Global streamflow and flood response to stratospheric aerosol geoengineering

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Abstract:
Flood risk is projected to increase under projections of future warming climates due to an enhanced hydrological cycle. Solar geoengineering is known to reduce precipitation and slowdown the hydrological cycle, and may be therefore be expected to offset increased flood risk. We examine this hypothesis using streamflow and river discharge responses to the representative concentration pathway RCP4.5 and Geoengineering Model Intercomparison Project (GeoMIP) G4 experiments. We also calculate changes in 30, 50, 100-year flood return periods relative to the historical (1960-1999) period under the RCP4.5 and G4 scenarios. Similar spatial patterns are produced for each return period, although those under G4 are closer to historical values than under RCP4.5. Under G4 generally lower streamflows are produced on the western sides of Eurasia and North America, with higher flows on their eastern sides. In the southern hemisphere northern parts of the land masses have lower streamflow under G4, and southern parts...
increases relative to RCP4.5. So in general solar geoengineering does appear to reduce flood risk in most regions, but the relative effects are largely determined by this large scale geographic pattern. Both streamflow and return period show increased drying of the Amazon under both RCP4.5 and G4 scenarios, with more drying under G4.

1. Introduction

Floods cause considerable damage every year (UNISDR, 2013) that increases with economic development and rate of climate change (Ward et al., 2017). Generally, people and assets exposed to extreme hydrology disasters, including flooding, increase under global warming (Alfieri et al., 2017; Arnell and Gosling, 2013; Tanoue et al., 2016; Ward et al., 2013). Previous studies have shown that flood risk co-varies with runoff and streamflow (Arnell and Gosling, 2013; Hirabayashi et al., 2013; Hirabayashi et al., 2008). Hirabayashi et al. (2013) analyzed CMIP5 projections for the RCP4.5 and RCP8.5 scenarios (Meinshausen et al., 2011), and found shortened return periods for floods, especially in Southeast Asia, India and eastern Africa, especially under the RCP8.5 scenario.

Koirala et al. (2014) analyzed the changes in streamflow conditions, that is high flow (Q₉₅), low flow (Q₀₅) and mean flow (Qₐ₅) under different RCP scenarios. Under the RCP8.5 scenario, high flow increases at high latitudes, Asia and central Africa, while mean and low flows decrease in Europe, western parts of North and central America. Streamflow indicators under RCP4.5 show similar, but muted, spatial pattern as RCP8.5.
Other studies also show similar results with other hydrologic indicators and under other future scenarios. For example, Arnell and Gosling, (2013) used a global scale daily water balance hydrologic model (Mac-PDM.09; Gosling et al., 2010), forced by 21 climate CMIP3 models and analyzed 10-year and 100-year return period of maximum daily flood under various scenarios. They found that the uncertainty in projecting river streamflow is dominated by across-model differences rather than driven by the climate scenario. Dankers et al. (2014) used 30-year return period of 5-day average peak flows to study the changing patterns of flood hazard under the RCP8.5 scenario. They used nine global hydrology models, together with five coupled climate models from CMIP5 and showed that simulated increases in flood risk occur in Siberia, Southeast Asia and India, while decreases occur in northern and eastern Europe, and northwestern North America. Flood frequency also decreased where the streamflow is dominated by spring snow melt.

River flood models such as CaMa-Flood (Yamazaki et al., 2011) are important tools for simulating flood hazard. These models have been combined with high resolution digital elevation models, flow direction maps (e.g. HYDRO1k and HydroSHEDS; Lehner et al., 2008), and hydrological models. The high-resolution models have contributed to better simulation of river discharge (Yamazaki et al., 2009; Yamazaki et al., 2013 and Mateo et al., 2017). Trigg et al., (2016) showed that six global river flood models reproduced the flood patterns of large rivers satisfactorily. Inter-model variability in
forcing from earth system models (ESM) are the major source of uncertainty in modeling the river discharge (Vano et al., 2014; Winsemius, 2013; Mateo et al., 2017), although the model ability to handle complex channels (e.g. deltas and floodplains) also has an important impact on simulation realism.

Solar Radiation Management (SRM) is geoengineering designed to reduce the amount of sunlight incident on the surface. Stratospheric aerosol injection is one SRM method inspired by volcanic eruptions, that utilizes the aerosol direct effect to scatter incoming solar radiation. Under the Geoengineering Model Intercomparison Project (GeoMIP; Robock et al., 2011; Kravitz et al., 2011, 2012, 2013a), G4 experiment a constant 5Tg per year of SO₂ is introduced into the lower tropical stratosphere of climate models during the period of 2020-2069, while greenhouse gas forcing is defined by the RCP4.5 scenario. Indirect, potentially undesirable, side-effects of the injected sulfur aerosol include changing ice particle distributions in the upper-troposphere, and the distribution of ozone and water vapor in stratospheric (Visioni et al., 2017). The direct radiative effects mainly result in the sharp reduction of TOA net radiative flux with a significant drop in global surface temperature, and concomitant decrease in global precipitation (Yu et al., 2015). The decline of precipitation under SRM is mainly due to increasing atmospheric static stability, together with a reduction of latent heat flux from the land surface to the atmosphere (Bala et al., 2008; Kravitz et al., 2013b; Tilmes et al., 2013). Both the reduction of latent heat flux and precipitation result a slow-down of the global hydrological cycle (Niemeier et al., 2013; Kalidindi et al., 2014; Ferraro and Griffiths,
The spatial pattern of runoff roughly follows that of precipitation. Previous studies have shown that under RCP4.5, precipitation would decrease over southern Africa, the Amazon Basin and central America, and runoff follows these patterns. Over dry continental interiors relatively large evaporation means that runoff does not follow precipitation (Dai, 2016). SRM affects both precipitation and evaporation and hence global patterns of runoff and thence streamflow. The risk of drought in dry regions under SRM appears to be reduced (Curry et al., 2014; Keith and Irvine, 2016; Ji et al. 2018). While many studies have looked at the impact of geoengineering on the hydrologic cycle, none has specifically considered the potential changes of river flow and flood frequency.

We investigate the potential scenario of streamflow using annual mean and extreme daily discharge, and changes in the pattern of flooding using flood return period. Section 2 describes the models and methods used in this study; section 3 presents the results of projected streamflow and return period under the G4 and RCP4.5 simulations. Finally, section 4 provides a discussion of results and implications of this study.

2. Data and Methods

2.1 GeoMIP experiments

To analyze the potential changes of flood under stratospheric sulfate injection
geoengineering, we compare the streamflow patterns under the RCP4.5 and G4 scenarios. Six models were used here (Table 1). We analyze the streamflow patterns changes during the period 2030-2069 from each of model’s G4 and RCP4.5 simulations. The historical simulation during the period 1960-1999 is used as the reference for the return period analysis. We used the same 40 years of G4 as Ji et al. (2018) used to analyze extreme temperatures and precipitations.

In addition to the five ESM that provide the three simulation experiments in Table 1, we utilize the GEOSCCM model that couples the Goddard Earth Observing System, version 5 (GEO-5) (Rienecker et al., 2011) and a stratospheric chemistry module (Pawson et al., 2008), but which has no historical simulation, and is only used for streamflow simulations. The RCP4.5 and G4 experiments from GEOSCCM are forced with sea surface temperature (SST) and sea ice concentrations simulated by the Community Earth System Model (CESM; Gent et al., 2011). The single MIROC-ESM-CHEM realization of the historical experiment is used as the reference in return period calculations for all its realizations of the RCP4.5 and G4 experiments.

Table 1: GeoMIP models and experiments used in this study.

<table>
<thead>
<tr>
<th>Model</th>
<th>Resolution (lon × lat, level)</th>
<th>Historical</th>
<th>RCP4.5</th>
<th>G4</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNU-ESM (Ji et al., 2014)</td>
<td>128 × 64, L26</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>CanESM2 (Arora et al., 2011; Chylek et al., 2011)</td>
<td>128 × 64, L35</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>GEOSCCM (Oman et al., 2011; Rienecker et al. 2008)</td>
<td>144 × 91, L72</td>
<td>×</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>MIROC-ESM (Watanabe et al., 2011)</td>
<td>128 × 64, L80</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM (Watanabe et al., 2011)</td>
<td>128 × 64, L80</td>
<td>1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>NorESM1-E (Bentsen et al. 2013, Tjiputra et al. 2013)</td>
<td>144 × 96, L26</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
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2.2 The river routing model

The river routing model used here is the Catchment-based Macro-scale Floodplain Model (CaMa-Flood; Yamazaki et al., 2011). The CaMa-Flood uses a local inertial flow equation (Bates et al., 2010; Yamazaki et al., 2014a) to integrate runoff along a high-resolution river map (HydroSHEDS; Yamazaki et al., 2013). Sub-grid characteristics such as slope, river length, river channel width, river channel depth were parameterized in each grid box by using the innovative up-scaling method, FLOW (Mateo et al., 2017; Yamazaki et al., 2014b; Zhao et al., 2017). In addition, the CaMa-Flood implements channel bifurcation and accounts for floodplain storage and backwater effects, which are not represented in most global hydrological models (Zhao et al., 2017). CaMa-Flood is able to reproduce relatively realistic flow patterns in complex river regions such as deltas (Ikeuchi et al., 2015; Yamazaki et al., 2011, 2013) this makes it a well evaluated model in hydrological research (Emerton et al., 2017; Ikeuchi et al., 2017; Suzuki et al., 2017; Yamazaki et al., 2017; Zsótér et al., 2016).

We use only the daily runoff outputs from climate models to drive CaMa-Flood v3.6.2 which calculates the river discharge along the global river network. The spatial resolution of CaMa-Flood was set to 0.25° (~25km at mid-latitude), and an adaptive time step approach was applied in simulation. In order to conserve the input runoff mass, an area-weighted averaging method was used in CaMa-Flood to distribute the coarse input runoff to the fine resolution hydrological model. This down-scaling method is available in the latest version of CaMa-Flood (Mateo et al., 2017). CaMa-Flood
performs a 1-year spin-up before simulating 40-year river discharge in our historical, RCP4.5 and G4 experiments. The runoff and river discharge from Antarctica and Greenland are not included in CaMa-Flood simulations. For each streamflow level, cells with less than 0.01 mm/day are excluded from the analysis.

2.3 Indicators of streamflow

We analyze the streamflow change under RCP4.5 and G4 scenarios using three streamflow indicators during 2030-2069, that is annual daily mean flow ($Q_m$), and extreme high or low flow ($Q_5$, $Q_{95}$: streamflow exceeded 5% or 95% of a year). $Q_m$, $Q_5$ and $Q_{95}$ are averaged over 40 years for each model, respectively, then averaged between models to get the multi-model mean response under different scenarios. We compared the multi-model mean and multi-model median responses of the six models used in this study, and found no obvious difference between the two averages.

We employ the two-sample Mann-Whitney U (MW-U) test to measure the significance of streamflow differences between G4 and RCP4.5. The MW-U test is a non-parametric test which does not need the assumption of normal probability distributions. We use a bootstrap resampling method (Ward et al., 2016), with the MW-U test to increase sample size and to minimize the effects of outliers that can arise from the relatively short study period (Koirala et al., 2014). Specifically, we first apply the MW-U test to the G4 and RCP4.5 raw annual mean daily runoff data for each model to get the value of the rank sum statistical value, $U_0$. We generate 1000 random paired series of 40-
year data from RCP4.5 and G4. Then the MW-U test was applied to each sample pair of generated data to get a series of statistical values: $U_j$, $j = 1, 2 \cdots 1000$. The rank of $U_0$ is then used to calculate the non-exceedance probability (Cunnane, 1978):

$$p_0 = \frac{R_0 - 0.4}{N_b + 0.2}$$

Where $p_0$ is the non-exceedance probability and $R_0$ is the rank of $U_0$. $N_b$ is the number of the bootstrap samples. Finally, a non-exceedance probability less than 0.025 (or greater than 0.975) indicates a significant increase (or decrease) from RCP4.5 to G4, respectively.

### 2.4 Changes in flood frequency

The return period of a flood event is as an indicator of flood frequency (e.g. Dankers et al., 2014; Ward et al., 2017). The N-year return period indicates the probability of flood exceeding a given level in any given year of 1/N. For each model, we choose the historical period of 1960-1999 as a reference for the return period calculation based on the annual maximum daily river discharge, then analyze the return period change under RCP4.5 and G4 scenarios during the period of 2030-2069. In this study, we choose the 30, 50 and 100-year return period levels of river flow at each grid cell to study the change of flood probability. To estimate the return period, the time series of annual maximum daily discharge for historical, RCP4.5 and G4 from each ESM are first arranged in ascending order and then fitted to a Gumbel probability distribution. The Gumbel distribution was used as a statistic of extreme flood events in previous research (e.g. Hirabayashi et al., 2013; Ward et al., 2014) Using the Gumbel distribution, the
cumulative distribution function, F(x), of river discharge (x) can be expressed as

\[ F(x) = e^{-e^{\frac{x-b}{a}}} \]

where the two parameters a (scale) and b (location) are the parameters of Gumbel distribution (Gumbel, 1941). The parameters are estimated using an L-moments based approach (Rasmussen et al., 2003), where

\[ L_1 = \frac{1}{N} \sum_{i=1}^{N} X_i \]
\[ L_2 = \frac{2}{N} \sum_{i=1}^{N} \frac{i-1}{N-1} X_i - L_1 \]

and \( X_i \) is the annual maximum daily river discharge and is sorted in ascending order and \( N \) is the number of sample years, then:

\[ a = \frac{L_2}{\ln 2} \]
\[ b = L_1 - ac \]

where \( c = 0.57721 \) is Euler’s constant. Changes in return period under geoengineering are expressed as differences G4 - RCP4.5 relative to the corresponding historical level.

3. Results

3.1 Projected changes in streamflow

Figure 1 shows the relative changes of three characteristic indicators of streamflow, while Figure 2 presents the degree of across-model agreement. Figures S1-S6 show the results for each of the models listed in Table 1. In Fig. 1, positive values mean G4 streamflow is larger than RCP4.5 levels. Generally, decreases of the mean streamflow \( (Q_m) \) occur at high northern latitudes such as Siberia, Northern Europe and the Arctic.
Ocean coast of North America, along with Southeast Asia, middle and southern Africa.

Increases appear in Western Europe, central Asia, southwestern North America and central America (Fig. 1a). Significant changes are generally distributed around the globe. Based on the ensemble response of the six models analyzed here, 57% of global continental grid cells excluding Greenland, Antarctica and masked cells show decreases in Q$_m$ under G4 compared with RCP4.5, and about 43% of grid cells show increases.

Figure 2 showing areas with robust agreement between models allows the primary regions affected to be seen more clearly. Globally, only 4.0% of grid cells exhibit robust decreases and 4.4% increases under G4 (Fig. 2 a). Despite the few grid cells with robust agreement between models, the general patterns are similar for the mean changes in Fig. 1a. Consistent decreases occur at high northern latitudes and in Papua New Guinea and the semi-arid region south of the Sahara desert. Increases are mainly in the southern hemisphere but also parts of Western Europe, and the southwestern USA. The GEOSCCM (Fig. S3) and MIROC-ESM (Fig. S4) contradict the ensemble in having larger areas with increases in Q$_m$ under G4 than RCP4.5.

Figures 1b and 2b show that under G4, 55% of unmasked grid cells are projected to increase their high flow Q$_5$ levels under G4. Europe, western North America, Central Asia and central Australia show increases in Q$_5$ under G4 compared with RCP4.5.

Differences at the 95% significance level are distributed fairly similarly as for Q$_m$ in Figure 1a. The Amazon Basin shows decreases in both high flow and Q$_m$ and the southwestern USA shows increases in both. Globally, 4% of land cells show robust
increases and 2% show decreases under G4 (Fig. 2b). Robust increases generally are confined to the extra-tropics, while decreases are mainly, but not only, in the tropics. The projections of Q₅ from CanESM2 under G4 show largest differences in spatial pattern from the ensemble mean (Fig. S2) and it is the only model with more decreases than increases in Q₅ under G4. Though high flow levels usually lead to flood events (Ward et al., 2016), changes in flood levels do not necessarily translate into increases in flood frequency. We elaborate further on flood return period in section 3.2.

Low flow (Q₉₅, in Figs. 1c and 2c) has a noisier spatial pattern than those for mean and high flow. Low flow shows a relatively uniform decrease around the globe. 44% of unmasked global land cells show increases in Q₉₅ under G4. Despite the generally noisier pattern, the regions with differences significant at the 95% level are more defined for Q₉₅ than either Q₅ₐve or Q₅. The high northern latitudes become drier under G4, the southern high latitudes wetter. Robust increases cover about 2% of global land grid cells, mainly in Europe and South America. Robust decreases appear mainly in northern high-latitude regions, central Africa and northern Asia, and occupy about 6% of global land grid cells. Projections by NorESM1-E (Fig. S6) and GEOSCCM (Fig. S3) show different patterns from the ensemble mean (Fig. 1c) with bigger areas showing increases than decreases in Q₉₅ under G4.
Figure 1: Relative difference of three streamflow indicators between G4 (2030-2069) and RCP4.5 (2030-2069), as percentages of the mean of G4 and RCP4.5: $100\% \times \frac{G4 - RCP4.5}{G4 + RCP4.5}$. Top, long-term mean flow ($Q_m$); Middle, high flow ($Q_5$); Bottom, low flow ($Q_{95}$). For each streamflow level, cells with less than 0.01
mm/day are masked out. Hashed areas indicate locations where the streamflow changes are significant at the 95% level.

Figure 2: Number of model agreeing in sign (red means G4 - RCP4.5 <0, blue means G4 - RCP4.5 >0) of streamflow indicator changes. Top, $Q_m$; Middle, $Q_5$; Bottom, $Q_{95}$. Shaded grid cells indicate a relatively robust response (more than 4 models show same change direction).
Some of the regions show contrasting responses under G4 for high and low streamflow. Figure 3 shows regions where both high and low flow decrease under G4 cover about 27% of grids cells, mainly in eastern and southeastern Asia, central Africa, and Amazon Basin, together with central and eastern Siberia. In 16% of the cells high flows are projected to increase while low flows decrease, mainly in the remaining parts of south Asia, central Africa and South America. Increased high flow and simultaneous decrease in low flow suggests the potential for increased flood and drought frequencies. In 27% of global cells, high flows decrease and low flows increase, which suggests these would see a decline in streamflow extremes, and are mainly at northern mid- and high-latitudes.

Areas with both increased high and low flow also cover 27% of the land surface, mainly in Europe, central America and the southern hemisphere mid latitudes. Perhaps the clearest overall pattern is the generally lower streamflow under G4 on the western sides of the large continents of Eurasia and North America, with higher flows on their eastern sides. In the southern hemisphere the pattern is meridional with northern parts of the land masses having lower streamflow under G4, and southern parts increases.
Figure 3: The ensemble mean differences (G4 - RCP4.5) of high and low streamflows. Color bar is defined such that grids where G4 is less than RCP4.5 for both Q5&Q95 is in red; Q5&Q95 greater in G4 than RCP4.5 is in green. Q5 greater in G4 and Q95 greater in RCP4.5 in yellow and vice versa in blue. Grid cells with Q95 less than 0.01 mm/day were masked.

3.2 Projected changes in return period

Changes in flooding between RCP4.5 and G4 scenarios are measured by the changes in the return period of particular river discharge magnitude. Previous studies have also used 30-year return period as a relatively modest indicator of flood frequency (Dankers et al., 2014). We choose both the same flooding frequency indicator and also the more extreme 50 or 100-year return levels. The discharge for each model’s 30, 50 and 100-year return periods in the simulated historical period define the reference magnitudes at each grid cell. The return period of discharge corresponding to those levels are then found under the RCP4.5 and G4 scenarios. Dry regions, defined as mean annual streamflow during the historical period (1960-1999) less than 0.01 mm/day, are masked. The 40-year time series of the historical period (1960-1999) and 40-year future
projections (2030-2069) then are fitted to the Gumbel probability distribution for each grid cell. Figure 4a and 4b show the global distribution of multi-model ensemble median return period of the historical 30-year return level, under the RCP4.5 and G4 scenarios. Figs. S7 and S8 show the relevant patterns for 50 and 100-year return periods. The elongation of return period in some regions (such as central Asia and the Amazon basin) indicates relatively less frequent flooding events compared with the past. Very close to half the grid cells (49%) show increases in return period under RCP4.5 scenario, while the other half experience decreases. Increases of return period are mainly in Asia and eastern Africa while decreases occur in Europe and North America. Our results agree with similar previous studies (e.g., Hirabayashi et al., 2013) for RCP4.5. Under the stratospheric aerosol injection G4 experiment the spatial pattern is very similar as RCP4.5, with similar large differences from the historical levels. Figure 4c shows the difference of return period between the G4 and RCP4.5 scenarios. A negative value means a shorter return period under G4 than RCP4.5, which indicates an increase of flood frequency under G4. Decreasing flood frequency appears in India, China, Siberia, parts of the Amazon basin, and northern Australia. Increasing flood frequencies are projected mainly in Europe, the southwestern USA and much of Australia. The regions which are projected to experience an increased flood frequency under the RCP4.5 scenario (Fig. 4a; Dankers et al., 2014; Hirabayashi et al., 2013)
would experience a consistent decline of the flood frequency under G4, such as southern and southeastern Asia. In general, the G4 return periods are less changed from the historical levels than under RCP4.5.

Figure 5 shows the regions of robust agreement between models in changes of 30-year return period under RCP4.5 and G4. Slightly fewer grid cells show robust responses under G4 than RCP4.5. As with Fig. 4 there is close agreement in spatial pattern of return period under the RCP4.5 and G4 scenarios. The spatial pattern of the changes in 50 and 100-year return levels shown in Figs. S7 and S8 are similar to those for the 30-year return level (Fig. 4), while the spread between two different return period levels is slightly different from the 30-year levels. These results suggest a consistent changing pattern of flood frequency as defined by the three return levels, but with different magnitudes of differences between RCP4.5 and G4, with G4 being closer to the historical levels.
Figure 4: Multi-model ensemble median of return periods for discharge which correspond to 30-341-year return period in the historical simulation (1960-1999) under (a) G4, (b) RCP4.5 scenarios and (c) the relative difference of G4 and RCP4.5, as percentages of mean of return periods: 100% \times 2(G4 - RCP4.5) / (G4 + RCP4.5). Grid cells in extremely dry regions, i.e. Q_m<0.01 mm/day were masked out.

Figure 5: The number of models agreeing on the sign of change in 30-year return period under G4 (top panel) and RCP4.5 (bottom panel). Blue colors indicate decreases and red increases relative to the historical simulation.
4. Discussion and Conclusions

We analyzed the streamflow response under the stratospheric aerosol injection geoengineering, G4, and the RCP4.5 scenario using the daily total runoff from six climate models that participated in GeoMIP. We investigated the mean change patterns of mean and extreme high and low streamflow and analyzed the global flood frequency change in terms of return period. There is pattern of generally lower streamflow under G4 on the western sides of the large continents of Eurasia and North America, with higher flows on their eastern sides. In the southern hemisphere the pattern is meridional with northern parts of the land masses having lower streamflow under G4, and southern parts increases.

These streamflow changes under G4 contrast with the pattern under RCP4.5 (Koirala et al., 2014). For example, in southeastern Asia and India, both high flows and low flows are projected to increase under the RCP4.5 scenario, while both of them would decrease under G4. In contrast, Spain, Italy and Greece are projected to have decreases in both high and low flow under RCP4.5, while the projected streamflow shows increases under G4. However, in the Amazon basin, the streamflow decreases in both high and low flow under both RCP4.5 and G4 relative to the historical period. In Siberia both high and low streamflow increases under RCP4.5 relative to historical, while the pattern is mixed under G4. This means that geoengineering offsets the impact...
introduced by anthropogenic climate warming in some regions, while in other regions such as the Amazon basin and Siberia, geoengineering further enhances the decreasing trend of streamflow under the RCP4.5 scenario. The pattern seen is suggestive of the role of large scale circulation patterns, westerly flows over the northern hemisphere continents and the Asian monsoon systems, with relative increases in mid-latitude storm systems and decreases in monsoons under G4 compared with RCP4.5; similar mechanisms may also account for the north-south pattern seen in Australia and South America. Monsoonal indicators do decrease under the much more extreme G1 experiment that is designed to offset quadrupled CO$_2$ levels (Tilmes et al., 2013).

We investigated the change of flooding corresponding to the magnitudes of the historical 30, 50 and 100-year return period levels; the flooding frequencies change dramatically from historical levels under both RCP4.5 and G4, but show similar spatial patterns. The projected return period pattern under RCP4.5 scenario agrees well with previous studies, such as Dankers et al., (2014) and Hirabayashi et al., (2013). Generally, stratospheric aerosol injection geoengineering relieves flood stress especially for Southeast Asia, and in turn increases the probability of flooding in the southwestern USA and much of Australia – which are of course drought-prone places that might benefit from increased flooding. The Amazon Basin shows a relatively elongation of flood return period, while Europe shows shortening of return period under G4, and this was also implicit in streamflow character in these regions.
Previous studies (Dankers et al., 2014; Hirabayashi et al., 2008) have noted that the flood frequency for rivers at high latitude (e.g. Alaska and Siberia) decrease under global warming even in areas where the frequency, intensity of precipitation, or both, are projected to increase. The annual hydrograph of these rivers is dominated by snow melt, so changes of peak flow reflect the balance between length and temperature of winter season, and the total amount of winter precipitation. Under the G4 experiment, some recent studies (Jones et al., 2018; Sonntag et al., 2018) have pointed out that the increased P–E (difference between precipitation and evaporation) in northern Asia caused by global warming could be partly counteracted by solar geoengineering. On the other hand, compared with the RCP4.5 scenario, the SRM process reduces polar temperatures (Berdahl et al., 2014). The balance among precipitation, evaporation and temperature accounts for the complex spatial pattern of streamflow and flood frequency at northern high-latitudes under G4, that has been previously been related to soil moisture content (Dagon and Schrag, 2017).

The relatively dry pattern of streamflow in the Amazon basin under G4 is notable and consistent with changes in P–E (e.g. Jones et al., 2018). This drying pattern would lead to a decline of the Amazon tropical rainforest (Boisier et al., 2015). Amazon basin drying is complicated by factors including the movement of Intertropical Convergence Zone (ITCZ) under geoengineering (Smyth et al., 2017; Guo et al., 2018); changes in SST reflecting changes in frequency of El Niño Southern Oscillation (Harris et al., 2008; Jiménez-Muñoz et al., 2016), although there is no evidence of changes occurring under.
SRM (Gabriel and Robock, 2015); and changes carbon cycle feedbacks (Chadwick et al., 2017; Halladay and Good, 2017), which would certainly affected by changes in diffuse radiation under SRM (Bala et al., 2008).

Limitations exist in our study. Model internal variability may be larger than across-model spread in eastern and southeastern Asia (Yu et al., 2016). We assume that systematic model bias relative to observations can be corrected by subtracting historical simulations, and thus that model bias does not change with future climate scenario. We ignore the effects of changing river routes and river network silt-up over time (Chezik et al., 2017), which would impact local runoff and streamflow. The CaMa-Flood river routing model also does not consider anthropogenic effects on rivers (e.g. dams), so the results presented here are for a hypothetical natural condition.

Changes in flooding are strongly connected with the economic cost of damage due to climate change and sea level rise (Jevrejva et al., 2016, Hinckel et al., 2014) and thorough studies should be made for further policy and decision making, especially applied to high value economic or ecological entities. This may be done in the framework of specific impact models applied to local cities or regions, and would hence benefit from local knowledge, especially in the developing world where resources for adaptation measures are scarce. Linkages between the developing world climate impacts researchers and the GeoMIP community will be encouraged and funded by the DECIMALS project (Rahman et al., 2018).
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