Estimating catchment scale evapotranspiration based on forest measurement using airborne LiDAR

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1. Introduction

Evapotranspiration (*ET*) is key of hydrological processes in forested catchment with 40~100% of precipitation in depending on forest stand condition and climate (Otsuki, 2016). *ET* consists of canopy interception loss (*Ei*), canopy transpiration (*Et*) and forest floor evaporation (*Ef*). Among *ET*, *Ei* is dominant component of *ET*. For instance, *Ei* becomes more than 50% of *ET* in a 32 years old Japanese cypress forest (Sun et al., 2014). Also, Lin et al (2012) reported that *Ei* was 75% of *ET* in 80-100 years old Chinese fir forest.

Based on detail field monitoring, number of studies showed that amount and rate of *Ei* differs depending on precipitation type and forest stand condition. Murai (1970) reported rate of *Ei* to precipitation in forest with 2373 stems/ha was 0.20, while that in forest with 793 stems/ha was 0.14 in coniferous forest. Park et al (2000) also reported *Ei* rate was high with high stand density condition (0.25 with 5070 stems/ha) than low stand density condition (0.14 with 3502 stems/ha) in deciduous broadleaved forests. Despite the accumulation of these studies of Ei measurement, most of the study focused on relatively small plots with 100 and 400 m^2.

Estimating *Ei* in large scale is still limited because throughfall is highly spatially varied. For overcome the problems, Komatsu et al (2015) developed the model to estimate *Ei* rate from stand density. However, that model can be applied to limited because Komatsu et al (2015) focused on cedar and cypress plantation forests. For applying the various species and stand conditions, developing *Ei* models for other species such as larch and broadleaved forest need to be conducted.

Once after developing models, accurate estimation of stand conditions with wide range of areas need to be applied. For this purpose, airborne LiDAR information is an effective approach. For instance, Oono and Sasaki (2015) estimated stand density in 15km^2 larch forest in Hokkaido.

For developing the methods for estimating *Ei* with wider areas (10km^2), the objectives of this study are (1) to develop the models from data on *Ei* for various tree species, (2) to estimate stand density using airborne LiDAR for providing the information to the *Ei* model.

2. Methodology

This study was conducted in three catchments of the Kamanashi-River tributaries, located in Hokuto City, Yamanashi Pref. (35°49′N, 138°17′E, area: 21km^2, elevation: 680 to 2200 m). The area is covered by various forest types such as deciduous broadleaved forest (such as *Fagus crenata*), evergreen coniferous forest (such as *Chamaecyparis obtuse*), and deciduous coniferous forest (*Larix kaempferi*). Mean annual precipitation and temperature are 1216 mm and 14°C respectively (AMeDAS Nirasaki: 2001 to 2020).

The models were developed as a function with *Ei* rate (*r*) and stand density (*N*) on each forest type (evergreen coniferous forest, deciduous coniferous forest and broadleaved forest) for different precipitation input as rainfall and snowfall. We collected the data for *Ei* in Japan: 20 cases for deciduous broadleaved forests during rainfall, 17 cases for coniferous forests during rainfall, 12 cases for evergreen coniferous forests during snowfall, 9 cases for deciduous coniferous forests during snowfall and 5 cases for deciduous broadleaved forests during snowfall. Developing models was conducted with SciPy.optimize. curve_fit within python 3.8. We also considered the applicability of the model developed by Komatsu et al (2015) to other tree species such as *pinus densiflora* and *Larix kaempferi*.

To estimate stand density (*N*), Digital Terrain Model (DTM) and Digital Surface Model (DSM) were created as 0.5 m resolution raster data by LiDAR data obtained in 2015 (7 points/m^2). Digital Canopy Height Model (DCHM) was calculated as difference between DSM and DTM for extracting individual tree (Popescu et al., 2002). Individual tree extraction was performed after DCHM was smoothed, using the TreeSeg function with watershed algorithm, within FUSION/LDV (McGaughey, 2010). The extracted trees were totaled for each 50m mesh to calculate *N*.

For accuracy verification of *N* based on LiDAR, field investigation was conducted on November 19 and 20, 2020. We selected 18 plots for measuring species, number of tree, height, and DBH at 10×10 m plots. In the location that was difficult to survey, manual tree extraction from LiDAR point data was conducted. Accuracy was evaluated by calculating Mean Absolute Error (MAE) taking the result of field investigation and manual tree extraction as the true value.

3. Result

3.1. Developing the models

In addition to model developed by Komatsu et al (2015) for Japanese cypress and cedar [Eq. (1)], we confirmed that equation (1) can be applicable for other coniferous forests such as *pinus densiflora*:

$$r = 0.308\{1 - \exp(-8.80 \times 10^{-4} N)\} \quad (1)$$

where *r* is rate of *Ei* in precipitation and *N* is stand density. The coefficient of determination of equation (1) was 0.35

Because we could not find the relationship between *r* and *N* in broadleaved forest, we used the relationship between Leaf Area Index (LAI) (or Plant Area Index

(PAI)) and *r* value (Toba and Ohta, 2005; [Eq. (2)]). LAI were estimated from *N* by previous studies in *Fagus crenata* forest [Eq. (3)]. The coefficient of determination was 0.08 and 0.36 respectively.

$$r = 4.13 \times 10^{-2} LAI \quad (2)$$

$$LAI = \left(\frac{N}{0.082}\right)^{0.18} \quad (3)$$

For interception of snow, *Ei* rate (*r*) was estimated by three forest type, evergreen coniferous forests, deciduous coniferous forests and deciduous broadleaved forests. In coniferous forests, we created equations to estimate *r* value from stand density (*N*) (evergreen: Eq. (4); deciduous: Eq. (5)). The coefficient of determination was 0.24 and 0.43 respectively. Because we could not find the relationship between *r* and *N* in broadleaved forest due to the small number of data, it was calculated as a uniform 5% of precipitation (Nakai et al., 1993).

$$r = \left(\frac{N}{1.43 \times 10^{7}}\right)^{0.112} \quad (4)$$

$$r = \left(\frac{N}{7.92 \times 10^{5}}\right)^{0.210} \quad (5)$$

3.2. Estimating stand density

Stand density (*N*) for each 50 m meshes were from 0 to 1595 stems/ha (Average: 534 ± 183 stems/ha, MAE: 211 ± 157 stems/ha) in the entire study area. The mean *N* and MAE on each forest type was: 531 ± 131 and 255 ± 150 stems/ha in broadleaved forests, 532 ± 136 and 117 ± 69 stems/ha in deciduous coniferous forests and 601 ± 231 and 215 ± 169 stems/ha in other coniferous forests. The mean Ei rate (*r*) was 0.15 ± 0.05 during rainfall and 0.16 ± 0.12 during snowfall in the entire study area (Figure.1). The mean *r* value during rainfall and snowfall in each forest type was 0.20 and 0.05 in broadleaved forests, 0.11 and 0.21 in deciduous coniferous forests, 0.12 and 0.32 in evergreen coniferous forests.

4. Discussion

Applying the model into the field observation data of Park et al (2000) and Murai (1970), the average relative error was 16% in Murai (1970) with larch forest, while 61% in Park et al (2000) with deciduous broadleaved forest. The relationship between LAI and *Ei* rate has a remarkably low coefficient of determination (0.08). Thus the need to add other parameters is suggested to estimate *Ei* for deciduous broadleaved forest.

The error of stand density (*N*) may affect *Ei* rate (*r*). In general, *N* based on airborne LiDAR is underestimated (e.g., Lee et al., 2018) and it may cause the low *r* value. Supposing that for each tree species, the true *N* is bigger by the amount of MAE, average *r* value become slightly larger (rainfall: 0.17 ± 0.05; snowfall: 0.16 ± 0.12). In other words, the error of *N* in this study is expected to generate about 0.01 to 0.02 error in *r* value.

In this study, we were able to evaluate *Ei* in a large scale with a relatively high resolution of 50m mesh. Vivoni (2012) estimated *Ei* in 92km^2 basin with 250m resolution using MODIS data. The method of combining LiDAR with the model is thus considered superior in terms of resolution compared to satellite remote sensing. In addition, there is a research to expand the results of forest measurement using airborne LiDAR to a wider area using satellite imagery (Varhola and Coops, 2013) and this study also could expand to where without LiDAR data. In the future, we will continue to improve this models and also develop the models to estimate *Et* and *Ef*.

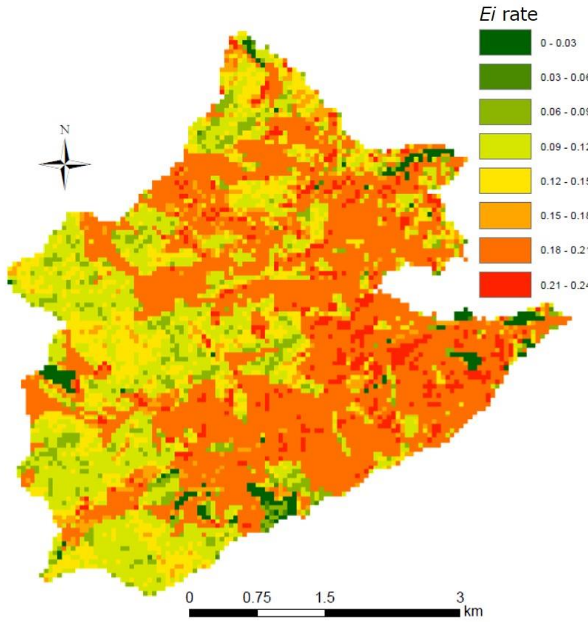

Figure.1 The distribution of *Ei* rate during rainfall.

5. References

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