Abstract:

This study aims to evaluate nutrient flux to the coast from the inland areas of Shiretoko in order to understand the key factors controlling the ecological systems of the coast. As an external force, rainfall is considered one of the most significant components controlling nutrient supply to coastal systems in this area. Therefore, to estimate nutrient supply in the future, the bias correction was applied by using Meteorological Research Institute Global Climate Model, which shows good agreement with Automated Meteorological Data Acquisition System data. A synthetic generation technique is used to produce hourly rainfall data, which is necessary for evaluating nutrient supply in Shiretoko. The robustness of the duplicated hourly rainfall intensity was investigated, which reveals that its standard deviation controls nutrient flux when nonlinearity becomes stronger for the evaluation of nutrient supply from a river basin.

KEYWORDS MRI-GCM; nutrient concentration; World Heritage; Shiretoko; Rausu; nutrient circulation

INTRODUCTION

On the Shiretoko Peninsula, nutrient circulation between inland areas and the coastal ocean is prevalent, even though the peninsula itself is only 20 km wide. This linked terrestrial-ocean system is one of the most significant factors in Shiretoko’s designation as a World Heritage area. However, the nutrient cycling of the area may be changing in response to climate change. Drift ice around Shiretoko has been shown to play an important role in the supply of nutrients from the ocean to the coastal areas of the Shiretoko Peninsula, but the amount of ice is declining. The decrease in drift ice may also decrease fish habitat, which further alters nutrient cycling and damages of the ecological value of Shiretoko. Since climate change may also change the flux of nutrients from the land to ocean, effective policy making demands an environmental assessment tool for evaluating the impact of climate change in the near future on Shiretoko.

There have been many studies related to the analysis of Global Climate Model (GCM). Widmann et al. (2003) demonstrated that statistical downscaling using singular value decomposition (SVD) (Bretherton, 1992; Prohaska, 1976) can duplicate field observation data with high accuracy. Furthermore, Harpham and Wilby (2005) applied many different downscaling methods to GCM data, which demonstrated high applicability and high duplicability from the view point of regional scale. Giorgi and Mearns (1991) and Hewitson and Crane (1996) reviewed previous studies related to the downscaling, and Zorita and Storch (1999) introduced many downscaling methods.

The study area, the Shiretoko Peninsula, has a longitudinal length of 50 km and width of 15 km, which corresponds to only about three meshes of the Meteorological Research Institute GCM with the 20-km mesh horizontal resolution (MRI-GCM20; Mizuta et al. 2006). Since there is only one Automated Meteorological Data Acquisition System (AMeDAS) station in Shiretoko at Rausu, it may not be necessary to analyze the spatial distribution of MRI-GCM20 when downscaling is applied. Therefore, we made an attempt to apply the simplest method – correction using average and standard deviation of the MRI-GCM20.

As Shiretoko is located in a cold region, there are two types of nutrient supply that are the main target of this study; nutrient supply due to rainfall, and nutrient supply due to the snow melt. The controlling factors for the nutrient supply due to the rainfall and the snow melt are different; the former being rainfall intensity only, but the latter including snow depth, air temperature, wind direction, wind speed, and solar radiation. In this study, we focus on the nutrient supply due to the rainfall, since the total river discharge from river basins due to the rainfall is larger than the snow melt, suggesting that the nutrient supply due to the rainfall may dominate. Firstly, we mention the application of the bias correction which is one of the simplest downscaling techniques into MRI-GCM20, then the applicability of the estimated rainfall intensity using MRI-GCM20 is discussed in terms of nutrient supply.

METHODS

To estimate nutrient supply from the inland areas of the Shiretoko Peninsula to the coast, the Rausu River basin was selected as the target area because the AMeDAS station data located in the Rausu River basin and it is the largest basin on the peninsula. It has been revealed that in the future spatial and temporal changes in rainfall intensity will increase at higher latitudes (IPCC 2007), such as Shiretoko. Thus, we investigated the rainfall intensity from May to October of 1980 to 1999 at the Rausu AMeDAS station. Although the 1 h interval rainfall intensity data from MRI-GCM20 is available, the other 1 h interval data, such as surface temperature, surface specific humidity and surface velocity, are not provided, which are necessary for the analysis of the snow melt. Also, since 6 h interval data is commonly provided from the other GCM, it is necessary...
for multi-model analysis to develop the method using 6 h interval data. Therefore, the 20 year rainfall intensity with an interval of 6 h from MRI-GCM20 (hereafter, GCM20/6h) was used for the bias correction and the 20 year average and standard deviation of 6 h average AMeDAS data (hereafter, AMeDAS/6h) was computed in order to make comparisons with the GCM20/6h at 17 grid points around the Rausu AMeDAS station (Figure 1 and Table I). Since the main target of this study was to estimate nutrient supply from inland areas to the coast, and not to develop a downscaling technique, coupled with the fact that the necessary rainfall intensity data was available from the Rausu AMeDAS station, a downscaling technique taking into account spatial distributions, such as proposed by Widmann et al. (2003), was not considered necessary. Instead the simplest method using average and standard deviation was applied. The average and standard deviation of AMeDAS/6h from May to October of 1980 to 1999 was computed as 0.226 mm h\(^{-1}\) and 0.884 mm h\(^{-1}\), respectively. In contrast, the average and standard deviation of GCM20/6h at 17 grid points around Rausu AMeDAS station was found to be less than AMeDAS/6h. A correction was applied using the average and standard deviation (Equations (1) to (4) and Figure S1).

\[
\text{rain}_{\text{modified}} = \text{amp}_1 \times \text{rain}_{\text{GCM20}},
\]

\[
\text{amp}_1 = \frac{\Sigma \text{rain}_{\text{AMeDAS}}}{\Sigma \text{rain}_{\text{GCM20}}},
\]

\[
\text{rain}_{\text{modified}} = \text{amp}_2 \times (\text{rain}_{\text{modified}} - \text{AVE}_{\text{AMeDAS}}) + \text{AVE}_{\text{AMeDAS}},
\]

\[
\text{amp}_2 = \frac{\Sigma \text{SD}_{\text{AMeDAS}} \Sigma \text{rain}_{\text{GCM20}}}{\Sigma \text{SD}_{\text{GCM20}} \Sigma \text{rain}_{\text{AMeDAS}}},
\]

where \(\text{rain}_{\text{GCM20}}\) is the rainfall intensity of GCM20/6h, \(\text{rain}_{\text{AMeDAS}}\) is the rainfall intensity of AMeDAS/6h, \(\text{AVE}_{\text{GCM20}}\) is the 20 year average of rainfall intensity of GCM20/6h, and \(\text{AVE}_{\text{AMeDAS}}\) is the 20 year average of rainfall intensity of AMeDAS/6h.

The four best GCM20/6h data were at no1, no2, no5 and no6, and there was no large differences in the correction coefficients, \(\text{amp}_1\) and \(\text{amp}_2\), among the four stations. Therefore, the histogram of no1, no2, no5 and no6 was compared with the AMeDAS/6h (Figures 2 to 3 and Figure S2), which showed that the histogram of no6 was the most similar to the AMeDAS/6h, being the closest to Rausu AMeDAS station though there was no large differences among them from the Kolmogorov-Smirnov test. Thus, GCM20/6h at no6 was chosen as the data set for the estimation of nutrient supply in the Rausu River basin.

Since the summits of the mountains in the Shiretoko Peninsula are about 1500 m high in a peninsula width of 20 km, the response of river discharge to rainfall is very rapid and the lag between the peaks of rainfall and discharge is only about a few hours. Therefore, 6 h interval rainfall data is not temporally fine enough to analyze discharge peaks, resulting in less precise estimation of nutrient flux. One hour interval rainfall data is thus necessary and synthetic generation (Menabde and Sivapalan, 2000) was applied to generate 1 h interval data from 6 h interval data. Synthetic Generation is a method for duplicating 1 h interval data from a certain number of hours interval data by making a cumulative density function (cdf) of the relationship between two different average data sets. Firstly, 2 h interval data is produced by averaging 1 h interval AMeDAS data. Since the absolute difference of rainfall intensity between 1 h and 2 h interval data is the same, the probability density function (pdf) and cdf of the absolute difference can be made as pdf\(_{2-1}\) and cdf\(_{2-1}\), respectively (Figure S3). Secondly, the same procedure is applied to compute the absolute difference between 2 h and 4 h interval data and the absolute difference between 3 h and 6 h interval data, which enable us to make pdf\(_{4-2}\), pdf\(_{6-3}\), cdf\(_{4-2}\) and cdf\(_{6-3}\), respectively. The pdf was modeled using Gamma distribution, which showed good

![Figure 1. Rausu AMeDAS station and MRI-GCM20 grid points from no1 to no17.](image)

Table I. Average and standard deviation of rainfall intensity (mm hr\(^{-1}\)) from May to October of 1980 to 1999 at Rausu AMeDAS station and MRI-GCM20 grid points from no1 to no17.

|        | Average | Standard deviation |
|--------|---------|--------------------|
| AMeDAS | 0.226   | 0.884              |
| GCM20no1 | 0.164 | 0.579              |
| GCM20no2 | 0.185 | 0.596              |
| GCM20no3 | 0.161 | 0.524              |
| GCM20no4 | 0.163 | 0.581              |
| GCM20no5 | 0.180 | 0.603              |
| GCM20no6 | 0.179 | 0.588              |
| GCM20no7 | 0.138 | 0.467              |
| GCM20no8 | 0.158 | 0.567              |
| GCM20no9 | 0.153 | 0.554              |
| GCM20no10 | 0.154 | 0.588              |
| GCM20no11 | 0.158 | 0.541              |
| GCM20no12 | 0.134 | 0.456              |
| GCM20no13 | 0.157 | 0.559              |
| GCM20no14 | 0.139 | 0.525              |
| GCM20no15 | 0.133 | 0.504              |
| GCM20no16 | 0.142 | 0.517              |
| GCM20no17 | 0.139 | 0.494              |
agreement as revealed by Menabde and Sivapalan (2000) and high applicability of the synthetic generation (Figure S4). As $cdf_{2.1}$ and $cdf_{4.2}$ are almost the same shape which was confirmed by using the Kolmogorv-Smirnov test, $cdf_{3.1.5}$ was found to be duplicated using $cdf_{4.2}$ or $cdf_{2.1}$.

Three hours interval data was produced from GCM20/6h no6 data by using $cdf_{6.3}$, which enables us to make 1.5 h interval data by using $cdf_{3.1.5}$. As 3 h rainfall intensity consists of 2 sequential 1.5 h interval data, the first 1 h of the 3 h data was made from the former 1.5 h interval data, and the third 1 h of the 3 h data was made from the latter 1.5 h interval data. The second 1 h of the 3 h data was given as the average of the former and latter 1.5 h interval data (Figure 4). Synthetic Generation showed consistent average values, with average rainfall intensity of 0.226 mm h$^{-1}$, before and after its application. This was confirmed from the comparison between duplicated 1 h interval MRI-GCM20 data (hereafter, GCM20/1h) and 1 h interval AMeDAS data (hereafter, AMeDAS/1h). However, the standard deviation of AMeDAS/1h was 1.120 mm h$^{-1}$, the standard deviation of GCM20/1h was 0.798 mm h$^{-1}$. The standard deviation of rainfall intensity is controlled by the small-scale high-intensity rainfall due to the steep slope of the mountainous areas in Shiretoko. It appears that the synthetic generation cannot duplicate such a high-intensity rain for a short period (Figure 4c). Therefore, nutrient flux estimated using GCM20/1h may not agree with the AMeDAS/1h. Thus, we made an attempt to correct the standard deviation of GCM20/1h by using Equations (3) and (4) (modified GCM20/1h), and to also use this in our estimate of nutrient flux.

**RESULTS**

The slope is steep enough to produce dominantly surface flow when it rains in the Rausu River basin, which suggests that a storage function model is highly applicable for the
reproduction of river discharge. Therefore, a storage function model was applied by using Equations (5) and (6).

$$\frac{dS}{dt} = R - Q,$$

(5)

$$S = KQ^\beta,$$

(6)

where $S$ is the amount of storage, $Q$ is the river discharge, $R$ is the effective rainfall intensity, and $K$ and $P$ are the coefficients for the storage function model.

It is revealed that $K$ can be taken to be 0.8 to 1.0 and $P$ 0.6 to 1.1, when a storage function model is applied to cold region such as Hokkaido. Nutrient concentrations are demonstrated to be a function of river discharge (Equation (7)), in which $\beta$ is taken from 0 to 2. In this study, to understand the duplicability of nutrient supply using both the GCM20/1h and modified GCM20/1h compared to the AMeDAS/1h, the total amount of nutrient integrated from May to October of 1980 to 1999 was computed by changing the value of $K$, $P$, and $\beta$. Comparisons are expressed relative to the total nutrient from AMeDAS/1h (Figure 5).

$$\text{Nutrient} = \alpha \ast Q^\beta,$$

(7)

where Nutrient is the nutrient flux, and $\alpha$ and $\beta$ are the coefficients for nutrient concentration.

Since non-dimensional values are used, $\alpha$ can be taken as an arbitrary value and can be ignored for the comparisons. When $\beta$ is zero, the estimated total nutrient flux was the same among AMeDAS/1h, GCM20/1h and modified GCM20/1h because the nutrient concentration $\alpha$ does not change with river discharge (Figures 5a and 5b). When $\beta$ is 1, the total nutrient flux estimated from GCM20/1h is 15% to 20% less than the AMeDAS/1h, with modified GCM20/1h 10% less than the AMeDAS/1h (Figures 5c and 5d). When $\beta$ is 2, the total nutrient flux estimated from GCM20/1h is 40% to 50% less than the AMeDAS/1h, and 15% less to 5% larger for modified GCM20/1h (Figures 5e and 5f). It is conceivable that the larger the non-linearity of nutrient concentrations becomes, the larger the error; for example, when $K$ and $P$ are taken to be smaller values further from 1.

**CONCLUSIONS**

The bias correction was applied to reproduce rainfall intensity at the AMeDAS Rausu station from May to October of 1980 to 1999 by using GCM20/6h. The best fit GCM20/6h data was selected from 17 mesh grid points by using the average, standard deviation and histogram of rainfall intensity. As slopes are very steep on the Shiretoko Peninsula and peak discharge lag is only a few hours, 1 h interval rainfall intensity data was required in the analysis. Therefore, Synthetic Generation was applied to convert 6 h interval data into 1 h interval data, which shows that the estimated average rainfall intensity is consistent with the AMeDAS data, but its standard deviation is less than the AMeDAS data because of the small-scale strong rainfall intensity for a short period. The duplicability of total nutrient flux using both GCM20/1h and modified GCM20/1h was investigated by comparing with the total nutrient flux obtained from AMeDAS/1h. As a result, when $\beta$ is from 0 to 2, the modified GCM20/1h data estimates 20% less than the AMeDAS/1h. Even when $\beta$ is 2, which means that non-linearity is very large, the modified GCM20/1h data estimates the maximum to be 15% less than the AMeDAS/1h. Although the bias correction was applied successfully in this study, the applicability depends on the shape of pdf of rainfall intensity. Therefore, if the downscaled rainfall intensity does not agree with field observation data statistically by using statistical test, such as the Kolmogorv-Smirnov test, the other type of downscaling should be applied, like downscaling using cdf.

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**SUPPLEMENTS**

Supplementary document including Figures S1 to S4:
- Figure S1 amp1 and amp2 for GCM20/6h at grid points from no1 to no17;
- Figure S2 Histogram of 6 h average rainfall intensity from MRI-GCM20. (a) no1, (b) no2, (c) no3, and (d) no4;
Figure S3 Schematic diagram for synthetic generation; and Figure S4 Histogram of absolute difference of rainfall intensity. Circles indicate the duplicated histogram from Gamma distribution. (a) Absolute difference value between 1 h and 2 h average, (b) Absolute difference value between 2 h and 4 h average, and (c) Absolute difference value between 3 h and 6 h average.

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