ASSESSMENT OF MIROC3.2 HIRES CLIMATE AND CLUE-S LAND USE CHANGE IMPACTS ON WATERSHED HYDROLOGY USING SWAT

J.-Y. Park, M.-J. Park, H.-K. Joh, H.-J. Shin, H.-J. Kwon, R. Srinivasan, S.-J. Kim

ABSTRACT. *The aim of this study was to evaluate hydrologic impacts of potential climate and land use changes in a mountainous watershed in South Korea. The climatic data predicted by MIROC3.2 HiRes GCM A1B for three time periods (2010-2039, 2040-2069, and 2070-2099) were prepared using a change factor statistical downscaling method. The future land uses were predicted using the Conservation of Land Use and its Effects at Small regional extent (CLUE-s) model by establishing logistic regression model for five land use types with 11 driving forces represented by spatial information. By applying the climate and land use predictions to the Soil and Water Assessment Tool (SWAT), the watershed hydrologic components (including evapotranspiration, surface runoff, groundwater recharge, and streamflow) were evaluated. For the predicted 2070-2099 temperature and precipitation changes (+4.8°C and +34.4%), and 6.2% decrease in forest areas and 1.7% increase in urban areas, the combined land use with climate change scenario resulted in more streamflow change (+55.4%) than the single climate and single land use change scenario (+39.8% and +10.8%), respectively. The predicted large increase in future precipitation and the corresponding decrease in forest land are predicted to have substantial impacts on watershed hydrology, especially on surface runoff and streamflow. Therefore, to mitigate negative hydrologic impacts and utilize positive impacts, both land use and climate changes should be considered in water resource planning for the Chungju dam watershed.*

Keywords. *Climate change, CLUE, Hydrologic component, Land use change, SWAT, Watershed hydrology.*

The Intergovernmental Panel on Climate Change (IPCC) report reaffirms that the climate is changing in ways that cannot be accounted for by natural variability and that global warming is occurring (IPCC, 2007). Climate changes can affect the hydrological cycle, thus modifying the transformation and transport characteristics of nutrients (Bouraoui et al., 2002). The scientific consensus is that future increases in temperature will result in elevated global-mean temperatures with subsequent effects on regional precipitation, evapotranspiration (ET), and soil moisture, as well as altered flow regimes in streams and rivers (Wilby et al., 1994; Arnell, 2003, 2004). In addition to the possible changes in the total volume of flow in rivers and streams, there may also be a significant change in the frequency and severity of floods and droughts (Dibike and Coulibaly, 2007).

In general, the assessment of the impacts of climate change on watershed hydrology will need to use watershed models and general circulation models (GCMs). Recently, several studies have been carried out on the impacts of climate change on water quantity. Merritt et al. (2006) evaluated the hydrologic response to scenarios of climate change in the Okanagan basin, British Columbia, using three GCMs (CGCM2, CSIROMk2, and HadCM3) and the University of British Columbia (UBC) watershed model. Zhang et al. (2007) estimated the effect of potential climate change on the available streamflow volume in the Luohe River basin using two GCMs (HadCM3 and CGCM3) and the Soil and Water Assessment Tool (SWAT).

Land use change has attracted much scientific interest due to the correlation between land use change and water resources management associated with climate change scenarios (e.g., Matthews et al., 1997; Fischer and Sun, 2001; Verburg and Veldkamp, 2001). Land use changes directly affect evapotranspiration, infiltration, and soil water storage, which change the dynamics of surface runoff, subsurface runoff, and groundwater recharge. The accompanying spatial and temporal distributions of vegetation cover change the parameters for calculating the evaporation from soil and transpiration from vegetation (Park et al., 2009). Thus, the

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prediction of future land use is an important consideration in sustainable water resource management.

Recently, many studies have evaluated the hydrologic impacts of land use change on urbanized or wetland watersheds (McClintock et al., 1995; Choi et al., 2003; Kim et al., 2005). The impact assessments are usually conducted by spatially preparing series of land use data classified by satellite images for a hydrologic model. A future land use prediction model should be able to match the statistical patterns of past growth and provide an estimate that matches the present reality (Clarke et al., 1997; Clarke and Gaydos, 1998). Lin et al. (2007) assessed the impacts of different land use change scenarios, which included various spatial and non-spatial policies on hydrology and land use patterns in the Wu-Tu watershed, northern Taiwan, using the Conservation of Land Use and its Effects at Small regional extent (CLUE-s) model and the generalized watershed loading functions model (Haith and Shoemaker, 1987).

The aim of this study was to evaluate the impacts of climate and land use changes on watershed hydrology using the SWAT model. The 2010-2039, 2040-2069, and 2070-2099 MIROC3.2 HiRes A1B future climate data were prepared, and the CLUE-s (Dyna-CLUE version 2.0) future land use was predicted using six past Landsat satellite images from 1975, 1980, 1985, 1990, 1995, and 2000 for the study watershed, a 6642 km^2 typical mountainous watershed in South Korea.

Methods

Study Area Description and Data for Model Evaluation

Figure 1 shows the Chungju dam watershed study area, which has a total area of 6642 km^2 and is located in northeast South Korea within the latitude and longitude range of 127.9° to 129.0° E and 36.8° to 37.8° N. The elevation ranges from 112 m to 1562 m, with an average slope of 36.9% and elevation of 609 m. The annual average precipitation was 1261 mm, and the mean temperature was 9.4°C over the last 30 years. At the watershed outlet is the Chungju multipurpose dam, which is 97.5 m in height, 447 m in length, and has a volume of 9.7 million m^3. This important dam provides energy (412 MW capacity) and water for Seoul (metropolitan city of South Korea) and adjacent urban areas, supplies irrigation for 22,000 ha, protects rural areas from floods, and outlets 334 million tons or water per year to maintain streamflow. More than 82.3% (5469 km^2) of the watershed area is forested, and 12.2% (811 km^2) is cultivated. The cultivated area is comprised of 728 km^2 of paddy fields and 83 km^2 of upland crops. Table 1 shows the 2000 land use of three subwatersheds (YW #1, YW #2 located upstream, and CD at the watershed outlet).

The spatial data for the watershed (i.e., elevation, land use, and soils) were prepared for SWAT and CLUE-s. The elevation data were rasterized as a 100 m resolution digital elevation model (DEM) from a 1:5000 vector map supplied by the Korea National Geography Institute. The soil data with

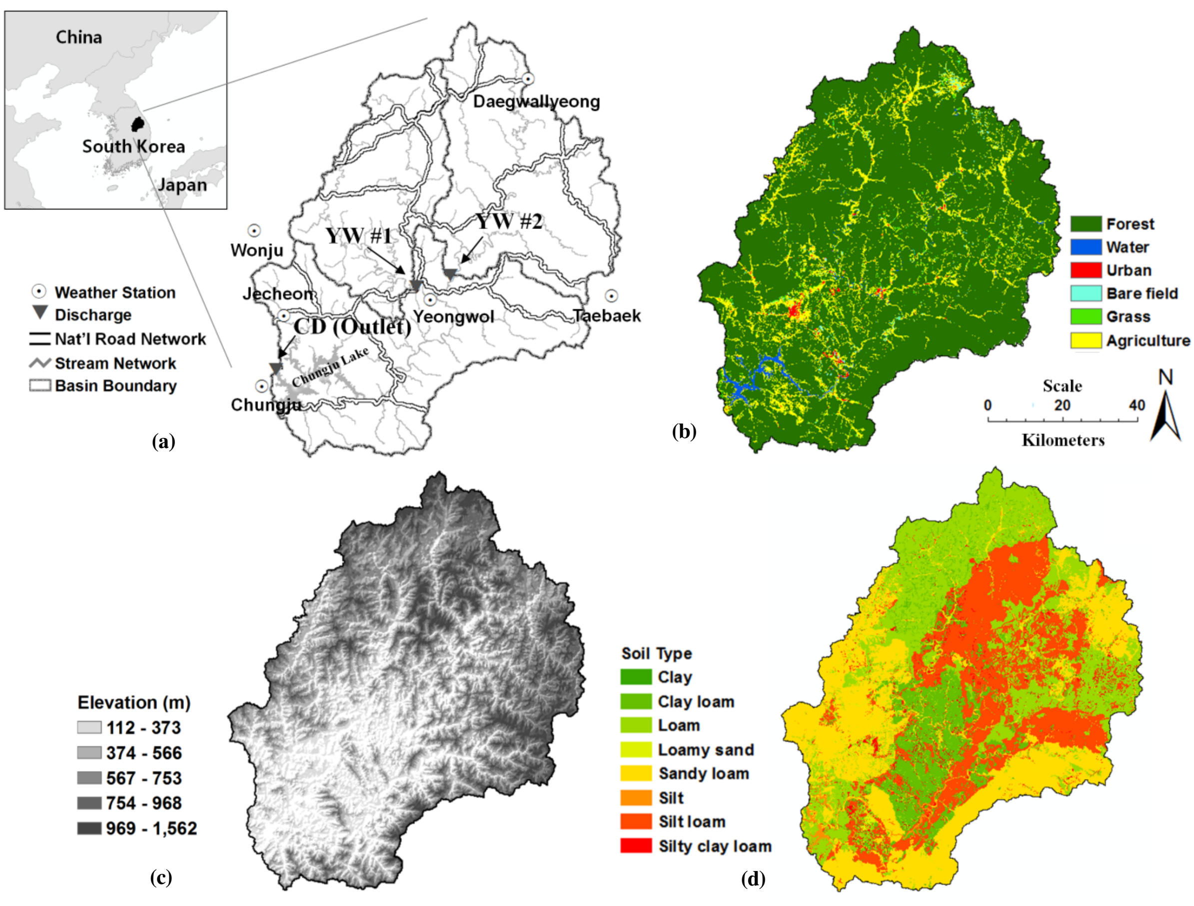

Figure 1. The Chungju dam watershed: (a) subwatershed gauging stations (YW #1, YW #2, and CD), (b) land use in 2000, (c) elevation, and (d) soil types.

Table 1. Area in 2000 for each land use type corresponding to streamflow gauging stations YW #1, YW #2, and CD.

Subwatershed Gauging Station	Land Use Area, km^2 (%)						
	Water	Urban	Bare field	Grass	Forest	Agriculture	Total
YW #1	8 (0.5)	12 (0.8)	24 (1.5)	43 (2.7)	1,327 (82.8)	188 (11.7)	1,602 (100.0)
YW #2	7 (0.3)	9 (0.4)	28 (1.3)	53 (2.3)	1,915 (84.7)	249 (11.0)	2,261 (100.0)
CD	50 (1.8)	33 (1.2)	19 (0.7)	76 (2.7)	2,227 (80.1)	374 (13.5)	2,779 (100.0)
All	65 (1.0)	54 (0.8)	71 (1.1)	172 (2.6)	5,469 (82.3)	811 (12.2)	6,642 (100.0)

respect to texture, depth, and drainage attributes were rasterized from a 1:25,000 vector map supplied by the Korea Rural Development Administration. The six Landsat land use images (1975, 1980, 1985, 1990, 1995, and 2000) for six classes (forest, agriculture, grass, bare field, urban, and water) were obtained from the Water Management Information System. The road and stream networks were also prepared for CLUE-s. Monthly leaf area index (LAI) values from Terra MODerate resolution Imaging Spectroradiometer (MODIS) satellite images (2000-2006) were prepared to calculate Penman-Monteith evapotranspiration in SWAT (Monteith, 1965; Allen, 1986; Allen et al., 1989). The crop parameters can be found in the SWAT theoretical documentation (Neitsch et al., 2002a). The MODIS LAI product (MOD15A2, Collection 3) at 1 km spatial resolution and at an eight-day interval were downloaded from the Earth Observing System Data Gateway (EOS, 2006).

For the climate data, the MIROC3.2 HiRes A1B monthly data for 1977 to 2100 were adopted, and 30-year (1977-2006) daily weather data from six ground meteorological stations were collected from the Korea Meteorological Administration for watershed-scale downscaling. The MIROC3.2 model, developed at the National Institute for Environmental Studies of Japan, has two MIROC3.2 setups of different resolutions. The higher resolution (1.1° × 1.1°) setup is referred to as HI (HiRes), and the lower resolution (2.8° × 2.8°) setup is referred to as MID (medres). The IPCC tried to capture a wide range of potential changes in greenhouse gas (GHG) emissions in its Special Report on Emission Scenarios (Nakićenović et al., 2000). The scenarios result in a wide range of emissions and concentrations of GHGs. Since likelihoods are not given by the IPCC, we used three scenarios from the IPCC that bracket the range of possible emissions scenarios: low (B1), mid-range (A1B), and high (A2) (Lazar and Williams, 2008). Kwon et al. (2007) reported that the A1B scenario would be appropriate considering the increasing tendency of CO_2 emission in South Korea; therefore, the mid-range scenario (A1B) of MIROC3.2 HiRes was used for the future in this study. For calibration and validation of the SWAT model, six years (1998-2003) of daily streamflow data from three gauging stations (YW #1, YW #2, and CD in fig. 1) were obtained from the Han River flood control office.

SWAT Model

The SWAT2005 version with the ArcSWAT2.0 interface was used in this research. SWAT is a physically based continuous, long-term, distributed-parameter model designed to predict the effects of land management practices on the hydrology, sediment, and contaminant transport in agricultural watersheds under varying soils, land use, and management conditions (Arnold et al., 1998). It is a public domain model supported by the USDA Agricultural Research Service (USDA-ARS) at the Grassland, Soil, and Water Research Laboratory in Temple, Texas.

SWAT is based on the concept of hydrologic response units (HRUs), which are portions of a subbasin that possess unique land use, management, and soil attributes. The runoff, sediment, and nutrient loadings from each HRU are calculated separately based on weather, soil properties, topography, vegetation, and land management and then summed to determine the total loading from the subbasin. The hydrologic cycle, as simulated by SWAT (Neitsch et al., 2002a), is based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \quad (1)$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), E_a is the amount of evapotranspiration on day i (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O), and Q_{gw} is the amount of return flow on day i (mm H_2O).

The SWAT model was calibrated for three years (1998-2000) of daily streamflow data at three locations (YW #1, YW #2, and CD) and validated with another three years (2001-2003) of data. Multisite calibration enhances the calibration results from the viewpoint of spatial variation of the hydrological response. The coefficient of determination (R^2), the Nash and Sutcliffe (1970) model efficiency (NSE), and the root mean square error (RMSE) were used to quantitatively assess the ability of the SWAT model to replicate temporal trends in the observed hydrologic data.

Downscaling Technique for GCM Climate Data

It is well known that precipitation and temperature outputs from GCMs cannot be used to force hydrologic models without some form of prior bias correction if a realistic output is sought (Feddersen and Andersen 2005; Hansen et al., 2006; Sharma et al., 2007). Therefore, the required statistical bias correction is calculated for precipitation and temperature using historical observed data. The spatial resolution from the output of GCMs cannot provide a good climate change scenario to a target watershed because GCMs are on a global scale. To represent the impact of climate change on a watershed, the output of GCMs needs downscaling to apply on a regional scale.

The downscaling was performed in two steps. First, bias corrections were carried out for each weather station by applying the Alcamo et al. (1997) and Droogers and Aerts (2005) method. The temperature and precipitation data of MIROC3.2 HiRes were corrected by fitting the 20C3M (20th century simulations, 1977-2006) data with the observed data

(1977-2006, baseline period) to give similar statistical properties. This method is generally accepted within the global change research community (IPCC-TGCIA, 1999). For the temperature, the absolute changes between historical and future GCM time slices were added to the measured values:

$$T'_{GCM,fut} = T_{meas} + \left(\overline{T}_{GCM,fut} - \overline{T}_{GCM,his}\right) \qquad (2)$$

where $T'_{GCM,fut}$ is the transformed future temperature, T_{meas} is the measured 30-year (baseline period) average annual temperature, $\overline{T}_{GCM,fut}$ is the average future GCM temperature, and $\overline{T}_{GCM,his}$ is the average historical GCM temperature. For precipitation, the relative changes between the historical data and the GCM output were applied to the measured historical values:

$$P'_{GCM,fut} = P_{meas} \times \left(\overline{P}_{GCM,fut} / \overline{P}_{GCM,his}\right) \qquad (3)$$

where $P'_{GCM,fut}$ is the transformed future precipitation, P_{meas} is the measured 30-year (baseline period) average annual precipitation, $\overline{P}_{GCM,fut}$ is the average future GCM precipitation, and $\overline{P}_{GCM,his}$ is the average historical GCM precipitation.

Second, the MIROC3.2 HiRes data were downscaled using the change factor (CF) method (Diaz-Nieto and Wilby, 2005; Wilby and Harris, 2006; Park et al., 2009). The two key assumptions of the CF method approach are (1) that the relationship between macroclimates and microclimates is constant over time and (2) that model bias is constant over time. These are assumptions of stationarity, in which spatial and temporal patterns from the observed 20th century data set are projected to a future climate period despite the possibility that climate patterns or proportion of model bias might otherwise have changed (Wilby et al., 2004; Diaz-Nieto and Wilby, 2005).

The CF method cannot be used to explore transient changes in the local climate scenario, which means that the data variability and the number of days with rain remain unchanged because the method is calculated for a specific year. In addition, the spatial pattern of the present climate will remain unchanged in the future. Therefore, the CF method cannot reflect future changes in precipitation patterns and extreme meteorological years. However, key advantages of the monthly CF approach are the ease and speed of application and the direct scaling of the scenario in line with changes suggested by the GCM (Diaz-Nieto and Wilby, 2005). The CF method is a relatively straightforward procedure for constructing regional climate change scenarios and has been widely used for the rapid assessment of climate change impacts (Arnell, 2004; Diaz-Nieto and Wilby, 2005).

The downscaling procedure is as follows. First, the monthly mean precipitation, temperature, wind speed, relative humidity, and solar radiation from 30 years (1977-2006) of data were calculated, and the values were adopted as a baseline period for downscaling. Next, the monthly mean changes in the equivalent variables from the climate change scenario of MIROC3.2 HiRes were calculated. Finally, the percentage changes in the monthly means of the weather variables were applied to a selected base year.

Monthly mean changes in equivalent variables from the 30 years of observed data and the climate data for three future time periods (2010-2039, 2040-2069, and 2070-2099) were calculated for the MIROC3.2 HiRes grid cell. The percentage changes in the monthly means were applied to all weather data in the year 2000 for each weather station. The 2000 data were selected as a base year for future assessment because 2000 was a typical meteorological year with precipitation and temperature values similar to the average values for the 30-year period (1977-2006) for the six weather stations.

CLUE-s Land Use Change Model

The CLUE-s model is comprised of two parts: a non-spatial demand module, and a spatially explicit allocation procedure. The non-spatial module calculates the area change for all land uses at the aggregate level (Verburg et al., 2002). In the spatially explicit allocation procedure, non-spatial demands are converted into land use changes at various locations in the study area. Yearly land use demands, which have to be defined prior to the allocation procedure, can be set using various approaches, such as economic models (Lin et al., 2007). The allocation is based on a combination of empirical and spatial analyses and dynamic modeling (Verburg et al., 2002). In addition to land use, data were collected that represent the assumed factors driving the land use changes (Turner et al., 1993; Kaimowitz and Angelsen, 1998; Lambin et al., 2001). The relationships between land uses and the driving factors were evaluated by following stepwise logistic regression (Verburg et al., 2002):

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \qquad (4)$$

where P_i is the probability of a grid cell for the occurrence of the considered land use type, X is the driving factor, and β_i is the coefficient of each driving factor in the logistical model.

The relative operating characteristic (ROC) curve (Swets, 1973; Mason, 1982; Harvey et al., 1992) was used to evaluate the goodness of fit of the regression models. The ROC is based on a curve relating the true-positive proportion and the false-positive proportion for a range of cutoff values in classifying the probability. The ROC statistic measures the area beneath this curve and varies between 0.5 (completely random) and 1 (perfect discrimination) (Zhu et al., 2010). Validation for this type of study typically includes calculation of the kappa (κ) coefficient (Cohen, 1960). The kappa coefficient is one of the most popular measures in addressing the difference between actual and chance agreement; κ values greater than 0.8 (i.e., >80%) represent strong agreement, and values between 0.6 to 0.8 represent high agreement between the classification map and the ground reference information.

Next, the spatial policy (such as the development-restricted area) and the decision rules for changing from one land use to another were specified for the study watershed. For each land use type, its specific conversion elasticity was specified to account for the typical conversion conditions of the different land uses. The model allocates a land use change in an iterative procedure, using probability maps, decision rules in combination with actual land use maps, and the demand for the different land uses (Verburg et al., 2002). For each grid cell, the total probability is calculated for each land use type based on the logistical model results, elasticity of the land use change, and the iteration variable. Each cell is assigned to the land use with the highest probability. For land use types where the allocated area is smaller than the demand area, the value of the iteration variable is increased. The iteration is continued until the aggregated cover of all grid cells equals the land use demand (Lin et al., 2007). The model procedure has been described in detail by Verburg and Overmars (2009).

Results and Discussions

SWAT Calibration and Validation

In this study, twelve parameters were selected for calibration of three subwatersheds (table 2). Among these parameters, five are associated with snow processes (SFTMP, SMTMP, SMFMX, SMFMN, and TIMP). The other parameters are related to runoff (CN2), groundwater (ALPHA_BF and GW_DELAY), soil (SOL_AWC), channel (CH_N and CH_K2), and evaporation (ESCO) processes. Most of the parameters were adjusted on a trial-and-error basis within reasonable limits after due consideration of physical characteristics, and final values were selected by statistical results (table 3).

The observed and simulated daily streamflow at the three locations matched reasonably well (fig. 2). NSE values were typically greater than 0.50, which indicates satisfactory simulation according to Moriasi et al. (2007) (table 3). However, it can be seen that the flows during the winter period (December-February) were consistently underestimated by the model, especially for YW #2, and that the peak flows were also overestimated for some years (fig. 2).

Errors in low flow predictions are attributed to uncertainties in quantifying the storage function of forest soils and in estimating soil and groundwater parameters. The peak runoff errors may be caused by poor simulation of anthropogenic effects on runoff mechanisms in paddy fields (728 km^2). Unlike typical runoff mechanisms, rice paddy hydrology is managed with irrigation scheduling and levee height adjustment, which increase the difficulty of simulating water budgets. For example, irrigating before rainfall and draining after rainfall can significantly affect streamflow; however, irrigation options were not input and factored into the simulation in this study because of limited data.

Table 2. Calibrated model parameters at three subwatersheds.

Parameters[a]	Description	Calibration Range	Adjusted Value YW #1	Adjusted Value YW #2	Adjusted Value CD
ALPHA_BF	Baseflow alpha factor (days)	0 to 1	0.35	0.50	0.30
CH_N	Manning coefficient for channel	0.01 to 0.3	0.01	0.01	0.01
CH_K2	Effective hydraulic cond. of main channel	-0.01 to 150	50	70	70
CN2	Curve number adjustment ratio	±20%	9	2	9
ESCO	Soil evaporation compensation	0 to 1	0.8	0.8	0.4
GW_DELAY	Groundwater delay time (days)	0 to 500	120	110	110
SOL_AWC	Available water capacity	±20%	5	--	--
SFTMP	Snowfall temperature (°C)	0 to 5	0.5	0.5	0.5
SMTMP	Snowmelt base temperature (°C)	0 to 5	1	1	1
SMFMX	Max. snowmelt factor (mm °C^{-1} d^{-1})	0 to 10	7	7	7
SMFMN	Min. snowmelt factor (mm °C^{-1} d^{-1})	0 - 10	4.5	4.5	4.5
TIMP	Snowpack temp. lag factor	0.01 - 1	0.5	0.5	0.5

[a] Source: Neitsch et al. (2002b).

Table 3. Statistical summary of the model calibration and validation results.

Gauging Station	Statistic		Calibration 1998	Calibration 1999	Calibration 2000	Validation 2001	Validation 2002	Validation 2003
YW #1	Rainfall (mm $year^{-1}$)		1421.1	1294.4	1016.6	766.0	1307.0	1432.6
	Streamflow (mm $year^{-1}$)	Obs.	705.5	882.8	726.8	332.2	777.0	1166.4
		Sim.	1122.4	930.2	712.4	280.4	791.5	1266.3
	Runoff ratio (%)		49.6	68.2	71.5	43.4	59.5	81.4
	Evaluation criteria (mm d^{-1})	RMSE	2.91	3.95	1.54	1.34	3.18	2.61
		R^2	0.84	0.56	0.89	0.50	0.82	0.80
		NSE	0.72	0.56	0.91	0.46	0.80	0.79
YW #2	Rainfall (mm $year^{-1}$)		1398.0	1497.0	1253.0	946.0	1645.0	1780.5
	Streamflow (mm $year^{-1}$)	Obs.	932.5	966.7	704.7	437.1	1072.6	1371.7
		Sim.	1040.3	913.1	620.4	402.2	925.9	1325.8
	Runoff ratio (%)		66.7	64.6	56.2	46.2	65.2	77.0
	Evaluation criteria (mm d^{-1})	RMSE	2.97	4.56	1.40	0.67	4.31	3.04
		R^2	0.68	0.67	0.92	0.76	0.77	0.54
		NSE	0.54	0.56	0.90	0.73	0.69	0.32
CD	Rainfall (mm $year^{-1}$)		1503.6	1427.0	1155.1	820.9	1441.7	1703.9
	Streamflow (mm $year^{-1}$)	Obs.	871.5	804.1	608.5	310.7	840.8	1051.1
		Sim.	1044.8	897.9	691.2	385.2	889.5	1235.2
	Runoff ratio (%)		58.0	56.3	52.7	37.8	58.3	61.7
	Evaluation criteria (mm d^{-1})	RMSE	2.08	2.67	1.29	0.76	2.03	1.94
		R^2	0.87	0.84	0.95	0.81	0.95	0.84
		NSE	0.78	0.75	0.89	0.64	0.92	0.79

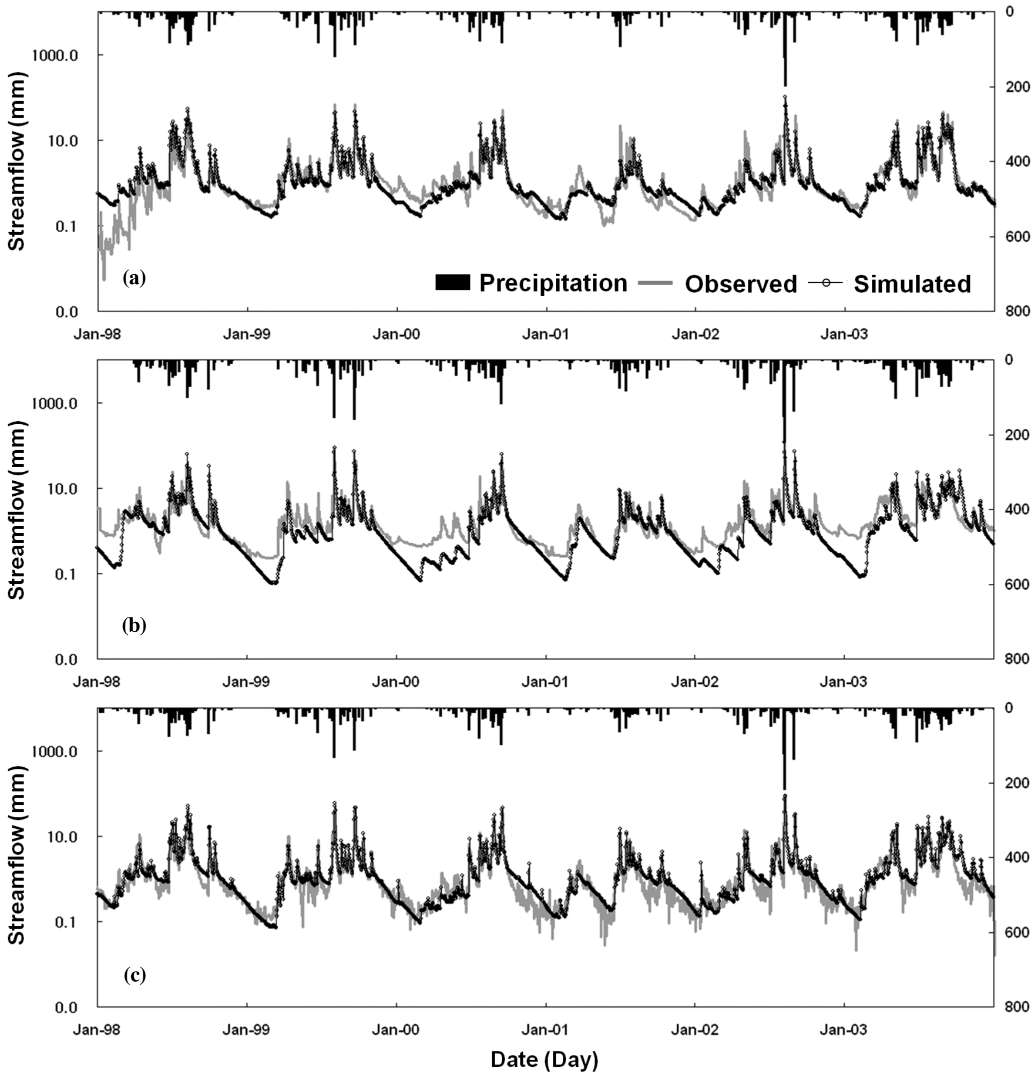

Figure 2. Comparison of the observed and simulated streamflows at three locations: (a) YW #1, (b) YW #2, and (c) CD.

MIROC3.2 HiRes A1B Future Climate Data

As described above, the bias of the MIROC3.2 HiRes A1B data was initially corrected using 30 years (1977-2006) of observed data. Figure 3 shows the corrected MIROC3.2 HiRes annual precipitation and temperature. Secondly, the bias-corrected data were downscaled by applying the CF statistical downscaling method. The mean annual precipitation values of the observed and MIROC3.2 HiRes (20C3M) data during the last 30 years were 1261 and 1371 mm, respectively. Precipitation in 1982, 1994, 1996, and 2001 was below average, while 1980, 1990, and 2006 were wet years with more than 1500 mm of precipitation. However, as seen in figure 3, the MIROC3.2 HiRes simulated data exceeded actual precipitation for most years from 1977 to 2006, which is attributed to the difference in spatial scale between the MIROC3.2 HiRes grid data and the ground observed point data. Figure 4 shows the monthly changes in the 2010-2039, 2040-2069, and 2070-2099 downscaled precipitation and temperature based on the 2000 data. The average bias of the MIROC3.2 HiRes temperature was +2.20°C. Regarding the relatively high elevation of the watershed within the MIROC3.2 HiRes grid cell, it seems that the correction was performed in an acceptable direction. The future 2070-2099 temperature increased by 6.1°C in winter, 5.3°C in autumn, 4.3°C in summer, and 3.6°C in spring. The future precipitation increased 12.9% for 2010-2039, 23.1% for 2040-2069, and 34.4% for 2070-2099, with the exception of August and September. The seemingly large increase in future precipitation likely resulted from the increasing trend observed from 1977 to 2006.

Future Predicted Land Use by CLUE-s

Probability maps of each land use type were prepared from the logistic regression results. The forward stepwise logistic regression and ROC analyses between five land use types and 11 driving factors were conducted using SPSS (SPSS, 2005). Table 4 summarizes the logistic regression model results. The ROC values in the model ranged from 0.602 to 0.778, showing correlation for the spatial variation of land use patterns. Looking at the derived coefficients of each land use, forest land use was dependent on all 11 driving factors, and urban land use was fully dependent on the distance factors. The grass and agriculture land uses showed a mixed relationship with the altitude, distance, and soil driving factors. Bare field was independent of the soil factors. The high ROC values indicate that the spatial pattern of five land use types can be reasonably explained by 11 driving factors. To evaluate the

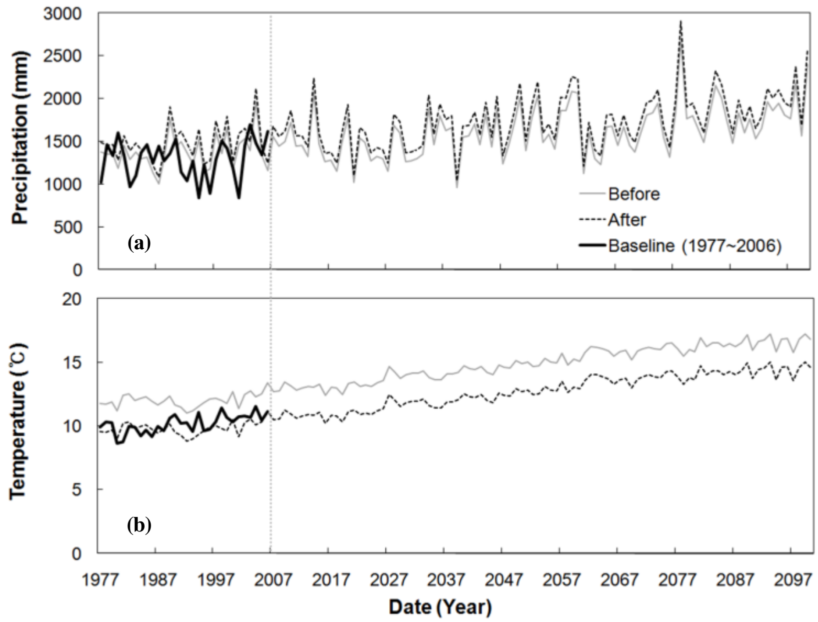

Figure 3. Bias-corrected MIROC3.2 HiRes A1B: (a) annual precipitation and (b) temperature.

CLUE-s generated land use for the study watershed, the 2000 Landsat land use and CLUE-s land use were compared. The kappa coefficient was 0.79, representing high agreement between two land uses.

By applying the derived regression models and the prepared land uses, the future land uses for 2010-2039, 2040-2069, and 2070-2099 were predicted (fig. 5). The CLUE-s model in this study was applied by combining the driving factors, land use demands, and government policies. The highest degree of change occurred more frequently at low elevations, around Lake Chungju and urban areas. By 2070-2099, forest and agriculture are predicted to decrease by 6.2% and 1.6%, respectively, compare to 2000. Meanwhile, urban, bare field, and grass increased by 1.7%, 1.3%, and 4.8%, respectively. The big increase in grass within the watershed was the result of steady pasture construction during the 1970s and 1980s and golf course construction in the 1990s. According to the Korea National Statistical Office (2008), golf course land use has increased dramatically since 1990. The increasing trend of grass area is likely to continue into the future due to increasing demand for golf courses and pasture farming. This result is consistent with the study by Ahn et al. (2008) for future land use change using the CA-Markov technique, which also showed a tendency of decreasing forest and paddy land and increasing urban, grassland, and bare fields by 2090.

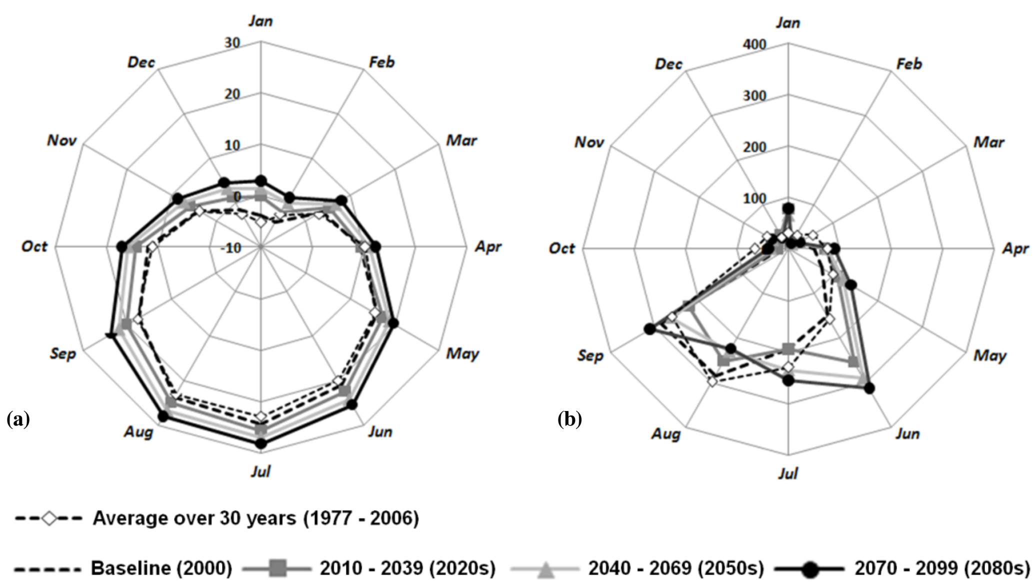

Figure 4. Monthly changes in the 2010-2039, 2040-2069, and 2070-2099 MIROC3.2 HiRes A1B (a) temperature and (b) precipitation based on a 2000 baseline.

Table 4. Logistical regression model results for the five land use types with 11 driving factors.

Driving Factor	Urban	Bare Field	Grass	Forest	Agricul-ture
	Land Use Type[a]				
Altitude	--	0.0014	0.0010	0.0019	0.0007
Slope	--	--	--	0.0081	--
Aspect	--	-0.0024	--	-0.0006	--
Distance to nat'l road	-0.0003	-0.0001	-0.0001	-0.0001	-0.0002
Distance to local road	--	--	--	0.0002	--
Distance to city	-0.0001	--	-4.0E-05	0.0001	--
Distance to stream	-0.0004	--	--	4.0E-05	--
Soil drainage class	--	--	--	-0.1256	-0.0960
Soil type	--	--	0.1100	0.0774	--
Soil depth	--	--	--	-0.0027	--
Land use in the soil	--	--	--	-0.0346	--
Constant	-3.5653	-5.2972	-4.800	-1.6195	-2.2253
ROC	0.7340	0.7480	0.6020	0.7780	0.6460

[a] -- = value not significant at the 0.05 significance level, and thus excluded from the model.

Impact of Climate and Land Use Changes on Watershed Hydrology

By applying the future MIROC3.2 HiRes downscaled climate and CLUE-s land use conditions, SWAT was run to evaluate the future impact of climate and land use changes on watershed hydrology (specifically evapotranspiration, surface runoff, groundwater recharge, and streamflow). The large predicted increase in precipitation (and the resulting increasing precipitation inputs to SWAT) had dramatic effects on watershed hydrology. Thus, climate change created much larger impacts than land use change. Table 5 shows a summary of the future predicted hydrologic components for three scenarios: land use change only, climate change only, and land use change with climate change. The future evapotranspiration and surface runoff were more affected by climate change than by land use change. The 2070-2099 evapotranspiration showed an increase of +23.1% with climate change only, but an increase of +29.4% with the land use and climate change scenario. The 2070-2099 surface runoff showed an increase of +47.7% with climate change only, but an increase of +52.0% with the land use and climate change scenario. The climate change impacts on watershed hydrology are larger because their relative changes for future precipitation (13% to 34%) are larger than for future land use (less than 10%, as shown in fig. 6).

As seen in table 5, the effect of both land use change and climate change are larger for surface runoff and streamflow than for ET and groundwater recharge. The impact of future land use change only on ET, surface runoff, groundwater recharge, and streamflow had maxima of +7.8%, +7.6%, +6.7%, and +10.8%, respectively, in 2070-2099. The 2070-2099 groundwater recharge showed an increase of +28.1% with climate change only, but an increase of +38.5% with the land use and climate change scenario. The 2070-2099 streamflow showed an increase of +39.8% with climate change only, but an increase of +55.4% with the land use and climate change scenario. The results show that future land use changes need to be considered in conjunction with climate change, which in this case is a large increase in pre–

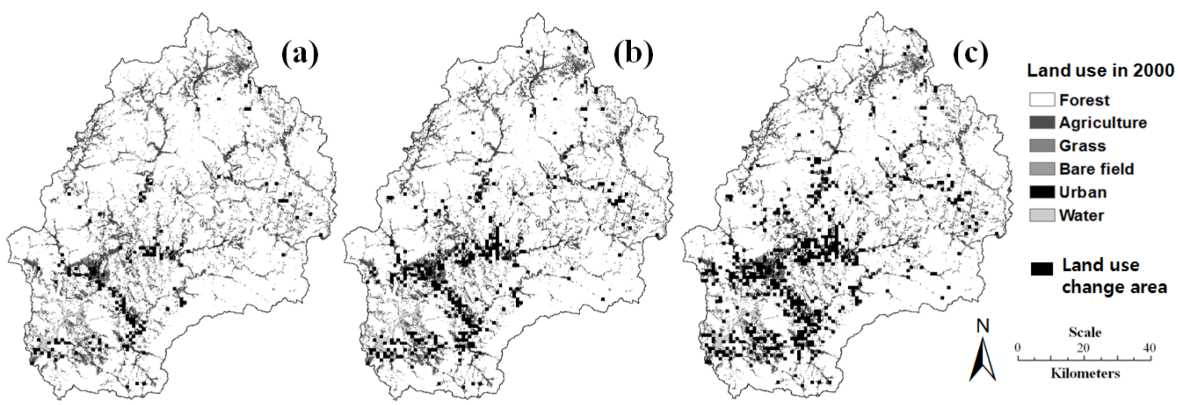

Figure 5. Comparison of the land use change areas in (a) 2010-2039, (b) 2040-2069, and (c) 2070-2099 based on 2000 land use.

Table 5. Summary of the future predicted annual hydrological components by climate and land use change scenarios (values in parentheses indicate percent of increase based on baseline).

Scenario	Years	Rainfall (mm)	ET (mm)	Surface Runoff (mm)	Groundwater Recharge (mm)	Streamflow (mm)
Baseline	2000	1155	407	419	233	691
Land use	2010-2039	1155 (0.0)	421 (3.4)	423 (0.9)	234 (0.6)	712 (3.0)
	2040-2069	1155 (0.0)	428 (5.1)	436 (4.0)	241 (3.7)	743 (7.5)
	2070-2099	1155 (0.0)	439 (7.8)	451 (7.6)	248 (6.7)	766 (10.8)
Climate	2010-2039	1304 (12.9)	454 (11.5)	470 (12.2)	263 (13.1)	773 (11.8)
	2040-2069	1422 (23.1)	479 (17.7)	538 (28.3)	279 (19.9)	862 (24.7)
	2070-2099	1552 (34.4)	501 (23.1)	619 (47.7)	298 (28.1)	966 (39.8)
Land use and climate change	2010-2039	1304 (12.9)	460 (13.0)	474 (13.1)	270 (16.1)	811 (17.3)
	2040-2069	1422 (23.1)	491 (20.6)	569 (35.7)	293 (26.0)	953 (37.9)
	2070-2099	1552 (34.4)	527 (29.4)	637 (52.0)	322 (38.5)	1074 (55.4)

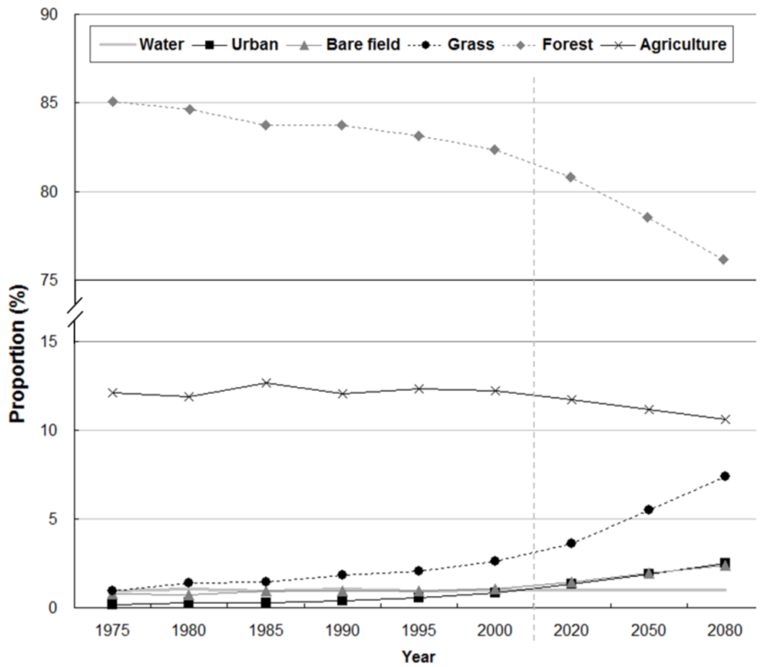

Figure 6. Proportion of future predicted land uses by CLUE-s.

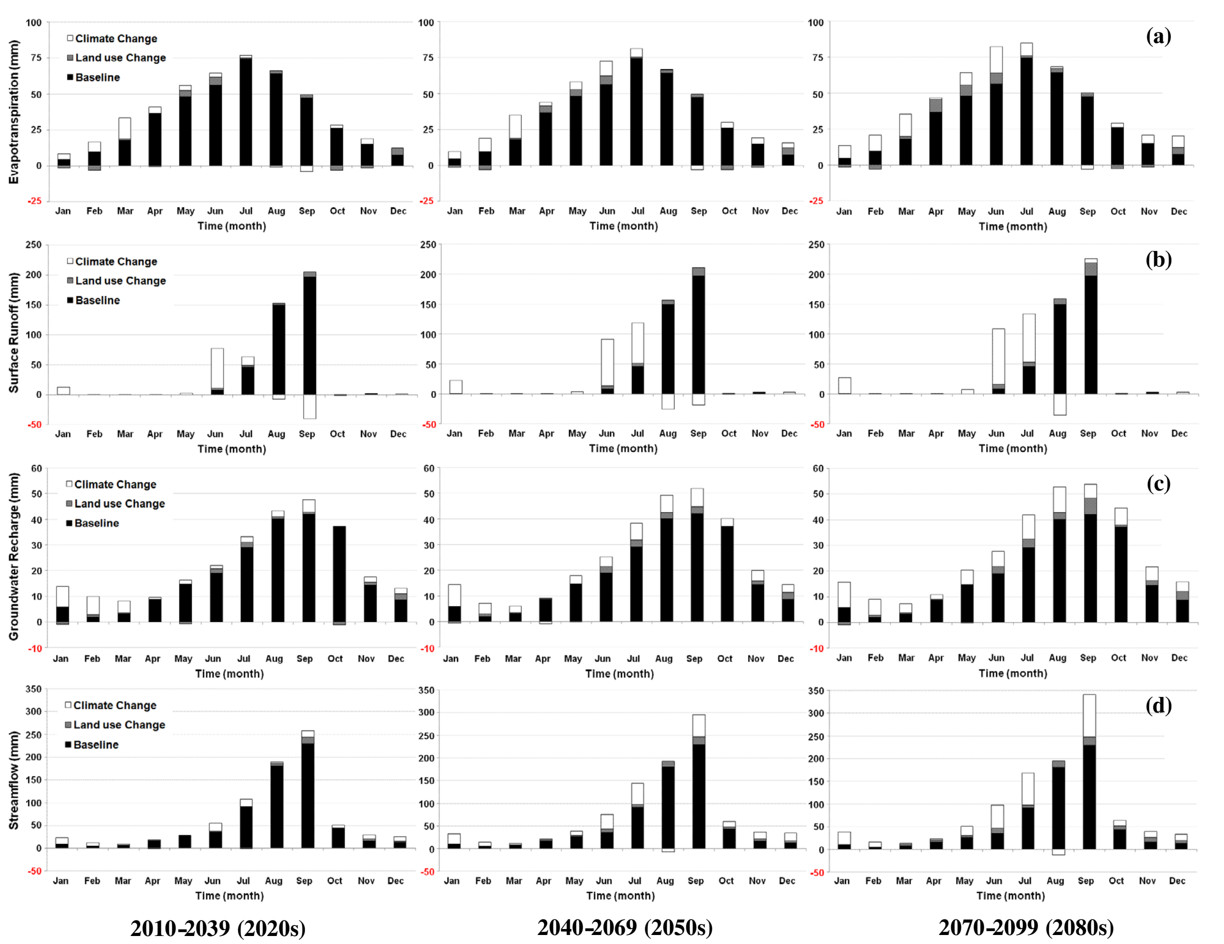

Figure 7. Future monthly change in each hydrological component by MIROC3.2 HiRes climate and CLUE-s land use change scenarios: (a) evapotranspiration, (b) surface runoff, (c) groundwater recharge, and (d) streamflow.

dicted precipitation, because of their cumulative impacts on watershed hydrology.

Another key for the long-term planning and management of water resources is consideration of the seasonal effects of climate and land use change (Park et al., 2009). In this study, land use change increased ET up to +63.6% (12.4 mm) in December of 2010-2039, while climate change increased ET up to +183.4% (13.7 mm) in January of 2070-2099 (fig. 7). For surface runoff, climate change increased surface runoff in June (+1099.9%, 101.4 mm) and July (+173.1%, 126.9 mm) of 2070-2099 but decreased it in August (-23.3%, 115.0 mm) of 2070-2099 and September (-19.9%, 157.7 mm) of 2010-2039. The land use change (+1.7% increase of impervious area in 2070-2099) increased surface runoff up to +88.5% (15.9 mm) in June of 2070-2099. For groundwater recharge, land use change resulted in changes between -14.9% (5.0 mm) in January of 2010-2039 and +48.1% (3.1 mm) in February of 2040-2069, while climate change generally resulted in increases, up to +338.6% (9.2 mm) in February of 2010-2039. For streamflow, land use change with climate change resulted in a +323.3% (39.4 mm) increase in January of 2070-2099. The land use change increased streamflow +55.2% (26.4 mm) in November of 2070-2099, while the climate change increased streamflow up to +304.0% (37.6 mm) in January of 2070-2099. The primary factor in the increased surface runoff and streamflow was the 34.4% increase in precipitation for 2070-2099; however, the 6.2% decrease of forest and 1.7% increase of urban areas also contributed to the increases.

Summary and Conclusions

This study evaluated the impacts of future potential climate and land use changes on the hydrologic components of a 6642 km^2 watershed in South Korea. For the future climate conditions, the MIROC3.2 HiRes GCM A1B data for 2010-2039, 2040-2069, and 2070-2099 were prepared using a change factor simple statistical downscaling method. The future 2070-2099 temperature changes were +6.1°C in winter, +5.3°C in autumn, +4.3°C in summer, and +3.6°C in spring. Monthly precipitation was predicted to increase in every month except August and September, and dramatic increases in annual precipitation totals were predicted (+397 mm by 2070-2099). The future land uses were predicted by CLUE-s using Landsat satellite images from 1975 to 2000. By 2070-2099, forest and agriculture land uses were predicted to decrease by 6.2% and 1.6%, while urban, bare field, and grass land uses were predicted to increase by 1.7%, 1.3%, and 4.8%, respectively, based on a 2000 baseline.

The assessment of watershed hydrological components in the future was conducted by inputting the predicted climate and land use data into SWAT, which was calibrated and validated with a total of six years of stream flow data from the watershed. The future evapotranspiration was more affected by climate change than by land use change. The 2070-2099 ET showed an increase of +23.1% due to climate change only, but an increase of +29.4% due to land use and climate changes. The 2070-2099 groundwater recharge showed an increase of +28.1% due to climate change only, but an increase of +38.5% due to land use and climate changes. The 2070-2099 streamflow showed an increase of +39.8% due to climate change only, but an increase of +55.4% due to land use and climate changes. The results indicate that the predicted dramatic increases in precipitation will have a greater impact on watershed hydrology than the predicted land use changes, but that land use change also plays an important role because it can magnify these impacts. Therefore, to mitigate negative hydrologic impacts and utilize positive impacts, both land use and climate changes should be considered in water resource planning for the Chungju dam watershed.

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