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

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Climate model response (M) and greenhouse gas emissions (S) uncertainties are consistently estimated as spreads of multi-model and multi-scenario climate change projections. There has been less agreement in estimating internal climate variability (V). In recent years, an initial condition ensemble (ICE) of a climate model has been developed to study V. ICE is simulated by running a climate model using an identical climate forcing but different initial conditions. Inter-member differences of an ICE 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. 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 and Qinghai-Tibetan Plateau) tend to have greater temperature change uncertainties. In dry regions (e.g., northwest China), all three uncertainties tend to be great for changes in average and extreme precipitations. 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 assuming V as constant is an appropriate approach to study climate change uncertainty.

KEYWORDS
China, climate change, global climate model, greenhouse gases emissions scenario, internal climate variability, uncertainty

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 (Pachauri et al., 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 and Swart, 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 the 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 (Stocker et al., 2013). There is also an inherent source of climate change uncertainty in the chaotic nature of the 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 natural processes within atmosphere and ocean, and their interactions in the real climate system.

However, not all sources of climate change uncertainties are equally important in their contributions to the total climate change uncertainty. 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 the near future particularly for precipitation (e.g., Hawkins and Sutton, 2011; Trenberth, 2012; Hingray and Saïd, 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 a climate change uncertainty to the mean climate change has been used recently (e.g., Cox and Stephenson, 2007; Hawkins and Sutton, 2009, 2011). The numerator of a fractional uncertainty can be identified with the 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 (S/N) ratio is also commonly used. Signal is defined to be the mean climate change while noise is a 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 S/N 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 modelling of climate sensitivity and radiative forcing for temperature. Most of other studies (e.g., Hawkins and Sutton, 2009, 2011; Blázquez and Nuñez, 2012; Booth et al., 2012) 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, 1999) 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 the best of 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 usually judged to have the potential to be reduced with the development of climate model science 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; Fasullo 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 the real climate system, internal climate variability is in a relatively steady state (without an increasing or a decreasing trend) but actually not constant (Stocker et al., 2013, chapter 12, p. 1039). In fact, there are initial condition ensembles (ICEs) 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 the recent literatures, internal climate variability is usually investigated using ICEs (Selten et al., 2004; Pachauri et al., 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 ICEs are capable of capturing observed patterns of internal variability for temperature and precipitation. However, using ICEs to investigate the relative importance of climate change uncertainties derived from different sources has not been conducted in the literature, especially for climate extremes.

Accordingly, this study proposes a method of using 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 the 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 RCP 8.5 from the Community Earth System Model version1 (CESM1) and a 10-member ensemble under RCP 8.5 from the Commonwealth Scientific and Industrial Research Organization Mark version 3.6.0 (CSIRO-Mk3.6.0) are used. Model climate data were all uniformly interpolated to 1°×1° longitude–latitude resolution using a triangulation-based linear interpolation method.

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 a 0.5°×0.5° grid dataset of Chinese surface daily precipitation and daily temperature. The dataset is derived from 2,472 national meteorological stations and provided by the China Meteorological Data Service Center (http://data.cma.cn/data/cdcindex/cid/00f8a0e6c590ac15.html).

Supporting Information Figure S1 presents national mean climate changes estimated by 20 GCMs under RCP 2.6, 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 RCP 8.5, 1.7–4°C under RCP 4.5 and 0–2.5°C under RCP 2.6 at the end of the 21st century. Annual precipitation is projected to change from −6 to 35% under RCP 8.5, −8 to 20% under RCP 4.5 and −8 to 18% under RCP 2.6. Annual extreme precipitation is projected to change 10–40% under RC P8.5, 0–25% under RCP 4.5 and −4 to 20% under RCP 2.6. The estimated climate changes in China are consistent with global climate change (Pachauri et al., 2014). Climate changes under RCP 2.6, 4.5, 8.5 (averaged over 20 climate models) of grids nationwide are also provided as appendix Supporting Information Figures S2–S4 for three future periods (the 2nd, 6th and 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 ICE 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 over various temporal scales including inter-annual variability, decadal variability and multi-decadal variability. This study focused only on decadal variability, which is one of the key manifestations of internal climate variability and is one of the most important ones in future climate change impact studies. 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 1-year increment. Climate data are averaged over each one of the 111 time periods. Thus, 111 values are obtained for each climate projection. This time period division is conducted prior to estimating the 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 (Nm = 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 fourth-order polynomial over reference period [1981–2010]), the climate change signal x (i.e., the fitted fourth-order polynomial relative to the reference climate r), the climate noise ξ (i.e., the residual from the fitted fourth-order polynomial). For precipitation, x, ξ are relative changes to the reference climate r, while they are absolute changes for temperature.

\[ X(m,s,t) = x(m,s,t) + r(m,s,t) + \xi(m,s,t) \]  

(1)
where the subscript \( m \) means for each GCM and \( s \) means for each RCP scenario. For trend fitting, the subscript \( t \) refers to the 111 time periods over 1981–2100 since 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 the RCP climate scenarios start at 2006.

### 3.1.1 Internal climate variability

The method of Hawkins and Sutton (2009, 2011) (hereafter, HS0911) assumes that internal climate variability (\( V_{\text{HS0911}} \)) is constant over time. Internal climate variability is manifested as 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

\[
V_{\text{HS0911}} = \sum_{m} w_m \left[ \mathbb{E}_{s,t} \left[ \xi^2_{(m,s,t)} \right] \right]
\]  

where \( \mathbb{E} \) denotes mathematical expectation for this and following equations.

### 3.1.2 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. The 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 mean of these variances is defined to be an estimate of model response uncertainty (M) (Hawkins and Sutton, 2009, 2011). The calculation can be written as

\[
M_{(t)} = \frac{1}{N_s} \sum_{s} \left[ \mathbb{E}_m \left[ x_{(m,s,t)} \right] - \mathbb{E}_m \left[ x_{(m,t)} \right] \right]^2
\]

### 3.1.3 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. The multi-model mean climate change signals under each RCP scenario are first calculated. Then, scenario uncertainty (S) is defined as the variance of the three multi-model means (Hawkins and Sutton, 2009, 2011). The calculation can be written as

\[
S_{(t)} = \mathbb{E}_s \left[ \left( \sum_{m} w_m x_{(m,s,t)} \right)^2 - \mathbb{E}_s \left[ \sum_{m} w_m x_{(m,s,t)} \right]^2 \right]
\]

For Equations (2)–(4), a simple model weighting method (e.g., Hawkins and Sutton, 2009, 2011) is used to give weights (i.e., \( w_m \)) 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 Supporting Information Table S1.

### 3.2 ICE method

An 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 ICEs with the most members. The results of other ICEs, for example, 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; Pachauri et al., 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 10-year mean values are first calculated over the 111 time periods for each of the 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

\[
Y_{(i,t)} = y_{(t)} + r + \xi_{(i,t)}
\]

where reference climate \( r \) is estimated as the fitted trend of ensemble mean averaged over the 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 the 40 members (for precipitation, \( y, \xi \) are absolute changes to the reference climate; for temperature, they are relative changes). A second-order origin moment of climate noises of the 40 members is defined as internal climate variability (\( V_{\text{ICE}} \)). The calculation can be written as

\[
V_{\text{ICE}(i)} = \mathbb{E}_t \left[ \xi_{(i,t)}^2 \right]
\]

### 3.3 Estimation of total climate change uncertainty

Similar to most of other studies (e.g., Papoulis and Pillai, 2001; 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 \( (V_{HS0911} \text{ or } V_{ICE}) \), climate model uncertainty \( (M) \) and scenario uncertainty \( (S) \). When considering the SD for total uncertainty, it can be defined as the sum of scaled SDs 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 SDs of \( V \), \( M \), and \( S \), to the SD 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 S/N ratio. Fractional uncertainty (5–95% range) is a ratio of a climate change uncertainty to the mean climate change (e.g., Cox and Stephenson, 2007; Knutti et al., 2008; Hawkins and Sutton, 2009, 2011). The numerator, climate change uncertainty (i.e., 1.645 SDs), can be each one of three uncertainty components or the total uncertainty (Stocker et al., 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 the ratio of 1.645 SDs (5–95% range) of the total uncertainty to the mean climate change. The 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; Pachauri et al., 2014).

A superposition method is used to indicate possible future climate change. Specifically, the three components of

![FIGURE 1](https://example.com/figure1.png)  
**FIGURE 1**  
Internal climate variability (V), model response uncertainty (M) and scenario uncertainty (S) (units: °C² or %²) for national averages of annual mean temperature (Temp), annual precipitation (Precip) and annual maximum precipitation (Extre) in China over 2006–2100, with V estimated using HS0911 method (a–c) and using initial condition ensemble (ICE) method with the 40-member ensemble of Community Earth System Model version1 (CESM1) (d–f). The significances of the change in internal climate variability estimated using ICE (g–i). Note: the star-like symbols on the lines correspond to the left legend below each subplot from (g) to (i), meaning 1.7 times of the variance (internal climate variability) [Colour figure can be viewed at wileyonlinelibrary.com]
climate change uncertainty (i.e., ±1.645 times of the scaled SDs in Section 3.3) are superimposed onto the mean climate change in turn. Thus, the width of total uncertainty is ±1.645 SDs (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

The 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 the three uncertainties over time, for annual mean temperature, annual precipitation and annual maximum precipitation in China. The three climate variables were all calculated as decadal mean national averages. Figure 1a–c presents results using V_HS0911, while Figure 1d–f presents results using V ICE. The results show that V_HS0911 is about 0.01°C² for annual mean temperature and V ICE is mostly similar. For annual precipitation, V_HS0911 is constant with a value of 1.6%, while V ICE increases from around 2% before 2050s to almost 3.2% at 2080s and then decreases to 2.5% at the end of the 21st century. For annual maximum precipitation, V_HS0911 is about 4.9%, while V ICE increases from around 5% before 2050s to around 14% 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 1g–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 RCP 8.5 scenario. The resulting

![Figures](https://example.com/final_images)
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 requires long time periods and great samples. Since 40-member ensemble is already a great enough sample (400 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, model response uncertainty is several times larger at the end of the 21st century than that at early decades. Its scenario uncertainty has a huge growth throughout this century. For annual precipitation, scenario uncertainty is several times greater at the end of this century than that at the beginning of this century. Its model response uncertainty has a huge growth in this century. Both scenario uncertainty and model response uncertainty have a great 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 precipitation, the contribution of $V_{ICE}$ tends to be greater than that of $V_{HS0911}$ in the late 21st century, but both $V_{ICE}$ and $V_{HS0911}$ are small compared to the other two uncertainties. 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 Saïd, 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 Figure 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 increases rapidly and becomes the largest after about 2040 (Figure 3a–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 1d), 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.

Because of increase of annual precipitation change and steadiness of internal precipitation variability (Figure 1e), fractional uncertainty of internal precipitation variability decreases (Figure 3b,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 \( V_{\text{ICE}} \) is slightly greater than that of \( V_{\text{HS0911}} \) in the late 21st century. The annual maximum precipitation presents a similar pattern with the annual precipitation in fractional uncertainty (Figure 3c,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., 10–15 years earlier than those for annual precipitation).

The three climate change uncertainty components were superimposed on the mean climate change. Figure 4 shows this superposition for national averages of annual mean temperature, annual precipitation and annual maximum precipitation. Superposition using \( V_{\text{ICE}} \) is similar to that using \( V_{\text{HS0911}} \) for annual mean temperature. While for average and extreme precipitations, the band of \( V_{\text{ICE}} \) is wider than that of \( V_{\text{HS0911}} \) in the late 21st century. For example, in Figure 4e, the band of \( V_{\text{ICE}} \) represents how much annual precipitation change could “wander” if the future scenario and model response are perfectly known. In other words, the \( V_{\text{ICE}} \) 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 \( V_{\text{ICE}} \) 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 4d) is projected to be −0.8 to 7°C at the end of the 21st century due to total temperature uncertainty, and annual maximum precipitation change (Figure 4f) is projected to be −5 to
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

The three components of climate change uncertainty were also estimated for grids nationwide. Only \( \text{V}_{\text{ICE}} \) is presented to show internal climate variability. Figures 5–7 present absolute magnitudes of three climate change uncertainties 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.

In terms of the absolute magnitudes of annual mean temperature uncertainties (Figure 5), there are strong 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. If relative contributions to the total temperature change uncertainty (Supporting Information Figure S5) are considered, 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

FIGURE 6 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 initial condition ensemble (ICE) method with the 40-member ensemble of Community Earth System Model version1 (CESM1) [Colour figure can be viewed at wileyonlinelibrary.com]
relatively small in southwestern China. In the 6th decade, model response uncertainty is low while scenario uncertainty is large in most mid-western China.

For the absolute amplitude of annual precipitation change uncertainties (Figure 6), 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. In terms of relative contributions to the total precipitation change uncertainty (Supporting Information Figure S6), 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. As for spatial variation, for example, the contribution of internal climate variability 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 Supporting Information Figure S7) 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 ($S/N$) 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 $S/N$s 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 for most grids 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. But for example, in northeastern China, S/N is higher in the 6th than the 2nd decade. For seasonal mean temperatures (Figure 8), it does 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, that is, 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, 2012). 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 reflects the approximations required in the development of climate models (Stocker et al., 2013). In other words, model uncertainty in a far more comprehensive sense has not been discussed in this study.

For estimation of scenario uncertainty, the RCP scenarios were used. Although the RCP scenarios span a wide range of total forcing values, they do not span the full range of uncertainty in the future anthropogenic forcing, for example, uncertainty in aerosol forcings and ozone precursor (Pachauri et al., 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 GHGs, particularly on regional scales and for hydrological cycle variables (Pachauri et al., 2014). The carbon cycle climate feedbacks are also not represented in the concentration-driven RCP scenarios (Pachauri et al., 2014). RCPs only account for future changes in anthropogenic forcings. Neither future volcanic eruptions nor deviations from

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 initial condition ensemble (ICE) method with the 40-member ensemble of Community Earth System Model version1 (CESM1) [Colour figure can be viewed at wileyonlinelibrary.com]
the 1985–2005 mean solar cycle and their uncertainties are considered (Pachauri et al., 2014).

Some studies (e.g., Kiehl, 2007; Yip et al., 2011) considered model-scenario interaction, that is, nonconstancy 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 ICEs. It may be more reasonable to simultaneously use multiple ICEs 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 ICEs 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 ICEs in 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 Figure 11a–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 5–8% less internal climate variability than CESM1 after 2050s. Similar results are also observed for fractional uncertainties as presented in Figure 11d–f. Significanes of changes in internal climate variability (Figure 11g–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 three times (the ratio of two normal distribution variances by $F$-test) of that of a previous period. The results

![Figure 10](image-url) **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 initial condition ensemble (ICE) method with the 40-member ensemble of Community Earth System Model version1 (CESM1) [Colour figure can be viewed at wileyonlinelibrary.com]
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. This is because the investigation of climate variability, especially for extreme values usually requires 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 greater in dry regions (e.g., northwestern China).

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REFERENCES


SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.