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Research article

# Estimation of global soil respiration by accounting for land-use changes derived from remote sensing data





Minaco Adachi <sup>a, d, \*</sup>, Akihiko Ito <sup>b</sup>, Seiichiro Yonemura <sup>c</sup>, Wataru Takeuchi <sup>a</sup>

<sup>a</sup> Institute of Industrial Science, The University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo, 153-8505, Japan

<sup>b</sup> National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba, Ibaraki, 305-8506, Japan

<sup>c</sup> National Institute for Agro-Environmental Studies, NARO, 3-1-3 Kannondai, Tsukuba, Ibaraki, 305-8604, Japan

<sup>d</sup> Graduate School of Life and Environmental Science, The University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki, 305-8577, Japan

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#### ABSTRACT

Soil respiration is one of the largest carbon fluxes from terrestrial ecosystems. Estimating global soil respiration is difficult because of its high spatiotemporal variability and sensitivity to land-use change. Satellite monitoring provides useful data for estimating the global carbon budget, but few studies have estimated global soil respiration using satellite data. We provide preliminary insights into the estimation of global soil respiration in 2001 and 2009 using empirically derived soil temperature equations for 17 ecosystems obtained by field studies, as well as MODIS climate data and land-use maps at a 4-km resolution. The daytime surface temperature from winter to early summer based on the MODIS data tended to be higher than the field-observed soil temperatures in subarctic and temperate ecosystems. The estimated global soil respiration was 94.8 and 93.8 Pg C yr<sup>-1</sup> in 2001 and 2009, respectively. However, the MODIS land-use maps had insufficient spatial resolution to evaluate the effect of land-use change on soil respiration. The spatial variation of soil respiration  $(Q_{10})$  values was higher but its spatial variation was lower in high-latitude areas than in other areas. However, Q<sub>10</sub> in tropical areas was more variable and was not accurately estimated (the values were >7.5 or <1.0) because of the low seasonal variation in soil respiration in tropical ecosystems. To solve these problems, it will be necessary to validate our results using a combination of remote sensing data at higher spatial resolution and field observations for many different ecosystems, and it will be necessary to account for the effects of more soil factors in the predictive equations.

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#### 1. Introduction

Soil is a major carbon (C) reserve in terrestrial ecosystems. Soil respiration ( $R_s$ ) is a large carbon flux from terrestrial ecosystems to the atmosphere.  $R_s$  is related to the amount of soil carbon input, soil carbon stocks, root biomass, microbial biomass, temperature, and soil water content (Davidson and Janssens, 2006; Sato et al., 2015). Soil organic carbon (SOC) dynamics at global scales, which include  $R_s$ , have many uncertainties, and the estimation of global  $R_s$  is difficult because of high spatiotemporal variability (Smith and Fang, 2010). As a result, estimates of global  $R_s$  have varied widely, ranging

from 68 PgC yr<sup>-1</sup> (Raich and Schelesinger, 1992) to 98 PgC yr<sup>-1</sup> (Bond-Lamberty and Thomson, 2010). Soil temperature is the main factor that influences soil carbon dynamics (Carvalhais et al., 2014; Davidson and Janssens, 2006), including  $R_s$  (Bond-Lamberty and Thomson, 2010; Raich and Schelesinger, 1992; Reichstein and Beer, 2008; Zhou et al., 2009). In one study, the temperature sensitivity of  $R_s$  per 10 °C change in temperature (i.e.,  $Q_{10}$ ) at a global scale varied from 1.43 to 2.03 among ecosystems (Zhou et al., 2009), but in another, the mean global  $Q_{10}$  was lower, at 1.4 (Hashimoto et al., 2015). In other cases, low soil water content decreased  $R_s$  of a savanna landscape under extremely dry conditions (Chen et al., 2002), whereas a decrease in the depth to ground water decreased  $R_s$  in a tropical swamp forest (Hirano et al., 2014). As a result, some models of  $R_s$  also include a soil moisture term (e.g., Sotta et al., 2004).

Land-use change also affects the SOC content since the accumulation rates of soil carbon change in response to changes in the

<sup>\*</sup> Corresponding author. Graduate school of Life and Environmental Science, The University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki, 305-8577, Japan.Tel & Fax : +81-29-853-8857

*E-mail addresses*: adachi.minaco.gf@u.tsukuba.ac.jp (M. Adachi), itoh@nies.go.jp (A. Ito), yone@affrc.go.jp (S. Yonemura), wataru@iis.u-tokyo.ac.jp (W. Takeuchi).

input rates of organic matter, in decomposition rates, and in physical and biological conditions in the soil that result from landuse changes (Post and Kwon, 2000). According to a meta-analysis by Guo and Gifford (2002), the conversion of natural forest or pasture into cropland decreases soil carbon stocks. Therefore, estimates of global  $R_s$  should account for changes in land use and the differences in  $R_s$  among ecosystem types.

Satellite monitoring provides not only land cover maps but also useful vegetation and environmental data that can be used to estimate the global carbon budget in terrestrial ecosystems, and especially the carbon exchange between the atmosphere and ecosystems, because it permits estimates of the land surface temperature, gross primary production (GPP), net primary production (NPP), and leaf area index (Guo et al., 2012). For instance, these datasets from the Moderate Resolution Imaging Spectroradiometer (MODIS) have been used as inputs for carbon cycling models (e.g., Ise et al., 2010; Sasai et al., 2005, 2011; Yuan et al., 2015).

It is important to understand both the overall  $CO_2$  budget of terrestrial ecosystems and the  $CO_2$  dynamics in each compartment (e.g., plants versus soil). Although remote sensing cannot directly observe  $R_s$ , long-term and global  $R_s$  can be estimated based on the values of environmental factors (such as surface temperatures) that control  $R_s$  and that can be observed by remote sensing. Estimates of global  $R_s$  will provide accuracy comparable to that of other satellite data (e.g., data from the Greenhouse gases observing satellite; Yokota et al., 2009) and can be used to improve our understanding of the sources of changes in carbon cycling from ecosystems. However, no studies have evaluated the effect of land-use change on global  $R_s$  using MODIS remote sensing data.

In the present study, we provide preliminary insights into the estimation of global  $R_s$  by combining empirical equations derived from field studies with satellite data (climate and land cover). Our objectives were to (1) obtain soil temperature data using MODIS land surface temperature data, (2) identify the variation in global  $R_s$  and  $Q_{10}$  from 2001 to 2009, and (3) discuss the effects of land-use change on global  $R_s$ .

#### 2. Materials and methods

#### 2.1. MODIS data

Daily MODIS land surface temperatures during the day and night (LST<sub>d</sub> and LST<sub>n</sub>, respectively) were calculated by interpolation using some remote sensing data (e.g., the 8-day composite LST at a 4-km spatial resolution from the MOD11C3, and vegetation data at a 10-m resolution from the AVNIR2). This approach was necessary because data with high spatial resolution may not cover sufficiently large areas for a given study (Takeuchi et al., 2012), as was the case in the present global-scale study. When vegetation was present, LST<sub>d</sub> and LST<sub>n</sub> were estimated above the vegetation. Soil water content (SWC) was estimated using the modified Keetch-Byram drought index (KBDI) based on remote sensing data (Keetch and Byram, 1968; Takeuchi et al., 2010), as follows:

$$SWC = SWC_{max} \left[ 1 - (KBDI / 800) \right]$$
<sup>(1)</sup>

where SWC<sub>max</sub> is the maximum soil water content at each study site based on published data, but most  $R_s$  equations do not include SWC parameters (summarized in Table S1 of the supporting information). Land cover was distinguished for the 17 ecosystem types in the table using the MODIS MOD12Q1 (collection 5) at a 4-km spatial resolution. This classification scheme was developed by the International Geosphere–Biosphere Programme Data and Information Systems initiative (Friedl et al., 2002). This land cover map did not detect the paddy field and tundra classes. Each point in the land cover map from the MOD12Q1 was assigned to one of the 17 ecosystem classes.

## 2.2. Validation of MODIS surface temperatures using field observation

 $R_{\rm s}$  in this study was predominantly estimated as a function of soil temperature (Table S1). We compared the MODIS estimates (LST<sub>d</sub> and LST<sub>n</sub>) to empirical data based on field observations (daily mean air temperature and soil temperature) at five sites: an evergreen needleleaf forest in Alaska (64°52'N, 147°51'W; Ueyama et al., 2014), a mixed forest in Japan (36°08'N, 137°25'E; from the AsiaFlux database, http://asiaflux.net), cropland in Japan (36°01'N, 140°07'E; Kishimoto-Mo et al., unpublished data), an evergreen broadleaf forest in Thailand (14°29'N, 101°54'E, AsiaFlux database), and an evergreen broadleaf forest in Malaysia (2°58'N, 102°18'E, AsiaFlux database). The measurement height for air temperature and the depth of the soil temperature measurement differed among the five sites, with respective values of 800 cm and -10 cm in the evergreen needleleaf forest, 1800 cm and -1 cm in the mixed forest, 200 cm and -2 cm in the cropland, 4500 cm and -5 cm in the evergreen broadleaf forest in Thailand, and 5300 cm and -2 cm in the evergreen broadleaf forest in Malaysia. We could not quantify the effects of these different measurement heights on estimation of  $R_s$  in each ecosystem because LST<sub>d</sub> and LST<sub>n</sub> were measured at the top of the dominant vegetation, and that height varied with the type of vegetation.

Table S1 provides the empirical equations for estimating  $R_s$  in the 17 ecosystems from around the world. We selected empirical equations that were based on field measurements (not data obtained using incubation or manipulation experiments) conducted since 2000 from version 3.0 of a global R<sub>s</sub> database (Bond-Lamberty and Thomson, 2014). Daily  $R_s$  values were estimated using the empirical  $R_s$  equation corresponding to the land use type for each pixel, the estimated soil temperature, and the soil water content in each pixel of the grid (Fig. 1).  $R_s$  in the evergreen broadleaf forest, which is mainly a tropical forest, was estimated using only the soil water content when land surface temperature (LST) was >25 °C (Sotta et al., 2004). In addition, LST of grassland vegetation areas were sometimes more than 30  $^{\circ}$ C, and if we calculated  $R_{s}$  using an exponential function, the estimated  $R_s$  was unrealistically high in these areas. Richards et al. (2012) reported that  $R_s$  in a savanna decreased when the soil temperature was over 30 °C. Thus, if the LST for a savanna pixel was >30 °C, we recalculated LST to be less than 26 °C for the estimation of  $R_s$  in the ecosystems that included savanna vegetation (closed and open shrubland, grassland, savanna, woody savanna, grassland, cropland, and cropland-natural vegetation mosaic).

We modelled the dependency of  $R_s$  on temperature at a global scale according to the following relationship:

$$R_{\rm s \ est} = \alpha \times e^{\beta T} \tag{2}$$

where  $R_{s_{est}}$  is the estimated daily  $R_s$  in this study, T is the LST<sub>d</sub> at each point (4-km resolution), and  $\alpha$  and  $\beta$  are fitting parameters. We calculated  $R_s$  est using the least-squares method based on  $R_s$  (Table S1) and LST<sub>d</sub> over 365 days at a 4-km resolution. We calculated the  $Q_{10}$  of  $R_s$  as follows:

$$Q_{10} = e^{10\beta}$$
 (3)

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