Hydrology and Earth System Sciences Discussions

Quantifying uncertainty in urban flooding analysis caused by the combined effect of climate and land use change scenarios

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Abstract

How will the combined impacts of land use change and climate change influence changes in urban flood frequency and what is the main uncertainty source of the results? We attempt to answer to these questions in two catchments with different degrees of urbanization, the Fanno catchment with 84% urban land use and the Johnson catchment with 36% urban land use, both located in the Pacific Northwest of the US. Five uncertainty sources – general circulation model (GCM) structures, future greenhouse gas (GHG) emission scenarios, land use change scenarios, natural variability, and hydrologic model parameters – are considered to compare the relative source of uncertainty in flood frequency projections. Two land use change scenarios conservation and development, representing possible future land use changes are used for analysis. Results show the highest increase in flood frequency under the combination of medium high GHG emission (A1B) and development scenarios, and the lowest increase under the combination of low GHG emission (B1) and conservation scenarios. Although the combined impact is more significant to flood frequency change than individual scenarios, it does not linearly increase flood frequency. Changes in flood frequency are more sensitive to climate change than land use change in the two catchments for 2050s (2040–2069). Shorter term flood frequency change, 2 and 5 year floods, is highly affected by GCM structure, while longer term flood frequency change above 25 year floods is dominated by natural variability. Projected flood frequency changes more significantly in Johnson creek than Fanno creek. This result indicates that, under expected climate change conditions, an adaptive urban planning based on the conservation scenario could be more effective in less developed Johnson catchment than in the already developed Fanno catchment.

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1   Introduction

Human-induced land cover change and climate change are important factors in urban flooding. Rapid population growth and increasing migration from rural areas to cities lead to intense urbanization, which often increases flood risk (Chang and Franczyk, 2008). Most previous studies address anthropogenic urbanization as a main factor that amplifies the peak flow and increases the flood risk (Brun and Band, 2000; Chang et al., 2009; Changnon and Demissie, 1996; Crooks and Davies, 2001; Ott and Uhlenbrook, 2004; Ranzi et al., 2002; Rosso and Rulli, 2002; Smith et al., 2002; Wheater and Evans, 2009; Zhu et al., 2007). According to recent studies, the urban heat island effect and aerosol composition can alter the climate mechanism, which plays important role in the storm evolution of urbanized regions (Ntelekos et al., 2008, 2009). Global warming, which is the other key issue, could induce the acceleration of the water cycle (Huntington, 2006; Oki and Kanae, 2006), which could consequently affect the frequency and intensity of future storm events (Arnell, 2003; Booij, 2005; Hamlet and Lettenmaier, 2007; Milly et al., 2008). The Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) (Randall et al., 2007) projects that heavy precipitation events will be more frequent during the 21st century over most of the Pacific Northwest of USA based on the projection using Atmosphere-Ocean General Circulation Model (AOGCM). Although future climate projections have large uncertainty, identifying potential changes in flood risk according to climate and land use changes is an important area of concern to water resource managers and land use planners (Hine and Hall, 2010).

For mitigation and protection of potential flood risk in urban areas, we need to improve our understanding of the possible impacts of the ubiquitous uncertainty of urban flood projection. This uncertainty stems from several sources; internal variability of the climate system, future GHG and aerosol emissions, the translation of these emissions into climate change by GCMs, spatial and temporal downscaling, and hydrological modeling (Bates et al., 2008). Uncertainty will not be radically removed or reduced until

the development of the new technology of climate and hydrologic modeling based on additional observation of hydrometeorological variables, such as soil moisture, snow, actual evapotranspiration, and groundwater. Besides, uncertainty complicates the accurate interpretation of climate impact assessment. Therefore, many researchers have attempted to quantify the irreducible uncertainty in hydrologic projection for streamflow (New et al., 2007; Wilby, 2005; Chang and Jung, 2010; Kingston and Taylor 2010), low flow (Wilby and Harris, 2006), flooding (Booij, 2005; Kay et al., 2009; Raff et al., 2009; Baird et al., 2010), and drought (Ghosh and Mujumdar, 2007; Mishra and Singh, 2009). Despite substantial effort of previous studies, however, a large uncertainty in climate impact studies still remain (Bates et al., 2008).

Floods in urban areas are controlled by the integrated condition of geophysical characteristics, urban infrastructure, drainage system, and hydro-climatologic regime (Epting et al., 2009). Thus, different levels of urban development could lead to different hydrologic responses among catchments, though they are under identical climate change (Franczyk and Chang, 2009). Kay et al. (2009) investigated the uncertainty in climate change impact on flood frequency for two catchments in England, showing that uncertainty can vary significantly between catchments that have different rainfall regime and topographic characteristics. Prudhomme and Davies (2009) reported similar findings for four catchments in Britain. Additionally, the combined effects of climate change and anthropogenic land use change significantly aggravate the accuracy of hydrologic prediction associated with overall urban environmental management (Brath et al., 2006; Choi, 2008; Franczyk and Chang, 2009; Praskievicz and Chang 2009a; Tu, 2009). However, relatively few studies examined the combined effects of climate change and urban development on the uncertainty in urban floods in catchments with different degrees of urban development. This study attempts to fill this gap using future scenarios under projected future scenarios.

The three research questions are: (1) What are the main sources of uncertainties affecting the changes in urban flood frequency? (2) How will the combined impacts of land use change and climate change influence changes in flood frequency? and

(3) How is flood frequency projected to change in two urban catchments with different degrees of urban development for the 2050s (2040–2069) with respect to the reference period 1960–1989? This paper can contribute to a better understanding of the combined impact of climate and land use changes on urban flood frequency, and can thus help decision makers with practical urban planning and management to mitigate potential flood damage in urban areas in a changing climate.

2 Methodology

2.1 A framework for flood frequency change analysis

We investigate changes in flood frequency and the uncertainties associated with the combined effects of climate change and land use change in two catchments – Fanno Creek (80.5 km^2) and Upper Johnson (hereafter Johnson) Creek (68.3 km^2) in the Portland metropolitan area of Oregon, USA. The Fanno catchment is highly developed with 84% urban land use, and the Johnson catchment is moderately developed with 36% urban land use in 2001 (see Fig. 1).

To quantify uncertainty in flood frequency change, this study considers five uncertainty sources; GCM structures, future GHG emission scenarios, future land use scenarios, hydrologic model parameters, and natural variability of climate system. The GCM simulations are downscaled using the delta method to correct the bias between simulated and observed precipitation and temperature, which is attributed from scale mismatch between GCMs and catchment hydrologic models and missing in subgrid scale climate dynamics such as orographically convective precipitation (Im et al., 2010b).

PRMS, a physically-based, deterministic, and semi-distributed model, is employed to simulate daily runoff changes and resulting changes in flood frequency under different climate and land use conditions. PRMS has been applied successfully in several regions with varying climate and land use (Bae et al., 2008a; Clark et al., 2008; Hay et al.,

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2006; Qi et al., 2009; Viney et al., 2009). In the Willamette River basin, Oregon, PRMS is applied to a water quality study (Laenen and Risley, 1997) and to a climate change impact study (Chang and Jung, 2010). We estimate the PRMS model parameter uncertainty using Latin Hypercube Sampling. We estimate the acceptable parameter ranges according to the Nash-Sutcliffe (NS) efficiency criterion that estimates the degree of closeness between observed and simulated streamflow. A similar approach has been undertaken by Wilby and Harris (2006).

It is also important to find whether the changes in flood frequency for the future period are larger than the natural (or model internal) climate variability (Hagemann and Jacob, 2007). Especially, precipitation change derived from different initial conditions of GCMs could lead to different interpretation of the results due to large natural internal variability. To estimate natural climate variability, we employ the moving block Bootstrap resampling method (Ebtehaj et al., 2010), which produces a large number of new climate series through random selection of observed climate data. This method allows us to explore the range of different flood frequencies that could be obtained by our finite sampling of the internal climate variability (Kay et al., 2009). The US Geological Survey's PeakFQ program (Flynn et al., 2006) is applied to estimate flood frequency with different recurrence intervals such as 2, 5, 10, 25, 50, and 100 years. To represent realistic future land use changes, we use two land use change scenarios for comparing with 2001 land use: the conservation and the development scenarios, developed by the PNW-ERC (2002). Further details of data and each method used in this study are described in the following sections.

2.2 Study area and data

Fanno creek and the Johnson creek are important resources in the Portland metropolitan area, located in the valley of the Willamette River basin in Oregon (see Fig. 1). As a source of recreation and wildlife (Laenen and Risley, 1997), they contribute to the regional socio-economic and environmental systems. Two catchments are located in a modified marine temperate climate region in which summers are warm and dry but

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winters are cold and wet. More than 80% of the annual precipitation occurs from October through May and less than 10% precipitation falls during July and August (Praskievicz and Chang, 2009b). This seasonality of precipitation causes periodic flooding and companying travel disruptions in winter (Chang et al., 2010).

5   In our study areas, most precipitation is in the form of rainfall. Unusual snow melts quickly during subsequent rain storms (Lee and Snyder, 2009). Therefore, the surface hydrology of these regions is highly dominated by frequent rainfall. Although Fanno and Johnson are close to each other and have identical climate conditions, they show different hydrologic regimes. Fanno shows a higher runoff ratio, defined as the ratio

10   of total monthly runoff to precipitation, than Johnson for most months except March, which shows almost the same runoff ratio value in both catchments (see Fig. 2). For the dry season (June–August), monthly runoff rates show highest differences between catchments. This is attributed to different infiltration mechanisms as well as to geographic characteristics such as slope, soil, and shape of the catchment. Due to differ-

15   ent geology and soils, precipitation in Fanno is less infiltrated and rapidly reaches the river, while the more infiltrated precipitation in Johnson is evaporated in warm and dry climate conditions. In the wet season (November–April), continuing rainfall results in saturated soil condition that can behave like an impervious surface, so differences in the monthly runoff rate are smaller than those of the dry season. Coefficient of determi-

20   nation of daily streamflow between two catchments also shows higher linear relations (above 0.77) for the wet season and lower relations (below 0.63) for the dry season (see Fig. 2).

      Observed daily precipitation, maximum and minimum temperatures, and streamflow data are used for hydrologic modeling and downscaling of GCM simulations. The cli-

25   mate data are obtained from the National Oceanic and Atmospheric Administration Cooperative Observer Program (NOAA COOP, 2010) for 1958–2006, and streamflow data are collected from the USGS National Water Information System (USGS NWIS, 2010) for 2000–2006. To delineate hydrologic response units (HRU) and estimate PRMS parameters related to geographic layers, 10 m Digital Elevation Model (DEM) (DOGAMI,

2010), soil map (NRCS, 1986), and land cover (PNW-ERC, 2002) are used.

2.3 Climate simulations and downscaling methods

Generally, the coupled atmosphere–ocean general circulation models (GCMs) are the best tools for projecting future climate in response to GHG emission forcing. GCMs have diverse horizontal and vertical grid resolutions, climate process description and approximation, parameterization of subgrid-scale phenomena, and initial condition (Randall et al., 2007). These different structures among GCMs cause the wide variations and biases in regional climate reproduction and projection (e.g., Im et al., 2010a). Some GCMs fail to simulate regional inter-annual or decadal climate variability, which are important climate drivers of specific regional climate.

To estimate GCM performance in the Pacific Northwest, Mote and Salathé (2010) rank the 20 GCMs, implemented in IPCC AR4, based on 20th century bias, a global performance index (AchutaRao and Sperber, 2006), and North Pacific variability of temperature, precipitation, and sea-level pressures (Mote and Salathé, 2010). The North Pacific variability represents the teleconnection effects of El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) and other large-scale climate processes over the Pacific Northwest (Hamlet et al., 2010). Based on the study of Mote and Salathé (2010), this study selects the three best GCMs, which are CNRM-CM3, ECHAM5/MPI-OM, and ECHO-G. Better performance of GCM for simulating historical climate does not inevitably indicate a realistic projection under GHG forcing. However, if a GCM has poor performance for current important climate variability in the region, the derived regional changes for future should also be misleading (Prudhomme et al., 2002). No downscaling method can completely correct for the GCM's errors. Additionally, this approach provides some useful information such as weighted factor of GCM simulations (e.g., Tebaldi et al., 2005), or reducing of ensemble number for future climate projection (e.g., Mote and Salathé, 2010).

This study uses two GHG emission scenarios, the A1B and B1 emission scenarios. Most global climate modeling groups generally employ A2, the A1B and B1 GHG

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emission scenarios (Randall et al., 2007) as high, medium and low emission scenarios for the 21st century, respectively. We focus on mid-century change for 2040–2069, in which period A2 and A1B show similar GHG emission forcing. Therefore, A1B and B1 emission scenarios can cover high and low GHG emission conditions. The climate simulation of three GCMs with two GHG emission scenarios are obtained from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (WCRP CMIP3, 2010).

To downscale three GCM simulations with two emission scenarios, we use a simple delta method, which has widely been used in climate change impact studies (e.g., Lettenmaier et al. 1999; Wilby and Harris, 2006; Loukas et al., 2007; Graham et al., 2007; Kay et al., 2009; Choi et al., 2009). This method first calculates monthly precipitation and temperature differences between the reference and future GCM simulations. Then, the obtained monthly differences between the two periods are applied to historical daily data for the reference period by adding monthly absolute differences for temperature and by multiplying percent differences for precipitation. This method can preserve the spatial and temporal variation of observation and remove the bias of GCM simulations. However, the delta method does not capture changes in precipitation and temperature variability from climate models and does not allow for more complex changes in daily extreme of precipitation and temperature (Hamlet et al., 2010). Therefore, changes in day-to-day variability of climate simulations are not taken into account in this study. This could lead to an underestimation of future flood frequency change.

2.4 Hydrologic model and parameter uncertainty

The PRMS model, Modular Modeling System (MMS) version developed by US Geological Survey (Leavesley et al., 1996), is used in this study. This model simulates a water balance for each day and an energy balance for half-day in each Hydrologic Response Unit (HRU), which is assumed to be homogeneous in its hydrologic response to given climate and land use conditions (Hay et al., 2009). A detailed description of the PRMS model structure is found in Leavesley et al. (2005). This paper focuses on PRMS

parameters regarding land use change and parameter uncertainty analysis.

PRMS has seven parameters which are directly associated with land use change (see Table 1). Seasonal vegetation cover density (*covden_sum*, *covden_win*) and cover type (*cov_type*) affect the amount of interception on HRUs. The seasonal vegetation cover density is determined by different leaf loss of cover types, such as grass, shrub, deciduous and coniferous trees (Viger and Leavesley, 2007, p. 99). Maximum values of interception storage for each cover type are considered by season and precipitation type (*wrain_intcp*, *srain_intcp*, and *snow_intcp*). Ratio of impervious surface area on HRU (*hru_percent_imperv*) is a more important parameter in land use change impact on flood analysis, because it is highly sensitive to urbanization. High impervious surface area in this model induces less infiltration to soil and more overland flow to stream, potentially increasing peak flow volume.

PRMS is a physically-based hydrologic model, so some parameters can be obtained from physiographic characteristics and land surface features of the watershed using GIS layers, such as DEM, Land use, and Soil data (Chang and Jung, 2010). This study uses the fixed parameters from GIS layers over time, except parameters related to land use. Snow effect is less in both catchments, so this study uses recommended values by Leavesley et al. (1996) for snow modeling in PRMS. We calibrate eight parameters that are associated with the timing and amount of runoff components (see Table 1). These parameters are considered the most important parameters in previous studies because they are more sensitive than other parameters (e.g., Bae et al., 2008b; Hay et al., 2009; Im et al., 2010b; Chang and Jung, 2010).

For parameter uncertainty analysis, LHS (McKay et al., 1979) is employed to sample the parameters from plausible ranges. LHS is an efficient sampling method that provides larger sample space with less computational effort comparable to those obtained from the conventional Monte Carlo simulation (Davey, 2008). LHS divides the probability density functions (PDFs) of each model parameter into N discrete equal intervals, so that at least one sample of each parameter will be selected randomly from each interval (Yang et al., 2010). To do an exhaustive search of behavioral parameters we

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decide to sample 20 000 parameters using LHS. These parameter sets are used to determine the closeness between daily simulated and observed streamflow for the period of 2000–2006 in both catchments. The Nash-Sutcliffe (1970) non-dimensional model efficiency criterion (NS) is used as a goodness of fit measure, with a value in excess of 0.6 indicating satisfactory fit between observed and simulated hydrographs (see Wilby, 2005; Choi and Beven, 2007). This approach can show relative importance of parameter uncertainty in climate impact studies, although it cannot cover total equifinality of parameters (Beven, 2001). Therefore, the whole range of parameter uncertainty on flood frequency estimation is probably larger than what is presented in this study.

2.5 Natural variability

The climate system varies naturally without changes in external forcing such as anthropogenic GHG emission effect, because it is strongly affected by the short-term or long-term periodic effects, such as the earth's revolution and rotation, and Milankovitch cycles (Randall et al., 2007). However, the various components of climate system have very different response times and non-linear interactions by these periodic effects, inducing a non-periodic inter-annual or multi-decadal natural climate variability such as ENSO and PDO (IPCC, 2001). This indicates that flood frequency analysis could be sensitive to the finite sampling within the natural variability of the climate system (Kay et al., 2009). Therefore, it is essential that we compare the range of change in flood frequency between natural variability effect and climate change effect. This will reveal the main source of uncertainty and indicate which source is a key controlling factor for future flood frequency change.

To estimate the effect of natural climate variability, this study applied simple replacement of climate time series using a moving block bootstrap method. The moving block bootstrap method (Künsch, 1989) is a resampling method with replacement to obtain a large number of samples (pseudo time series) from a time series, which have independent data structure such as precipitation (Ebtehaj et al., 2010). This study used seasonally-based three month blocks, December–February (winter), March–May

(spring), June–August (summer), and September–November (fall), to demonstrate antecedent conditions and wet or dry season effect (Kay et al., 2009). For instance, the climate data of three months (December–February) in 1960 are randomly selected from any 3-month period between the water year 1960 and 1989. The selection of climate data with the same months is repeated 30 times until the years of new series are the same of original time series. This process allows the selection of data for a specific water year which could be repeated or may not be used at all. Flood frequency using 100 resampled climate series are compared to that obtained from original data. Also, the 100 resampled climate series are adjusted by the delta method described above to generate future climate conditions by the aforementioned three GCMs with two emission scenarios.

2.6 Flood frequency analysis – peak FQ

To estimate the impact of climate and land use changes on flood frequency, this study used typical statistical flood frequency analysis of maximum annual flood series using the PeakFQ program. PeakFQ provides estimates of instantaneous maximum annual peak-flows having diverse recurrence intervals such as 2, 5, 10, 25, 50, 100, 200, and 500 years as annual-exceedance probabilities of 0.50, 0.20, 0.10, 0.04, 0.02, 0.01, 0.005, and 0.002, respectively. Here, a 100 year flood describes a flood that is believed to have a probability of being equal or exceeding 0.01 in any one year (Raff et al., 2009). This program is developed based on the Bulletin 17B guidelines of the Interagency Advisory Committee on Water Data (IACWD, 1982), which is recommended for use by Federal agencies in the US. Bulletin 17B assumes that flood frequency can be described by a log-Pearson Type 3 (LP3) probability distribution (Griffis and Stedinger, 2007). Here, the LP3 distribution defines the probability that any single annual peak flow will exceed a specified streamflow. LP3 has three parameters: mean, standard deviation, and skew coefficient (Bobee and Ashkar, 1991). The skew coefficient is highly sensitive to the collected sample data of annual maximum floods, so that PeakFQ provides guidance on estimating the skew coefficient, such as the generalized skew from

a digitized copy of the map in Bulletin 17B, the approach applied in this study.

2.7 Land use change scenarios

Future land use scenario is essential for estimating the environmental effects of different land use planning options. Using such a scenario also facilitates more robust and realistic hydrologic impact studies than simply using a sensitivity analysis; e.g. assuming ±10%, ±20% change in urban land use. To consider possible future land use changes in both catchments, this study used two land-cover datasets developed by the Pacific Northwest Ecosystem Research Consortium (PNW-ERC, 2002). The PNW-ERC provides three different land use scenarios for every 10 years of 2000–2050, namely, the conservation, the plan trend, and the development scenarios (see Table 2). These scenarios represent different future landscapes, based on projected human population growth patterns and potential development characteristics throughout the Willamette River basin (Hulse et al., 2004). As shown in Table 2, the conservation scenario assumes that greater emphasis on ecosystem protection and restoration will be implemented. The Plan Trend scenario assumes that current land use trends continue. The development scenario depicts greater expansion of urban growth boundaries (UGBs) with free rein to market forces across all components of the landscape, resulting in sprawl urban development. More detailed description of these scenarios is found in Hulse et al. (2004). This study used the conservation and the development scenarios as two extreme cases. A similar approach has been used in Franczyk and Chang (2009) and Praskievicz and Chang (2011).

2.8 Comparison of uncertainty sources

To examine the main source of uncertainty, we used the maximum variation comparison approach (Jung et al., 2010). For example, to determine the maximum range by GCM simulations (GCM structures), we compared the results of flood frequency change that are derived by different land use changes, emission scenarios, PRMS pa-

rameters, and natural variability but from the same GCM. Then we obtained the range of flood frequency change for each GCM. Finally, we choose the highest value among these ranges (here, for three GCMs) that represent the maximum change by GCM. The same methodology is repeated to determine the maximum range for each uncertainty
5 source. This study uses the results at 95% confidence interval.

3   Results and discussion

3.1   Hydrologic model calibration

To calibrate PRMS model parameters, HRUs for the Fanno and the Johnson creek catchments are delineated based on streamflow network, slope and aspect, and soil
10 type. The geophysical parameters of each HRU are estimated from DEM, Land use, and Soil GIS layers (see Table 1). The ratio of impervious surface area in HRU (*hru_percent_imperv*) is strongly related to land use change, as mentioned in Sect. 2.4. However, the land use layers of PNW-ERC do not provide the specific information of impervious surface area. They only describe some urban-related land use, such as
15 residential, commercial, industrial, railroads, and roads. These land use categories contain both pervious and impervious surface areas. Therefore, if all urban land uses are assumed as impervious surface areas, flood frequency would be overestimated. To determine the ratio of impervious surface area to urban land use, we develop an empirical relation between urban land use (%) and mean impervious surface area (%) (see
20 Fig. 3) based on the data set of Waite et al. (2008). Waite et al. (2008) use different land use types, including mean impervious surface area, for 28 catchments in Oregon and Washington to estimate the effect of urbanization on steam ecosystems. As shown in Fig. 3, the estimated regression equation shows a good closeness between urban land use and mean impervious surface area (R^2=0.99). The regression coefficients are
25 used to estimate percent impervious surface areas in each HRU (*hru_percent_imperv*) in PRMS modeling for these two urban catchments.

3.2 Projected future climate change and land use change

Changes in monthly precipitation show different patterns by GCMs and GHG emission scenarios, but the changes are similar in the two catchments (see Fig. 4). The CNRM-CM3 and the ECHAM5/MPI-OM simulations project slight increasing winter (December, January, and February) precipitation, while predicting drier summers (June, July, August, and September) as indicated by previous studies (e.g., Mote et al., 2003; Graves and Chang, 2007; Chang and Jung, 2010). In the study catchments, winter precipitation is closely related to flood events. Therefore, rising water tables resulting from an increase of winter precipitation and soil moisture content are likely to lead to more frequent flooding in this region. However, the ECHO-G projects a slight decrease in winter precipitation. These different precipitation projections contribute to uncertainty in flood frequency analysis. Climate change projection for monthly temperatures ranges from +0.3° increase in February (CNRM-CM3, B1) to 6.1° in August (ECHO-G, A1B) for the 2050s (not shown).

Figure 5 shows changes in land use categories of three different land use data sets – reference land use in 2001, the conservation and the development land uses for the 2050s. Both catchments are projected to have different paths of future growth, as reflected in changes in each land use category. In the Fanno creek catchment, absolute changes in land use categories are small because it is already highly developed (85% in 2001). Hence, the Johnson creek catchment shows considerable differences in each land use among the three scenarios. Urban land use shows a 17% increase under the development (sprawl development) scenario and an 11% increase under the conservation (compact development) scenario because of population growth, construction of building and roads, and urban development in agricultural land use (Hulse et al., 2004). Agricultural land use in both future scenarios decreases by approximately 17%. Grassland and forest land uses are higher under the conservation scenario than under the development scenario.

3.3 Projected flood frequency

Figure 6 shows the range of flood frequency at the reference and future climate change conditions, excluding land use change effect. The reference period only considers the natural variability impact. Hence, the two futures represent impacts of climate change on flood frequency by the combined conditions of climate change and natural variability. The effect of climate change is much more dominant in both catchments as compared with natural variability (taller box and whisker). The t-test results show that the flood frequency of all return periods significantly changes by climate change at the 95% confidence interval (see Table 3). The GHG emission scenarios are only significantly different for 2-year flood frequency. The climate change impact on flood frequency between both catchments is similar. This is attributed to the fact that the catchments are located in same climate region in the Willamette Valley and analyses are made using data derived from coarse scale GCM simulations. In a contrasting case study, Kay et al. (2009) show different responses between two distant catchments in UK using regional climate model (RCM) simulations. They show that one catchment is highly dominated by natural variability, while the other catchment was strongly affected by climate change. Hulme et al. (1999) explain that if a region is dominated by natural variability than climate change, adaptation management that protects against natural variability may be sufficient to withstand climate change. Our results show that future flood management in the Fanno and Johnson creek catchments should consider climate change impact as well as historical natural climate variability.

As shown in Fig. 7, the natural variability impact is much greater than future land use change impact. The variation in flood frequency caused by land use change is similar to that due to natural variability in both catchments. However, under the development scenario, short-term floods (2 and 5 year floods) in Johnson Creek show significant changes at the 95% confidence interval (see Table 3). This indicates that land use change in less developed catchment could significantly lead to more frequent bankfull flooding although natural variability effect is pronounced for larger flood events. The

median values of flood frequency under the development condition are slightly higher than those of the conservation scenario. Also, shorter term floods increase more than longer term floods.

For the combined impact of climate and land use changes, flood frequency at the six different return periods slightly increased, though each change had high variations (Fig. 8). The range of flood frequency change gradually increases from shorter term floods to longer term floods. The variations under the A1B scenario are larger than those under the B1 scenario in both catchments. Since variation is high, an interpretation of flood frequency impact by each scenario solely based on Fig. 8 is difficult. Accordingly, we calculated ensemble mean value of flood frequency change for each scenario.

Figure 9 shows the ensemble mean of relative changes of flood frequency under two GHG emission, two land cover change, and the combined scenarios (four) that are calculated from the reference flood frequency. The A1B scenario shows the biggest change among the separate emission and land cover scenarios in both catchments. In the Fanno creek catchment, ensemble results of all 8 scenarios show higher changes than those caused by natural variability. However, in Johnson creek, the natural variability impact becomes more significant than the B1 and land cover change scenarios for short-term flood frequency of less than 25 year floods. In all cases, the combined impacts on flood frequency are higher than those of natural variability in both catchments. The combined impacts of land use and climate scenarios induce the highest increase in flood frequency by A1B scenario with the development scenario and the lowest increase by B1 scenario with the conservation scenario. The shorter term flood frequencies are more sensitive to the combined scenarios than longer term ones (see Table 4). Besides, the difference between A1B with development scenario and B1 with conservation scenario is higher in the Johnson than in the Fanno (see % difference between the two scenarios in Fig. 9). For the long term extremes, the Johnson creek shows significant difference between A1B with the development scenario (6.6% difference) and B1 with the conservation scenario (3.4% difference) (see Table 4).

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This result indicates that, under expected climate change conditions, an adaptive urban planning based on the conservation scenario could be more effective in less developed Johnson catchment than in the already developed Fanno. Also, this result demonstrates that the combined effect does not linearly increase catchment flood fre-
quency; e.g. for 2 years flood in the Fanno, +12.4% increase by A1B scenario versus +9.7% increase by the development scenario, but +14.8% increase by combination of A1B and development scenarios. This could be attributed to nonlinear hydrologic responses under different climate and land use conditions. Additionally, it implies that if we want to obtain more realistic future projections on urban flood risk analysis, we need
to develop possible climate change scenarios as well as land use change scenarios.

3.4 Comparison of five uncertainty sources

Figure 10 shows the relative size (uncertainty) of variation in flood frequency change under the combined impact of climate and land use change. Uncertainty due to land use change is the smallest in this study except the occurrence of 2 year floods at John-
son creek, although the Johnson's range is larger than the Fanno's. This could indicate that longer term floods could be less affected by land use change than climate change. However, this result also suggests that if land use at a catchment scale changes more abruptly than climate change, the land use change will become a more significant un-
certainty source for short term floods. Emission scenario also shows relatively smaller range than those of the other sources. The uncertainty from hydrologic parameters is
more significant at Fanno than Johnson, but it is smaller than uncertainty due to GCM and natural variability. GCM uncertainty highly affects shorter term 2 and 5 year floods, while longer term 25, 50, and 100 year floods are more controlled by natural variability. This demonstrates that both uncertainty sources, GCMs and natural variability, are
significant factors in urban flood frequency analysis.

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3.5 Caveats of this study

This research deals with uncertainty on future flood frequency analysis in two distinct urban areas. We consider several uncertainty sources; GCM structure, future GHG emission scenario, future land use scenario, hydrologic model parameter, natural variability, and different degree of urbanization. Our results contribute to an understanding of the combined effects of climate change and urbanization on urban flood analysis. While we identify the relative magnitude of uncertainties among these sources mentioned above, there are remaining uncertainty sources, such as GCM initial condition, downscaling method, and hydrologic model structure etc, which are not quantified in the current study. Therefore, our results should be cautiously interpreted along with other potential sources of uncertainties.

We carefully select the three best GCMs, but these GCMs do not necessarily project future climate accurately. Furthermore, three GCMs are insufficient to cover the full range of GCM structure uncertainty. However, our results show the uncertainty caused by GCMs is higher than that from other sources. This is consistent with the findings of previous studies (e.g., Wilby and Harris, 2006; Kay et al., 2009). Therefore, the end-to-end effect of GCM uncertainty on flood frequency projection could be larger than that represented in this study. The uncertainties due to future GHG emissions are not fully considered as proposed in the IPCC storyline (IPCC, 2000).

Our results are affected by GCM simulations with a simple delta downscaling method because this approach cannot consider changes in interannual or day-to-day variability of climate simulations (Im et al., 2010a; Prudhomme and Davies, 2009). Additionally, we do not include uncertainty due to hydrologic model structures (Clark et al., 2008; Jiang et al., 2007; Bae et al., 2010; Najafi et al., 2010b) and downscaling methods (Fowler et al., 2007; Im et al., 2010b; Wood et al., 2004; Najafi et al., 2010a), which are also important uncertainty sources on climate change impact studies. Therefore, future studies will need to address uncertainties due to hydrologic model structure and diverse downscaling methods to draw more robust conclusions.

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Urban climate is controlled by not only the natural climate system of global and regional scale but also by local urbanization effects, such as the urban heat island, the urban canopy layer, and varying aerosol composition (Ntelekos et al., 2010). Urbanization could significantly affect the precipitation climatology relating to flood event (Shepherd, 2005). Ntelekos et al. (2008) demonstrates that rainfall accumulations of 30% of the total extreme events are attributed to urbanization impact in the Baltimore metropolitan area, Washington DC. Therefore, the interaction between global climate change and urban climatology is another important uncertainty source in urban climate impact studies.

In changing climate conditions, a stationarity assumption of flood frequency analysis may not be valid (Milly et al., 2008; Smith et al., 2005). This study uses the PeakFQ based on the Bulletin 17B that assumes the constant distribution of flood events regardless of climate change. Some previous studies illustrate that a traditional approach to flood frequency estimation could not rely on stationarity assumptions (Raff et al., 2009; Sivapalan and Samuel, 2009). Now, a robust methodology for incorporating projected climate information into flood frequency analysis is needed.

4   Conclusions

This study examines the potential changes of flood frequency at the Fanno and the Johnson creek catchments using different land use change, climate change scenarios, and combined scenarios. Additionally, the uncertainties and limitations of this study are discussed. Here, the important conclusions are summarized.

(1)   In the 2050s period, flood frequency is projected to slightly increase in both catchments, although there are substantial uncertainties. Changes in flood frequency are more sensitive to climate change (A1B scenario) than land use change. Climate change impact on flood frequency change is similar over two catchments but land use change impact is only significant in the less developed Johnson catchment, which is projected to be more urbanized in the 2050s.

(2) For the combined scenarios, GCM uncertainty highly affects shorter term flood frequency such as 2- and 5-year floods, while longer term extremes, 25, 50, and 100 year floods, are more controlled by natural variability. Hence, the uncertainties due to future GHG emission scenarios and land use change scenarios are less important than natural variability. Also, hydrologic model parameter uncertainty is smaller than natural variability and GCM uncertainty.

(3) The combined impacts of land use change and climate change scenarios induce significant changes in the shorter term extremes in both catchments. However, for the long term extremes, the Johnson catchment shows a significant difference in flood between A1B with the development scenario and B1 with the conservation scenario. Additionally, flood frequency change demonstrates the highest increase under the A1B with the development scenario and the lowest increase under the B1 with the conservation scenario.

(4) Our results indicate that realistic land use change scenario is an essential factor for urban flood frequency analysis under climate change condition.

This research shows that both land use change and climate change are key factors in quantifying the range of uncertainties in future urban flood analysis. Credible land use change scenario could reduce the uncertainty range of future projection and help decision-making for flood management. Additionally, developing a risk-based decision making method is needed (e.g., Hine and Hall, 2010). With well quantified uncertainty, this method could help flood managers evaluate the effectiveness of their specific decision for urban flood planning.

CMIP3 multi-model dataset available. Support of this dataset is provided by the Office of Science, US Department of Energy.

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Table 1. PRMS model parameters for calibration. D: Digital elevation map, LU: Land use map, S: Soil map, OPT: Optimized (Modified from Chang et al., 2010).

Parameter	Description	Range	Calibrated values	Source
cov_type	Cover type (0=bare, 1=grasses, 2=shrubs, 3=Deciduous trees, 4=Coniferous trees)	0~4		LU
covden_sum	Summer vegetation cover density	0~1		LU
covden_win	Winter vegetation cover density	0~1		LU
wrain_intcp	Winter rain interception storage capacity, in inch	0~5		LU
srain_intcp	Summer rain interception storage capacity, in inch	0~5		LU
snow_intcp	Winter snow interception storage capacity, in inch	0~5		LU
hru_percent_ imperv	HRU impervious surface area, in decimal percent	0~1		LU
hru_elev	Mean elevation for each HRU, in feet	−300~30 000		D
hru_slope	HRU slope in decimal vertical feet / horizontal feet	0~10		D
soil_type	HRU soil type (1=sand, 2=loam, 3=clay)	1~3		S
soil_moist_max	Maximum available water holding capacity in soil profile, in inch	0~20		S
soil_rechr_max	Maximum available water holding capacity for soil recharge zone, in inch	0~10		S
soil2gw_max	Maximum rate of soil water excess moving to ground water	0.0–5.0	0.12–0.15	OPT
smidx_coef	Coefficient in nonlinear surface runoff contributing area algorithm	0.0001–1.0000	0.001	OPT
smidx_exp	Exponent in nonlinear surface runoff contribution area algorithm	0.2–0.8	0.20–0.21	OPT
ssrcoef_sq	Coefficient to route subsurface storage to streamflow	0.0–1.0	0.05–0.44	OPT
ssrcoef_lin	Coefficient to route subsurface storage to streamflow	0.0–1.0	0.0001	OPT
ssr2gw_exp	Coefficient to route water from subsurface to groundwater	0.0–3.0	0.5–3.0	OPT
ssr2gw_rate	Coefficient to route water from subsurface to groundwater	0.0–1.0	0.006–0.02	OPT
gwflow_coef	Ground-water routing coefficient	0.000–1.000	0.003–0.07	OPT

Table 2. Description of the three land cover scenarios used in this study to simulated land cover projections within the Fanno and Johnson Creek catchments by 2050 (Source: Hulse et al., 2004; Franczyk and Chang, 2009).

Classification	Land cover scenarios		
	Conservation	Plan Trend	Development
General	High priority on ecosystem protection & restoration	Recent trends continue, existing land use plans are implemented	Relaxed land use policies, market-driven approach to land development & use
Urban development	Emphasizes high-density development, UGBs similar to Plan Trend	Growth contained within UGBs & rural zones, small expansion of UGBs	Emphasizes lower-density development, greater expansion of UGBs
Agriculture	Conversion of some crop-land to natural vegetation	Minimal change in agricultural land use	Majority of development occurs on Agricultural land
Forest	Gradual decrease in clear-cut areas, riparian zones on all streams	Older conifer forests mainly confined to federally-owned lands	Increased clear-cutting & less stream protection

Table 3. *T*-test result of comparison between flood frequency change by GHG emission scenarios and land use change scenarios. Shaded values indicate significant p-values at the 95% confidence level.

| | | Climate change | | | | | Land use change | | | |
| | | Fanno | | Johnson | | | Fanno | | Johnson | |
	Emission	Ref	A1B	Ref	A1B	Land use	Ref	Con.	Ref	Con.
2	A1B	**0.00**	–	**0.00**	–	Con.	0.25	–	0.06	–
	B1	**0.00**	**0.01**	**0.00**	**0.00**	Dev.	0.15	0.77	**0.00**	0.22
5	A1B	**0.00**	–	**0.00**	–	Con.	0.46	–	0.21	–
	B1	**0.00**	0.06	**0.00**	**0.01**	Dev.	0.37	0.86	**0.04**	0.39
10	A1B	**0.00**	–	**0.00**	–	Con.	0.57	–	0.33	–
	B1	**0.00**	0.11	**0.00**	**0.03**	Dev.	0.46	0.86	0.11	0.54
25	A1B	**0.00**	–	**0.00**	–	Con.	0.65	–	0.48	–
	B1	**0.00**	0.16	**0.00**	0.07	Dev.	0.58	0.92	0.25	0.65
50	A1B	**0.00**	–	**0.00**	–	Con.	0.69	–	0.58	–
	B1	**0.00**	0.21	**0.00**	0.11	Dev.	0.64	0.94	0.35	0.70
100	A1B	**0.00**	–	**0.00**	–	Con.	0.73	–	0.66	–
	B1	**0.00**	0.24	**0.00**	0.15	Dev.	0.68	0.94	0.46	0.77

Table 4. *T*-test result of comparison between flood frequency change by combination of GHG emission scenarios and land use change scenarios. Shaded values indicate significant *p*-values at the 95% confidence level.

			Fanno				Johnson		
		Ref	A1B +Con	A1B +Dev	B1 +Con	Ref	A1B +Con	A1B +Dev	B1 +Con
2	A1B+Con	0.19	–	–	–	0.11	–	–	–
	A1B+Dev	0.11	0.75	–	–	**0.01**	0.27	–	–
	B1+Con	0.19	**0.01**	**0.01**	–	0.09	**0.00**	**0.00**	–
	B1+Dev	0.10	**0.03**	**0.01**	0.74	**0.00**	**0.04**	**0.00**	0.25
5	A1B+Con	0.34	–	–	–	0.21	–	–	–
	A1B+Dev	0.24	0.82	–	–	**0.03**	0.38	–	–
	B1+Con	0.32	0.06	**0.03**	–	0.16	**0.01**	**0.00**	–
	B1+Dev	0.22	0.09	0.06	0.82	**0.02**	0.10	**0.01**	0.35
10	A1B+Con	0.42	–	–	–	0.29	–	–	–
	A1B+Dev	0.32	0.85	–	–	0.08	0.48	–	–
	B1+Con	0.41	0.10	0.07	–	0.23	**0.03**	**0.00**	–
	B1+Dev	0.31	0.14	0.10	0.85	**0.05**	0.14	**0.03**	0.42
25	A1B+Con	0.53	–	–	–	0.41	–	–	–
	A1B+Dev	0.45	0.90	–	–	0.16	0.57	–	–
	B1+Con	0.50	0.15	0.12	–	0.33	0.07	**0.01**	–
	B1+Dev	0.41	0.20	0.16	0.88	0.11	0.20	0.06	0.53
50	A1B+Con	0.60	–	–	–	0.47	–	–	–
	A1B+Dev	0.51	0.90	–	–	0.25	0.66	–	–
	B1+Con	0.57	0.20	0.15	–	0.40	0.10	**0.03**	–
	B1+Dev	0.49	0.25	0.19	0.89	0.17	0.23	0.09	0.60
100	A1B+Con	0.64	–	–	–	0.55	–	–	–
	A1B+Dev	0.57	0.91	–	–	0.33	0.70	–	–
	B1+Con	0.62	0.23	0.19	–	0.47	0.13	**0.05**	–
	B1+Dev	0.55	0.27	0.22	0.92	0.24	0.26	0.12	0.66
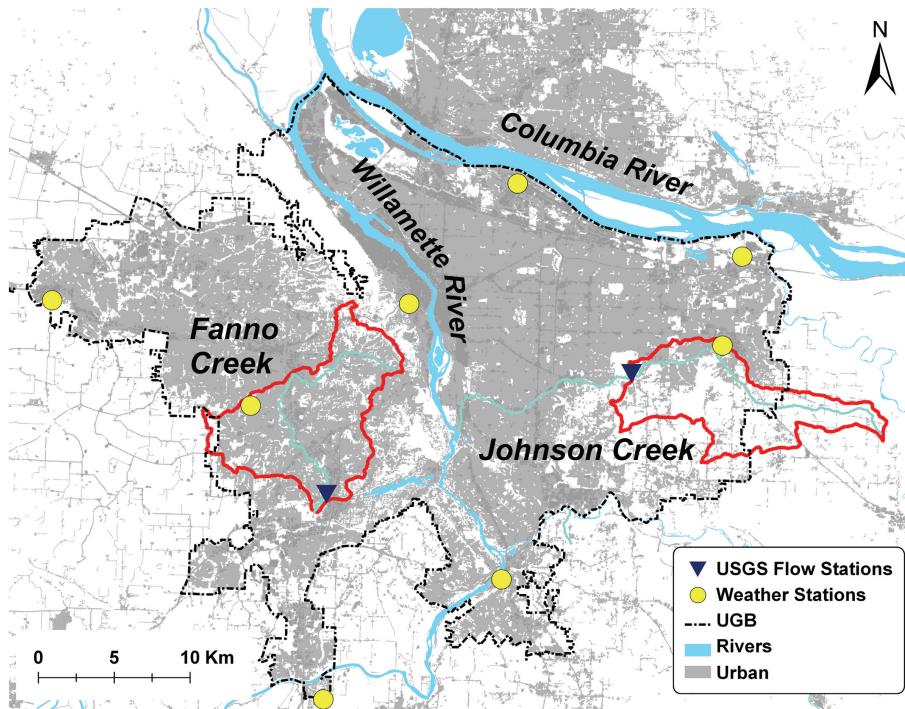
Fig. 1. Fanno and Johnson Creek catchment boundary, river network, and the Portland urban growth boundary (UGB).
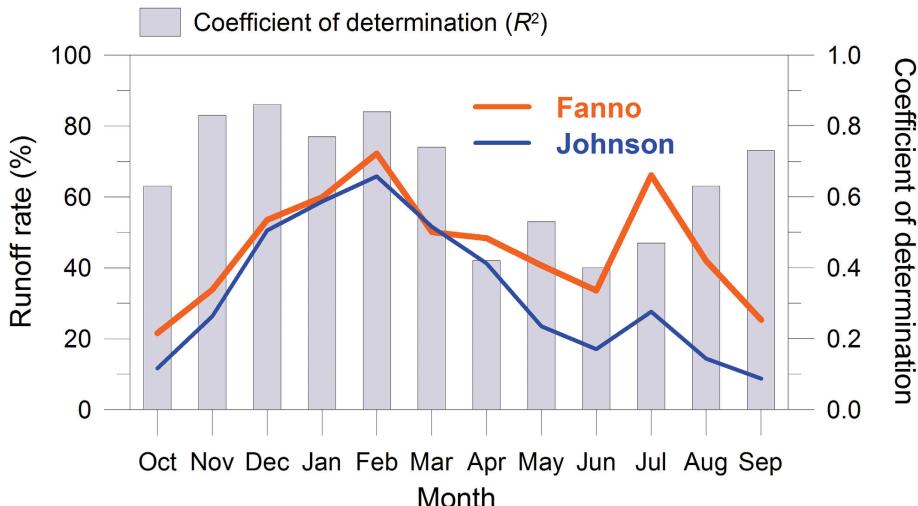
Fig. 2. Monthly runoff rate (%) that indicates the ratio of monthly runoff to monthly precipitation for 2000–2006 and monthly coefficient of determination between the Fanno daily streamflow (USGS 14206950) and the Johnson daily streamflow (USGS 14211500).
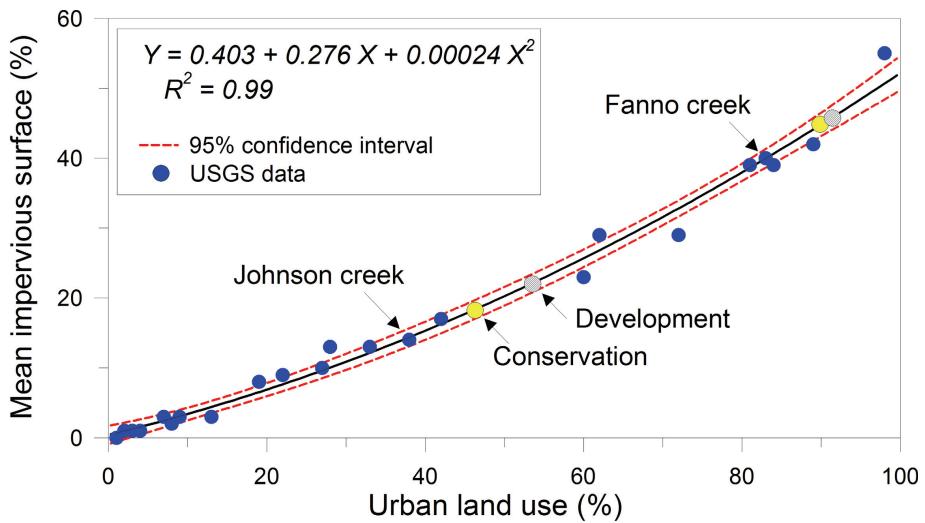
Fig. 3. Relation between urban land use (%) and mean impervious surface (%). Data are obtained from USGS Report 2006-5101-D (Waite et al., 2008, Table 1).
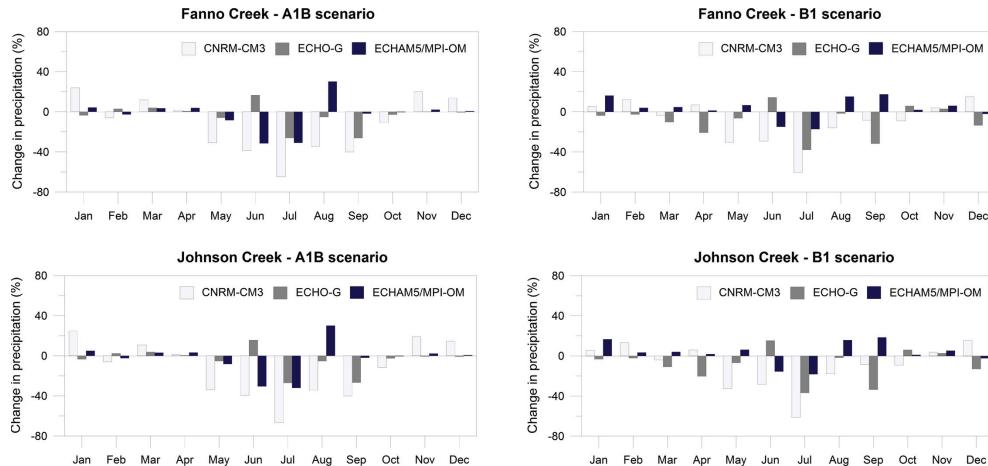
Fig. 4. Changes in precipitation according to three GCMs and two emission scenarios in Fanno Creek and Johnson Creek catchments.
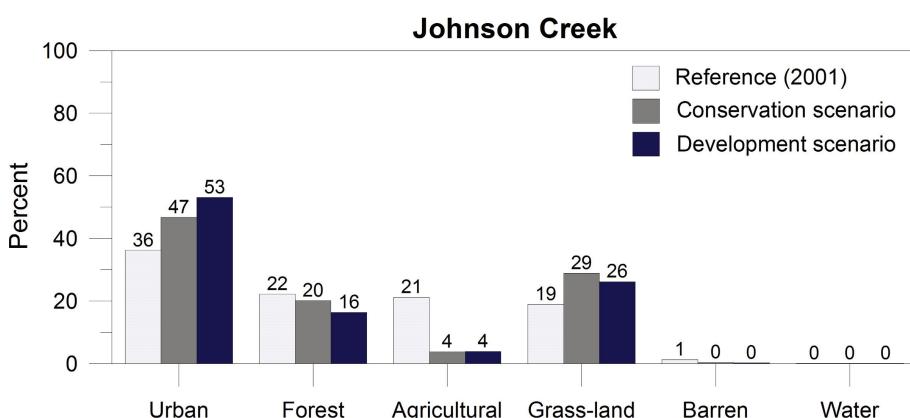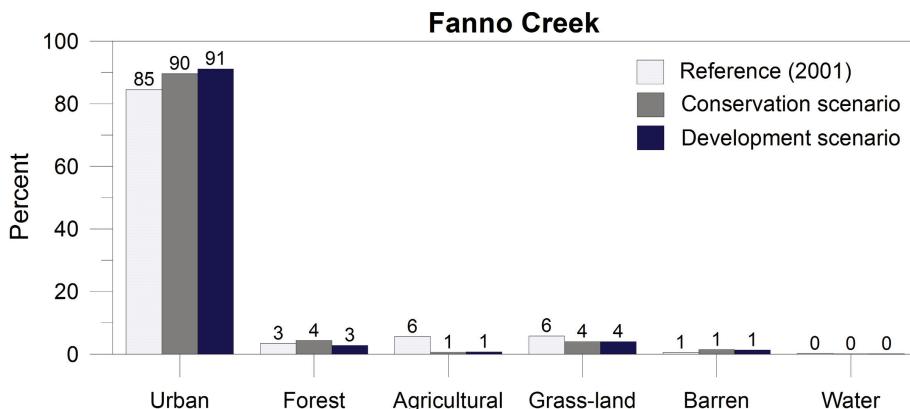
Fig. 5. Land use categories (%) for reference land use in 2001 and two future land use change scenarios for the 2050s.
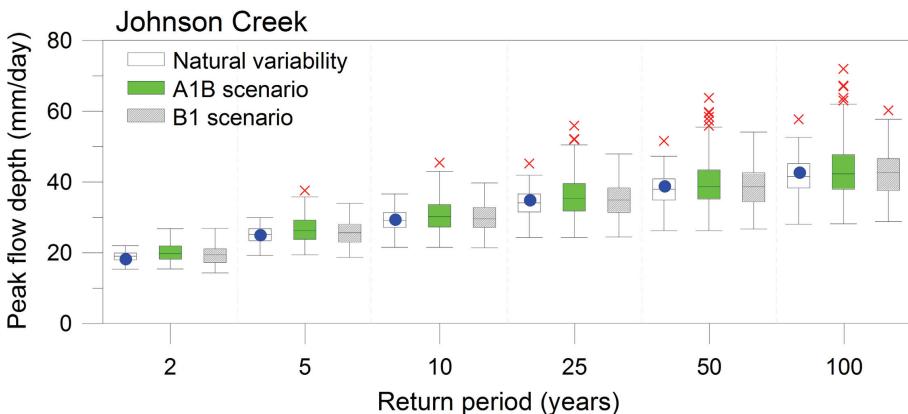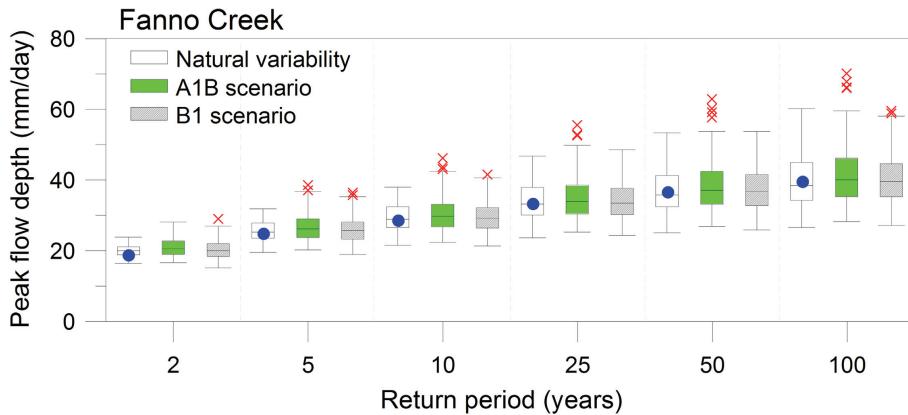
Fig. 6. Variation of flood frequency by climate change scenarios, with recurrence intervals of 2, 5, 10, 25, 50, and 100 years for the 2050s with respect to the reference period of 1960–1989. The blue dot indicates flood frequency using observed climate data and symbol (×) indicates outliers.
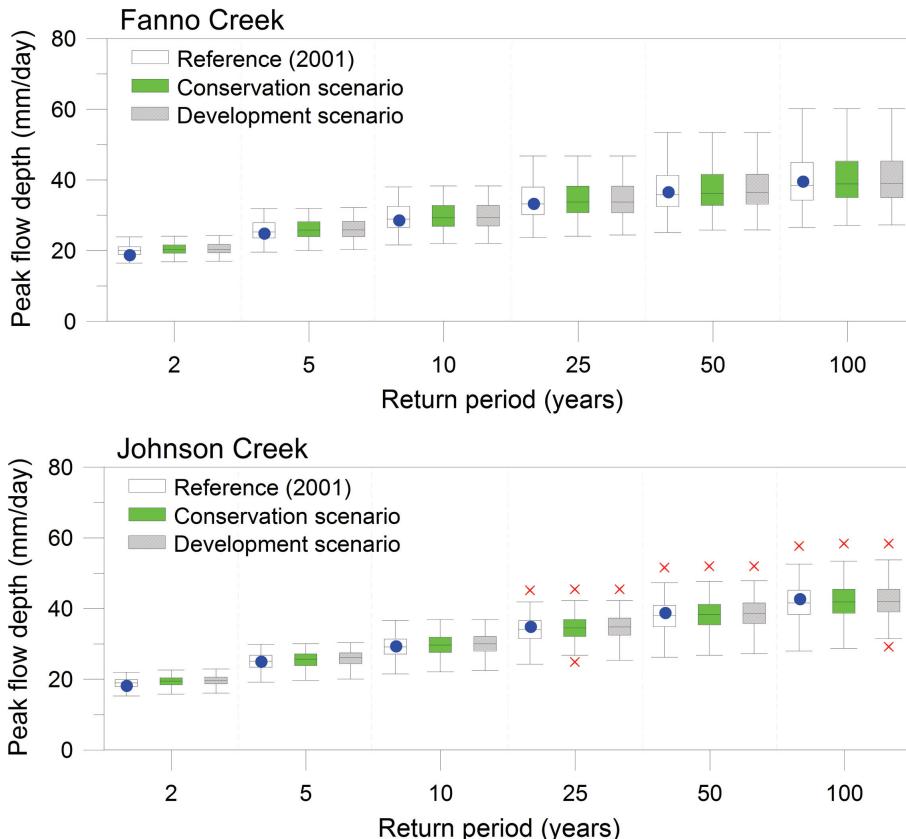
Fig. 7. Variation of flood frequency by land use change scenarios, with recurrence intervals of 2, 5, 10, 25, 50, and 100 years for the 2050s with respect to the reference period of 1960–1989. The blue dot indicates flood frequency using observed climate data, and symbol (×) indicates outliers.

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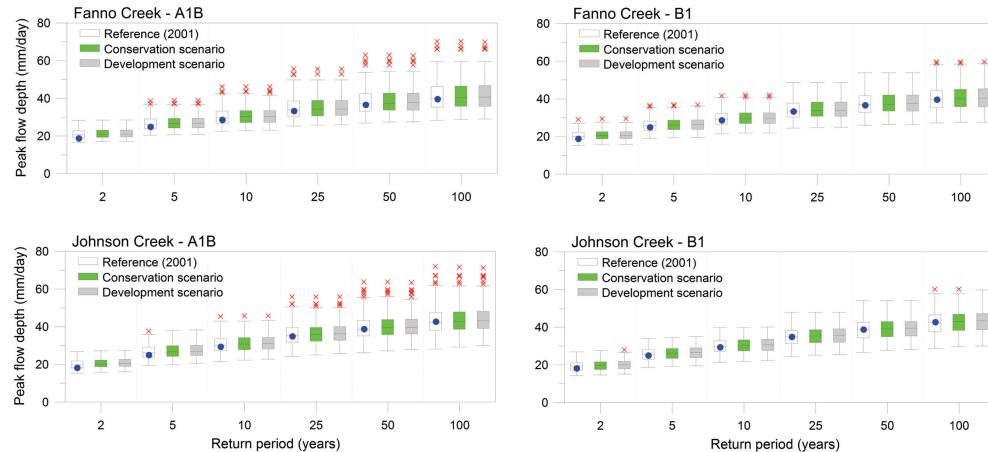
Fig. 8. Variation of flood frequency flows by combination of *land use change and climate change scenarios* with recurrence intervals of 2, 5, 10, 25, 50, and 100 years for the 2050s with respect to the reference period of 1960–1989. The blue dot indicates flood frequency using observed climate data, and symbol (×) indicates outliers.
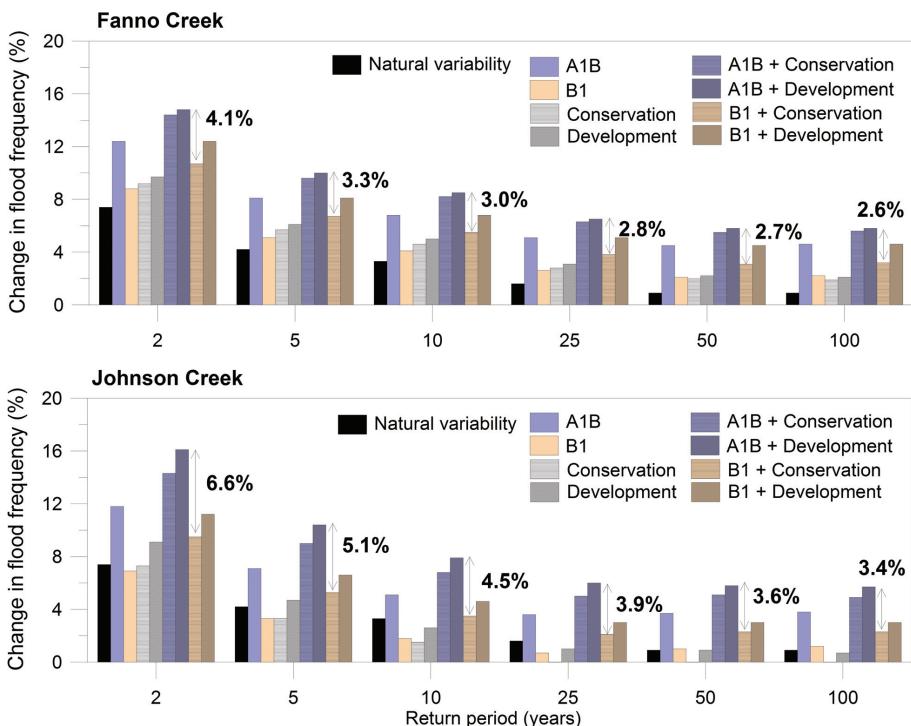
Fig. 9. Ensemble mean of changes (%) in flood frequency under different scenarios for the 2050s with respect to the reference period of 1960–1989.
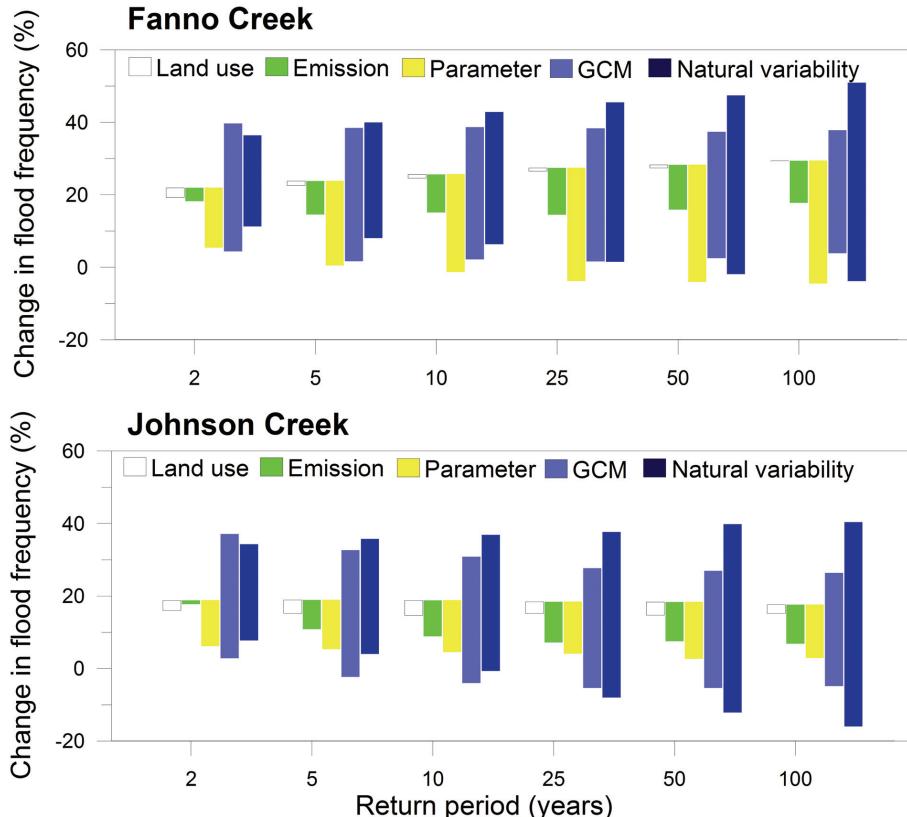
Fig. 10. Comparison of variation in flood frequency change by each uncertainty source. The vertical ranges show the 95% confidence bound.