three components of climate change uncertainty (i.e. V, M and S) were estimated, with the estimation of V using two methods of HS0911 (i.e. $V_{HS0911}$) and ICE (i.e. $V_{ICE}$, using the 40-member ensemble from CESM1). Figure 1 presents evolutions of three uncertainties over time, for annual mean temperature, annual precipitation and annual maximum precipitation in China. Three climate variables were all calculated based on decadal mean on national average. Figures 1(A) to 1(C) present results using $V_{HS0911}$, while figures 1(D) to 1(F) present results using $V_{ICE}$. The results show that $V_{HS0911}$ is about 0.01°C for annual mean temperature and $V_{ICE}$ is mostly similar. For annual precipitation, $V_{HS0911}$ is constant with a value of 1.6 $\%^2$, while $V_{ICE}$ increases from around 2 $\%^2$ before 2050s to almost 3.2 $\%^2$ at 2080s and then decreases to 2.5 $\%^2$ at the end of the 21st century. For annual maximum precipitation, $V_{HS0911}$ is about 4.9 $\%^2$, while $V_{ICE}$ increases from around 5 $\%^2$ before 2050s to around 14 $\%^2$ at 2080s then decreases till the end of this century.

With an assumption of internal climate variability following a normal distribution, the significance of the change in internal climate variability (i.e. normal distribution variances) is tested by using F-test [Figure 1(G-I)]. The change is significant (outside the 5-95% range), if internal climate variability (variance of 40 members) for one period is greater than 1.7 times (the ratio of two normal distribution variances by F-test) of those for another period. The results show that the change in internal variability is not significant for annual mean temperature. To the horizon of this century, $V_{ICE}$ is similar to $V_{HS0911}$ for annual mean temperature. However, internal variability of annual precipitation during 2075-2090 is greater than 1.7 times of that before 2020s, and internal variability of annual maximum precipitation during 2075-2090 is greater than 1.7 times of that before 2055. This implies that the internal variability is not constant for average and extreme precipitations. Changes in internal variability may depend on the chosen emissions scenario. In this study, internal climate variability is estimated from simulations made for the high end RCP8.5 scenario. The resulting change in it may be an upper estimate. This is especially true for annual maximum precipitation. Investigation of internal climate variability for extreme precipitation usually need long time periods and great samples. Since 40-member ensemble is already a great enough sample (1200 values), the variation in internal variability is more likely due to climate change rather than a stochastic process. The inconstant internal climate variability presents the advantage of using ICEs.

For annual mean temperature and annual precipitation, scenario uncertainty grows quickly while model response uncertainty only has a little growth over the 21st century. However, both scenario uncertainty and model response uncertainty have a gradual growth for annual maximum precipitation. Total climate change uncertainty grows remarkably for all three climate variables by the end of the 21st century. For example, total uncertainty of annual precipitation change increases from less than 3 $\%^2$ at the beginning to 44 $\%^2$ at the end of the 21st century. This is because that internal climate variability remains relatively constant, model response uncertainty grows by 26 $\%^2$ and scenario uncertainty grows by 16 $\%^2$ at the end of this century for annual precipitation change.

Figure 2 presents contributions of the three components to the total climate change uncertainty in national mean annual temperature, annual precipitation and annual maximum precipitation. Results of $V_{ICE}$ are consistent with those of $V_{HS0911}$ for average temperature. While for average and extreme precipitations, the contribution of $V_{ICE}$ tends to be greater than that of $V_{HS0911}$ in the late 21st century. For all three climate variables, internal climate variability plays an important role in climate change uncertainty during 2010s to 2040s. For example, internal variability takes up from 20% to 65% of total uncertainty for annual precipitation during 2010s to 2040s. This is consistent with previous studies (e.g. Hawkins and Sutton, 2011; Trenberth, 2012; Hingray and Said, 2014; Fatichi et al., 2016). Model response uncertainty also considerably contributes to total climate change uncertainty during early decades and its contribution becomes even greater in mid-century for both annual precipitation and annual maximum precipitation. In addition, the contribution of scenario uncertainty keeps growing for all three climate variables, and becomes dominant at the end of this century for temperature and extreme precipitation. For example, scenario uncertainty takes up 60%-85% of total uncertainty for annual mean temperature since the mid-term of the 21st century.

**4.2 Relative importance of climate change uncertainties**

Fractional total climate change uncertainty and its three components are shown in Fig. 3 for national means of annual mean temperature, annual precipitation and annual maximum precipitation. This indicates the variation of the importance of climate change uncertainty components relative to climate change over time.

For annual mean temperature, fractional uncertainty of internal variability presents a slight decrease, and that of model response uncertainty presents a slight decrease during the first decades of the 21st century while remains constant afterwards. Fractional uncertainty of scenario increase rapidly and becomes the largest after about 2040 (Figures 3(A and D)). Given that the temperature will increase over the 21st century and the internal temperature variability is estimated to remain relatively steady with time (i.e. figure 1(D)), decrease of its fractional uncertainty is expected. Fractional uncertainty of model response uncertainty remains approximately constant, since the mean temperature change signal and model response uncertainty increase at same relative rate with time. However, fractional uncertainties of scenario uncertainty and total uncertainty increase greatly. This indicates that the growth of scenario uncertainty is likely to overwhelm the magnitude of mean temperature change in this century. The great growth of scenario uncertainty implies that the average temperature change may be sensitive to GHG emission scenarios.

Due to increase of annual precipitation change and steadiness of internal precipitation variability (figure 1(E)), fractional uncertainty of internal precipitation variability decreases (figure 3 (B, E)). In particular, fractional uncertainties for model response uncertainty, scenario uncertainty and total uncertainty are observed to decrease first and then increase, resulting in different turning points. For scenario uncertainty, the turning point is in the 2025-2034 period; for model response uncertainty, it is in the 2025-2064 period; and for total precipitation uncertainty, it is in the 2055-2064 period. Take scenario uncertainty as an example, given the constant increase of annual precipitation change, the decrease of fractional uncertainty indicates that the increase of scenario uncertainty is relatively small compared to that of annual precipitation change. The later increase of fractional uncertainty indicates that the growth of scenario uncertainty becomes faster with time, exceeding the growth of annual precipitation change. Therefore, the turning point in the 2025-2034 period indicates a time when scenario uncertainty is the least relative to annual precipitation change. Compared to temperature, precipitation changes may not be that sensitive to GHG emission scenarios. For extreme precipitation, fractional uncertainty of $V_{ICE}$ is slightly greater than that of $V_{HS0911}$ in the late 21st century. The annual maximum precipitation presents a similar pattern with the annual precipitation in fractional uncertainty (figure 3 (C, F)). Its turning point is in the 2030-2039 period for model response uncertainty, while in the 2015-2024 period for scenario uncertainty and in the 2042-2051 period for total extreme precipitation uncertainty (i.e. 10 to 15 years earlier than those for annual precipitation).

Three climate change uncertainty components were superimposed on mean climate change. Figure 4 shows this superposition for annual mean temperature, annual precipitation and annual maximum precipitation on national average. Superposition using $V_{ICE}$ is similar to that using $V_{HS0911}$ for annual mean temperature. While for average and extreme precipitations, the band of $V_{ICE}$ is wider than that of $V_{HS0911}$ in the late 21st century. For example, in Figure 4(E), the band of $V_{ICE}$ represents how much annual precipitation change could 'wander' if the future scenario and model response are perfectly known. In other words, the $V_{ICE}$ band indicates that annual precipitation change could become as great as 10 % or as small as 7 % at the end of the 21st century, due to only internal climate variability. The combination of $V_{ICE}$ and M bands shows how much annual precipitation change could 'wander', as if the future scenario is specified. Specifically, it implies that annual precipitation change can be as great as 15 % or as small as zero at the end of the 21st century, due to the combination of internal climate variability and model response uncertainty. The combination of all three bands gives the spread of how much annual precipitation change could 'wander' due to total precipitation uncertainty. It indicates that annual precipitation change can be -3 % to 20% at the end of the 21st century due to total precipitation uncertainty.

Similarly, annual mean temperature change (figure 4(D)) is projected to be -0.8℃ to 7℃ at the end of the 21st century due to total temperature uncertainty, and annual maximum precipitation change (figure 4(F)) is projected to be -5 % to 35 % at the end of the 21st century due to total extreme precipitation uncertainty.

## 4.3 Temporal-spatial variation of climate change uncertainty

### 4.3.1 Contribution of climate change uncertainties

Three components of climate change uncertainty were also estimated for grids nationwide. Only $V_{ICE}$ is presented to show internal climate variability. Figures 5-7 present contributions of three climate change uncertainties to the total climate change uncertainty nationwide for annual mean temperature, annual precipitation and annual maximum precipitation, respectively. The 2nd, 6th and 10th decades of the 21st century are chosen to represent the temporal variation.

For annual mean temperature (figure 5), model response uncertainty and internal climate variability are dominant in the 2nd decade of the 21st century. Then in the 6th decade, dominant sources become model response uncertainty and scenario uncertainty. Scenario uncertainty overwhelms the other two uncertainty components, becoming the most important in the 10th decade. This temporal variation tendency applies to almost all grids nationwide. In addition, in the 2nd decade, the relative contribution of internal variability is small in mid-eastern China but still great in southwestern China. In the same period, the relative contribution of model response uncertainty is the largest in mid-eastern China while relatively small in southwestern China. In the 6th decade, model response uncertainty is low while scenario uncertainty is large in most mid-western China. In terms of the absolute amplitudes of temperature uncertainties (Appendix figure A5), there are much stronger spatial variation tendencies nationwide.

Internal climate variability is strongest in the Qinghai-Tibetan Plateau and northern China with its magnitude constant throughout the 21st century. Grids with great model response uncertainty are mainly distributed in the Qinghai-Tibetan Plateau, northern China in the 2nd decade of the 21st century, spreading to southern and eastern China in the 6th and 10th decades, with the greatest uncertainty still in the Qinghai-Tibetan Plateau and northern China. In the 2nd decade, some areas in the Qinghai-Tibetan Plateau, northern China have greater scenario uncertainty than other regions. While areas with great scenario uncertainty rapidly spread southward and eastward to cover almost whole China in the following decades.

For annual precipitation (figure 6), internal climate variability and model response uncertainty dominate until the 6th decade of the 21st century. Internal climate variability is not important in the 10th decade while model response uncertainty becomes more dominant in the 10th decade. This temporal variation tendency applies to most grids nationwide. For the absolute amplitudes presented in Appendix figure A6, grids with strong internal precipitation variability are mainly distributed in northern and southeastern China. Model response uncertainty is the strongest in northwestern China with its magnitude much greater in the end of this century. Scenario uncertainty becomes great for northwestern China since the 6th decade. However, the spatial patterns of the relative contributions remain similar with time as shown in Figure 6. For example, the contribution of internal climate variability to the total uncertainty of annual precipitation change decreases more in southwestern and northern China than the other regions in the 10th decade. While contributions of model response uncertainty and scenario uncertainty grow faster in these two regions. In addition, scenario uncertainty also has an obvious contribution in northeastern China at the end of the 21st century.

Annual maximum precipitation (Figure 7 and Appendix Figure A7) has a similar temporal variation pattern to that of annual precipitation. Difference lies in that internal climate variability and model response uncertainty dominate throughout the 21st century. In addition, the annual maximum precipitation presents more variations than the annual precipitation.

#### 4.3.2 Relative importance of climate change uncertainties in climate change

Climate change (signal) to the total climate change uncertainty (noise) ratio (signal-to-noise ratio, S/N) has been calculated for all grids nationwide. Internal climate variability as a part of noise is defined with $V_{ICE}$. This has been done at annual scale and for two seasons (i.e. winter and summer). Figures 8-10 present S/Ns of mean temperature, mean precipitation and maximum precipitation for the 2nd, 6th and 10th decades of the 21st century, respectively.

Results show that S/Ns of annual mean temperature decrease over time (Figure 8). Specifically, S/Ns are around 1.7 in the 2nd decade and around 0.9 in the 10th decade. This temporal variation tendency is consistent over most grids nationwide. This implies that, for most regions in China, the magnitude of annual temperature change is greater than the magnitude of total annual temperature uncertainty before the 6th decade while the other way round afterwards. In other words, the turning point around the 6th decade corresponds to S/N value of 1. Differently, seasonal mean temperatures (Figure 8) do not have a mono-directional temporal variation tendency for S/Ns. For example, S/Ns of winter mean temperature are around 0.9 for most grids in the 2nd decade and around 1.3 for most grids in the 6th decade, while they are less than 0.9 in the 10th decade. Spatial variations are observed in all cases. Specifically, S/Ns are less than one for annual and summer mean temperature in northeastern China but greater than one in other regions in the 2nd decade. The same applies in winter in the 6th decade.

S/Ns of precipitation increase over time while still less than one at the end of the 21st century (Figure 9). This indicates that annual precipitation change is less than its total uncertainty for the whole 21st century. This temporal variation tendency is consistent over most regions in China at both annual and seasonal scales. Spatial variation is mostly evident in the 2nd decade for both annual and seasonal precipitation, with the sign of the mean change (and hence S/N) being different between northern and southern China. For example, in the 2nd decade, S/Ns of annual precipitation are positive in most regions of China while negative in parts of southern China. Negative S/Ns are due to negative (decrease) precipitation change as the numerator. The area with negative S/Ns is more widespread in southern China for winter precipitation in the 2nd decade.

Similarly, S/Ns also increase over time but still remain less than one for maximum precipitation (Figure 10). This temporal variation tendency applies to almost all regions of China at both annual and seasonal scales. Spatial variation is observed for winter maximum precipitation in the 2nd decade, i.e. S/Ns are mainly negative in southern China, while positive in other regions.

### 4.4 Limitation discussion

In this study, model response uncertainty has been defined as spread among multiple climate models. This measure is often used in literature (e.g. Hawkins and Sutton, 2009, 2011), however it still has some limitations. For example, this method does not take into account climate model dependence (e.g. Masson and Knutti, 2011; Pennell and Reichler, 2011; Knutti et al., 2013). Some climate models may be similar in model structure or parameterization to some extent resulting in similar or close climate simulations, which is known as model dependence (e.g. Bishop and Abramowitz, 2013). If climate model dependence is taken into account, a sample of climate simulations may be more representative of the distribution of possible climate realizations. Based on this sample, the measure of model response uncertainty may be larger (e.g. Jewson and Hawkins, 2009). Future development in climate models for a better representation of the real climate system may result in quantitatively different estimates for the model response uncertainty, while the results are expected to remain qualitatively similar. Model response uncertainty belongs to model uncertainty, which comprehensively reflects how accurate climate models represent the real climate system and reflect the approximations required in the development of climate models (IPCC, 2013). In other words, model uncertainty with a far more comprehensive sense has not been discussed in this study.

For estimation of scenario uncertainty, RCP scenarios were used. Although RCP scenarios span a wide range of total forcing values, they do not span the full range of uncertainty in the future anthropogenic forcing, e.g. uncertainty in aerosol forcings and ozone precursor (IPCC, 2014). The range of anthropogenic aerosol emissions across all scenarios has a larger impact on near-term climate projections than the corresponding range of long-lived greenhouse gases, particularly on regional scales and for hydrological cycle variables (IPCC, 2014). The carbon cycle climate feedbacks are also not represented in the concentration-driven RCP scenarios (IPCC, 2014). RCPs only account for future changes in anthropogenic forcings. Neither future volcanic eruptions nor deviations from the 1985-2005 mean solar cycle and their uncertainties are considered (IPCC, 2014).

Some studies (e.g. Kiehl 2007; Yip et al., 2011) considered model-scenario interaction, i.e. non-constancy of the variance across scenarios in different models. To address this concern, they further decomposed model response uncertainty into scenario-independent uncertainty and scenario-dependent uncertainty. Since the goal of this study is to propose a method to estimate internal climate variability for studying the contribution of three uncertainty components, a further partition in model response uncertainty was not considered, especially taking into account the fact that the sum of scenario-dependent uncertainty and scenario-independent uncertainty is equivalent to model response uncertainty (Hawkins and Sutton, 2009, 2011).

This study estimates internal climate variability based on a large-member ensemble of CESM1. However, the estimated internal climate variability may be different when using different initial condition ensembles. It may be more reasonable to simultaneously use multiple initial condition ensembles to estimate the average internal variability (e.g. Ruosteenoja et al., 2016). However, one of our previous studies (i.e. Chen and Brissette, 2018) showed that initial condition ensembles performed similarly in estimating internal climate variability for average precipitation and temperature at the multi-decadal scale, if the number of ensemble member is more than five. In addition, not all CMIP5 models present multiple initial condition ensembles on the public domain. To address this concern to a certain extent, internal climate variability is also estimated based on a 10-member ensemble of CSIRO-Mk3.6.0. The results are presented in Figures 11(A) to 11(C). Overall, internal temperature variability estimated using CSIRO-Mk3.6.0 is mostly similar to that estimated using CESM1. For annual precipitation, CSIRO-Mk3.6.0 simulates a slightly greater internal climate variability than CESM1 for a few periods. However, for annual maximum precipitation, CSIRO-Mk3.6.0 projects 5 to 8 $\%^2$ less internal climate variability than CESM1 after 2050s. Similar results are also observed for fractional uncertainties as presented in Figures 11(D) to 11(F). Significances of changes in internal climate variability (Figures 11(G-I)) have been tested by using the F-test. The change is significant (outside the 5-95% range) if internal climate variability (variance of 10 members) of one period is greater than 3 times (the ratio of two normal distribution variances by F-test) of that of a previous period. The results show that the significances for average temperature and precipitation are consistent with those using CESM1. However, the change in internal variability for extreme precipitation using CSIRO-Mk3.6.0 is not significant, which is different from using CESM1. This implies that the use of the 40-member ensemble (CESM1) may perform better than the use of the 10-member ensemble (CSIRO-Mk3.6.0) at estimating internal variability for extreme precipitation, since the study of variability for extreme values usually needs long time periods and large samples. These results also emphasize the importance of using multiple large ensembles to estimate internal climate variability for climate change impact studies.

In general literature, there is little agreement in estimating climate change signals from climate projections. However, it is generally recognized that climate change signals follow a nonlinear trend. Following the previous studies (e.g. Hawkins and Sutton, 2009, 2011), this study uses a fourth-order polynomial to fit the climate change signal. The uncertainty related to the choice of a detrending method may need to be considered in future studies. Furthermore, definition of climate change uncertainty in this study refers to the spread of multiple climate simulations from climate models rather than the differences between climate model simulations and observed climate, because of the inexistence of future observations.

## 5. Conclusion

This study proposes a method of using ICEs to estimate internal climate variability without assuming that it is constant with time. Based on this method, contributions of internal climate variability, model response uncertainty and scenario uncertainty to overall climate change uncertainty were quantified for temperature and precipitation change projections over the 21st century in China. The following conclusions are drawn:

1. The ICE method gives results qualitatively similar to those obtained by using multi-model individual time series in estimating internal variability of annual mean temperature. However, internal variability of annual precipitation and annual

maximum precipitation are not constant during the studied period, which may imply the advantage of using ICEs for studying internal climate variability.

2. Internal climate variability and model response uncertainty dominate climate change uncertainty before 2050s, especially for precipitation. However, for the latter half of the 21st century, scenario uncertainty becomes the dominant source of uncertainty, especially for temperature.
3. Mean temperature change in China is projected to be greater than its total uncertainty before the mid-term of the 21st century. While at the end of the 21st century, the total temperature change uncertainty exceeds the change itself. However, the precipitation change in China is projected to be less than its total uncertainty throughout the whole 21st century.
4. In terms of spatial variability, cold regions (e.g. northern China, the Qinghai-Tibetan Plateau) tend to have great temperature change uncertainties. In addition, all sources of uncertainty for annual mean and annual maximum precipitation changes tend to be great in dry regions (e.g. northwestern China).

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# Table

**Table 1 General information of 20 GCMs used**

| ID | Modeling center | Institution | Model name | Horizontal resolution (Lon. x Lat.) |
|---|---|---|---|---|
| **1** | BCC | Beijing Climate Center, China Meteorological Administration | BCC-CSM1.1 | 2.815 x 2.815 |
| **2** | | | BCC-CSM1.1(m) | 1.125 x 1.125 |
| **3** | GCESS | College of Global Change and Earth System Science, Beijing Normal University | BNU-ESM | 2.8 x 2.8 |
| **4** | CCCma | Canadian Centre for Climate Modelling and Analysis | CanESM2 | 2.815 x 2.815 |
| **5** | | | CESM1-CAM5 | 1.25 x 0.9 |
| **6** | NCAR | National Center for Atmospheric Research | CESM1 | 1.25 x 0.9 |
| **7** | CNRM-CERFACS | Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique | CNRM-CM5 | 1.4 x 1.4 |
| **8** | CSIRO-QCCCE | Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queenland Climate Change Centre of Excellence | CSIRO-Mk3.6.0 | 1.875 x 1.875 |
| **9** | ICHEC | Irish Centre for High-End Computing | EC-EARTH | 1.125 x 1.1121 |
| **10** | IPSL | Institut Pierre-Simon Laplace | IPSL-CM5A-LR | 3.75 x 1.875 |
| **11** | | | IPSL-CM5A-MR | 2.5 x 1.25 |
| **12** | LASG-CESS | LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University | FGOALS-g2 | 1.875 x 1.25 |
| **13** | MOHC | Met Office Hadley Centre | HadGEM2-ES | 1.875 x 1.25 |
| **14** | MPI-M | Max Planck Institute for Meteorology | MPI-ESM-LR | 1.875 x 1.8496 |
| **15** | | | MPI-ESM-MR | 1.875 x 1.8496 |
| **16** | MRI | Meteorological Research Institute | MRI-CGCM3 | 1.125 x 1.125 |
| **17** | NCC | Norwegian Climate Centre | NorESM1-M | 2.5 x 1.8947 |
| **18** | NIMR-KMA | National Institute of Meteorological Research | HadGEM2-AO | 1.875 x 1.25 |
| **19** | NOAA-GFDL | National Oceanic and Atmospheric Administration/Geophysical Fluid Dynamics Laboratory | GFDL-CM3 | 2.5 x 2.0 |
| **20** | | | GFDL-ESM2G | 2.5 x 2.0 |
| **21** | | | GFDL-ESM2M | 2.5 x 2.0 |

# Figure list

Figure 1 Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: °C$^2$ or %$^2$) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using ICE method with the 40-member ensemble of CESM1 (D-F). The significances of the change in internal climate variability estimated using ICE (G-I).

Figure 2 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using ICE method with the 40-member ensemble of CESM1 (D-F).

Figure 3 Fractional uncertainty (F, units: 1) of internal climate variability (V), model response uncertainty (M), scenario uncertainty (S) and total climate change uncertainty (T) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using ICE method with the 40-member ensemble of CESM1 (D-F). Vertical bars indicate the lowest points.

Figure 4 Possible future climate changes (units: °C or %) due to internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (5-95% ranges) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using ICE method with the 40-member ensemble of CESM1 (D-F).

Figure 5 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual mean temperature over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 6 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 7 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual maximum precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 8 Signal-to-Noise ratios for annual and seasonal mean temperature over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 9 Signal-to-Noise ratios for annual and seasonal precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 10 Signal-to-Noise ratios for annual and seasonal maximum precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using ICE method with the 40-member ensemble of CESM1.

Figure 11 (A-C) Internal climate variability (V), model response uncertainty (M), scenario uncertainty (S), total climate change uncertainty (T) (units: °C$^2$ or %$^2$) and (D-F) their fractional uncertainties (F, units:1) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using ICE method with the 10-member ensemble of CSIRO-Mk3.6.0. The significances of the change in internal climate variability estimated using ICE (G-I).

Figure 1 Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: $°C^2$ or $\%^2$) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using ICE method with the 40-member ensemble of CESM1 (D-F). The significance of the change in internal climate variability estimated using the ICE (G-I).

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Figure 3 Fractional uncertainty (F, units: 1) of internal climate variability (V), model response uncertainty (M), scenario uncertainty (S) and total climate change uncertainty (T) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using the ICE method with the 40-member ensemble of CESM1 (D-F). Vertical bars indicate the lowest points.

Figure 4 Possible future climate changes (units: °C or %) due to internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (5-95% ranges) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using HS0911 method (A-C) and using the ICE method with the 40-member ensemble of CESM1 (D-F).

Figure 5 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual mean temperature over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

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Figure 7 Uncertainty fraction (units: %) of internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) for annual maximum precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

Figure 8 Signal-to-Noise ratios for annual and seasonal mean temperature over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

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Figure 10 Signal-to-Noise ratios for annual and seasonal maximum precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

Figure 11 (A-C) Internal climate variability (V), model response uncertainty (M), scenario uncertainty (S), total climate change uncertainty (T) (units: $°C^2$ or $\%^2$) and (D-F) their fractional uncertainties (F, units:1) for annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) on national average of China over 2006-2100, with V estimated using the ICE method with the 10-member ensemble of CSIRO-Mk3.6.0. The significance of the change in internal climate variability estimated using ICE (G-I).

# Appendix

**Table A1 Weights of 20 GCMs for national-mean climate changes**

| ID | Model name | Precip | Temp | Extre |
|---|---|---|---|---|
| 1 | BCC-CSM1.1 | 0.046 | 0.054 | 0.038 |
| 2 | BCC-CSM1.1(m) | 0.064 | 0.046 | 0.042 |
| 3 | BNU-ESM | 0.035 | 0.041 | 0.059 |
| 4 | CanESM2 | 0.028 | 0.037 | 0.028 |
| 5 | CESM1-CAM5 | 0.028 | 0.044 | 0.034 |
| 6 | CNRM-CM5 | 0.069 | 0.061 | 0.049 |
| 7 | CSIRO-Mk3.6.0 | 0.074 | 0.044 | 0.066 |
| 8 | EC-EARTH | 0.068 | 0.063 | 0.055 |
| 9 | IPSL-CM5A-LR | 0.049 | 0.041 | 0.060 |
| 10 | IPSL-CM5A-MR | 0.060 | 0.039 | 0.067 |
| 11 | FGOALS-g2 | 0.063 | 0.050 | 0.075 |
| 12 | HadGEM2-ES | 0.030 | 0.038 | 0.038 |
| 13 | MPI-ESM-LR | 0.088 | 0.051 | 0.063 |
| 14 | MPI-ESM-MR | 0.080 | 0.054 | 0.057 |
| 15 | MRI-CGCM3 | 0.041 | 0.072 | 0.063 |
| 16 | NorESM1-M | 0.044 | 0.052 | 0.067 |
| 17 | HadGEM2-AO | 0.030 | 0.047 | 0.036 |
| 18 | GFDL-CM3 | 0.016 | 0.029 | 0.025 |
| 19 | GFDL-ESM2G | 0.044 | 0.077 | 0.046 |
| 20 | GFDL-ESM2M | 0.044 | 0.061 | 0.034 |
| | Sum | 1.000 | 1.000 | 1.000 |

Figure A1 Climate changes estimated by 20 climate models forced by RCP2.6, RCP4.5 and RCP8.5 for the 1960-2100 period. Color shading represents a range of climate change given by $\pm 1.65$ standard deviations (5-95% range) of multi-model climate change projections under one RCP scenario. Color thick lines represent multi-model mean climate change under one RCP scenario. Black thick lines (Obs) represent observed climate change during historical period. (Temp: annual mean temperature; Precip: annual precipitation; Extre: annual one-day maximum precipitation)

Figure A2 Gridded annual mean temperature changes (°C) nationwide, averaged over 20 climate models forced by RCP2.6, 4.5, 8.5 over the 2nd, 6th, and 10th decades of the 21st century.

Figure A3 Gridded annual precipitation changes (%) nationwide, averaged over 20 climate models forced by RCP2.6, 4.5, 8.5 over the 2nd, 6th, and 10th decades of the 21st century.

Figure A4 Gridded annual maximum precipitation changes (%) nationwide, averaged over 20 climate models forced by RCP2.6, 4.5, 8.5 over the 2nd, 6th, and 10th decades of the 21st century.

Figure A5 Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: $°C^2$) for annual mean temperature over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

Figure A6 Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: $\%^2$) for annual precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.

Figure A7 Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: $\%^2$) for annual maximum precipitation over 2nd, 6th, 10th decades of the 21st century in China, with V estimated using the ICE method with the 40-member ensemble of CESM1.