Estimation of litter mass in nongrowing seasons in arid grasslands using MODIS satellite data

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**ABSTRACT**

Litter has a special ecological functioning in grasslands. Few studies have been conducted to estimate litter mass using remotely sensed data during nongrowing seasons in arid grasslands although it is important forage for livestock sustainability. With MODIS data, estimation methods were developed for litter mass in the desert steppe of Inner Mongolia calibrated with field surveys. As MODIS Band 7 is located in the lignocellulose absorption pit of litter near 2100 nm, the best models were obtained for NDTI (normalized difference tillage index) (normalized difference between Bands 6 and 7) and STI (soil tillage index) (ratio of Band 6–7) among soil-unadjusted indices, and for MSACRI (modified soil-adjusted crop residue index) (modification of NDTI by incorporating soil line) among soil-adjusted indices. NDTI and STI explained 63% of the variance of litter mass, while MSACRI explained 71% of the variance. If data are not available for calculating soil line, it may be appropriate to use the soil-adjusted NDTI (S-NDTI), a new index proposed in the study that incorporates a soil adjustment factor into the NDTI equation. The optimal S-NDTI explained 66% of the variance. The NDTI, STI, MSACRI and S-NDTI can be applied to estimate litter mass in arid grasslands.

**INTRODUCTION**

Litter (standing and surface litter) is a prominent component of biomass in grassland ecosystems and plays an important role in maintaining ecosystem structure, functioning and dynamics (Okin, 2010). It also is an important intermediate link of vegetation and soil, and plays an essential role in biogeochemical cycles and energy exchange in grassland ecosystems, maintaining soil organic matter and soil fertility (Geng & Shi, 2012; Liu & Peng, 2010). Litter accumulation is one of the most important ecological processes in grasslands and is also a key driver in regulating ecosystem services (Amatangelo, Dukes, & Field, 2008; Patrick, Fraser, & Kershner, 2008).

Accurate estimation of litter mass in grasslands will be of great significance to thoroughly understand ecosystem structure, functioning and processes. Traditional methods of litter mass estimation are time consuming, expensive, destructive and only feasible for small scale. Remote-sensing technologies provide an effective alternative method for accurate estimation of litter mass in grasslands at a national or regional scale (Jacques, Kergoat, Hiernaux, Mougin, & Defourny, 2014; Xu, Guo, Li, Yang, & Yin, 2014).

In contrast to the typical red-edge signature of green plants, the spectral curves of both soil and litter lack unique absorption reflectance features in the visible near-infrared wavelength portion (400–1100 nm) (Mcnairn & Protz, 1993). Furthermore, soil and litter are spectrally similar and differ only in amplitude at a given wavelength in the visible near-infrared wavelength region (Baird & Baret, 1997; Streck, Rundquist, & Connot, 2002). Therefore, it is nearly impossible or difficult to discriminate between litter and soil in the visible near-infrared wavelength region (Daughtry, Hunt, & Mcmurtrey, 2004). Nevertheless, a lignocellulose absorption pit near 2100 nm in the short wavelength infrared region (SWIR), caused by cellulose, hemicellulose, lignin, other structural compounds, has been observed in the spectral curves of litter (Elvidge, 1990; Roberts, Smith, & Adam, 1993). And this absorption feature is absent in the spectral curves of green plants and soil (Cao, Chen, Matsushita, & Imura, 2010; Streck et al., 2002). Using this absorption feature, a hyperspectral index, the cellulose absorption index (CAI), was proposed by Daughtry, Mcmurtrey, Chappelle, Hunt and Steiner (1996) to estimate crop residue coverage (Daughtry, Hunt, Dormaiswamy, & Mcmurtrey, 2005; Daughtry et al., 2004). Nevertheless, the CAI can only be calculated from fine spectral resolution hyperspectral data which is currently only provided by a single prototype satellite (EO-1 Hyperion) which is not able to...
cover large areas efficiently. With narrow SWIR bands from the ASTER sensor, the spectral indices, lignin cellulose absorption (LCA) (Daughtry et al., 2005) and shortwave infrared normalized difference residue index (SINDRI) (Serbin, Hunt Jr., Daughtry, McCarty, & Doraiswamy, 2009), were designed to monitor crop residue coverage using spectral properties near the cellulose absorption feature signature. However, there was a failure of the ASTER SWIR sensor in April 2008 (Jpl, 2012). Although WorldView-3 has SWIR bands similar to ASTER, its narrow swath width is not suitable for monitoring large areas (Sun, Tian, & Di, 2017).

Many vegetation indices have been proposed to estimate crop residue coverage using Landsat TM reflectance bands. The most common are NDI5 (normalized difference index 5) (Mcnairn & Protz, 1993), NDI7 (normalized difference index 7) (Mcnairn & Protz, 1993), NDTI (normalized difference tillage index) (Van Deventer, Ward, Gowda, & Lyon, 1997), NDSVI (normalized difference senescent vegetation index) (Qi et al., 2002), CRC (crop residue cover) (Sullivan, Truman, Schomberg, Endale, & Strickland, 2006) and STI (simple tillage index) (van Deventer et al., 1997). However, these vegetation indices may lose their abilities for estimating crop residue coverage in arid areas due to sparse vegetation cover (Daughtry, Serbin, Reeves, Doraiswamy, & Hunt, 2010). Biard, Bannari and Bonn (1995) therefore proposed the soil-adjusted corn residue index (SACRI) based on the algorithm of NDI5 by incorporating the soil line. Bannari, Haboudane and Bonn (2000) proposed the modified soil-adjusted crop residue index (MSACRI) based on the algorithm of NDTI by incorporating the soil line. Compared with CAI, LCA and SINDRI, the TM-based vegetation indices have been widely used in crop residue coverage estimation due to the accessibility and affordability of Landsat TM data (Bannari et al., 2000; Biard et al., 1995; Daughtry et al., 2010; Mcnairn & Protz, 1993; Qi et al., 2002; Serbin et al., 2009; Sullivan et al., 2006; Van Deventer et al., 1997).

We hypothesize that it should be possible to use these TM-based vegetation indices to estimate litter mass in grasslands, although very few studies have been conducted to examine this approach (Jacques et al., 2014; Kergoat et al., 2015; Ren & Zhou, 2012). Furthermore, MODIS (MODerate resolution Imaging Spectroradiometer) satellite data have long been the main remotely sensed data source in remote sensing of grasslands due to its large scene size, high frequency observation and low acquisition cost. Finding a MODIS-based vegetation index suitable to litter mass estimation in grasslands is hence really of interest to the community. The objective of the study is to explore the potential of TM-based soil-unadjusted and soil-adjusted vegetation indices for litter mass estimation using MODIS satellite data in the desert steppe of Inner Mongolia. The vegetation indices are evaluated, through linear regression models, against a set of field surveys conducted in non-growing seasons over 3 years in the desert steppe of Inner Mongolia.

**Materials and methods**

**Study area**

Field surveys were conducted in the desert steppe of Xilingol League, Inner Mongolia Autonomous Region, China. As shown in Figure 1, the desert steppe is mainly located in the East Sunite Banner and West Sunite Banner of Xilingol League. There is an arid temperate continental climate in the area, where precipitation is the principal environmental factor controlling grassland vegetation growth. Based on long-term meteorological data from weather stations in East Sunite Banner and

![Figure 1. Location of study area and distribution of sampling fields for litter mass measurements.](image-url)
West Sunite Banner, mean annual precipitation is approximately 140 mm, with 85% distributed in growing seasons (from May to September), and mean annual temperature is 4.1°C with mean monthly temperature ranging from −15.9°C in January to 22.5°C in July. The dominant soil is classified as brown calcic soil. The vegetation is dominated by *Stipa klemenzii* Roshev. and *Stipa gobica* Roshev. In the study area, the nongrowing seasons usually start around 1 October and cease near 1 May of the next year.

**Data collection**

Our field surveys were conducted in the middle of October during the nongrowing seasons of 2014, 2015 and 2016, respectively. As shown in Figure 1, 13 sampling fields encompassing different litter mass production levels were selected for litter mass investigation in 2014, 13 sampling fields were selected in 2015 and 12 sampling fields were selected in 2016. In total, 38 sampling fields were used to measure litter mass in the study area. Each sampling field was located within a homogeneous environment. The litter was evenly distributed within each sampling field. Longitude and latitude information of these sampling fields were obtained by differential global position system. A total of 10–20 plots were randomly selected within each sampling field to measure litter mass. The distances between different sampling fields were from tens to hundreds of meters. The litter (standing litter and surface litter) within each plot was collected at the field level and then dried at 65°C for 48 h. The dry weight was recorded on an electronic balance with a sensitivity of 0.01 g. Litter mass (g m$^{-2}$) of each plot was calculated by dividing the dry weight of litter by the area of the plot. The measurements of litter mass from all plots for each sampling fields were averaged to provide a single litter mass per sampling field.

Terra/MODIS daily surface reflectance products MOD09GA were used to establish vegetation indices and explore the relationships between observed litter mass and vegetation indices. The MOD09GA products were downloaded from the National Aeronautics and Space Administration Land Process Distributed Active Archive Center (https://ladsweb.modaps.eosdis.nasa.gov/search/). In the products, the MODIS Land Science Team already implemented the atmospheric corrections for aerosols, thin cirrus clouds and gases. The rate of observation coverage, viewing angle, cloud or cloud shadow coverage and aerosol loading were all assessed on a pixel-by-pixel basis. The products were further processed with the MODIS Reprojection Tool (MRT Version 4.0). The data format was converted from HDF to GeoTIFF, and the projection was converted from sinusoidal projection to WGS84/Albers projection. The MOD09GA data (500 m x 500 m) contain surface reflectance for Band 1 (red: 620–670 nm), Band 2 (near infrared: 841–876 nm), Band 3 (blue: 459–479 nm), Band 4 (green: 545–565 nm), Band 5 (shortwave infrared: 1230–1250 nm), Band 6 (shortwave infrared: 1628–1652 nm) and Band 7 (shortwave infrared: 2105–2155 nm).

**Vegetation indices**

The soil-unadjusted NDI5, NDI7, NDTI, NDSVI, CRC and STI and soil-adjusted SACRI and MSACRI were selected to evaluate their performance for litter mass estimation in the study. We associated the Landsat TM/ETM+ bands 1, 2, 3, 4, 5 and 7 with MODIS bands 3, 4, 1, 2, 6 and 7, respectively, and kept the same names for these indices, keeping in mind that bandwidths are slightly different. These indices were calculated by the following equations using MODDD09GA reflectance bands:

\[
\text{NDI5} = \frac{B2 - B6}{B2 + B6} \\
\text{NDI7} = \frac{B2 - B7}{B2 + B7} \\
\text{NDTI} = \frac{B6 - B7}{B6 + B7} \\
\text{NDSVI} = \frac{B6 - B1}{B6 + B1} \\
\text{CRC} = \frac{B6 - B4}{B6 + B4} \\
\text{STI} = \frac{B6}{B7} \\
\text{SACRI} = \frac{a(B2 - aB6 - b)}{abB2 + B6 - ab} \\
\text{MSACRI} = 5 \times \frac{a(B6 - aB7 - b)}{abB6 + B7 - ab}
\]

where B1, B2, B4, B6 and B7 are reflectance at MOD09GA Bands 1, 2, 4, 6 and 7, respectively; a and b are the slope and intercept of the soil line equation, respectively. The soil line, a linear relationship between bare soil reflectance measured in two different bands, is widely used for interpretation of remotely sensed data (Baret, Jacquemoud, & Hanocq, 1993). We assumed that soil moisture was not a factor causing variation in the soil line parameters in the study area. For SACRI, a and b are the slope and intercept of the soil line in the B2/B6 spectral
space, respectively. For MSACRI, $a$ and $b$ are the slope and intercept of the soil line in the B6/B7 spectral space, respectively. In the study, the slopes and intercepts of the soil line were selected based on long-term field surveys from the Institute of Botany, Chinese Academy of Sciences.

In addition to the earlier reported indices (Equation 1–8), we propose a new soil-adjusted NDTI (S-NDTI) by incorporating a soil adjustment factor $L$ into NDTI to explore the potential of NDTI for estimating litter mass in the study area. The S-NDTI was calculated by the following equation:

$$S - NDTI = \left(1 + L\right) \frac{B6 - B7}{B6 + B7 + L} \quad (9)$$

where $B6$ and $B7$ are reflectance at MOD09GA Bands 6 and 7, respectively; $L$ is the soil adjustment factor.

In the study, the physical basis of the soil adjustment factor may be shifting the origin toward the intersected point between litter isoline and soil line in the B6–B7 spectral plane. This approach is equivalent to adding a constant $L$ to the B6 and B7 reflectance data. The optimal $L$ for the soil adjustment varies with the amount of litter present. At low litter mass, a large $L$ value would best describe soil–litter interactions. With increasing litter mass, $L$ should become smaller. A constant $L$ may reduce soil noise considerably throughout a wide range of litter mass. In the study, Equation (9) was tested with values of $L$ from 0 to 1 at an interval of 0.1 to find an optimal value of $L$ for modeling the litter mass.

**Data analysis**

No saturation occurred for the tested vegetation indices for litter mass estimation in the study area, and results using linear regression were significantly better than results using nonlinear regression. Therefore, linear regression analyses were performed to test the performance of these vegetation indices for estimating litter mass in the study. The performance was evaluated using $R^2$ (coefficient of determination), RMSECV (root mean square error of leave-one-out cross-validation) and rRMSECV (relative RMSECV), expressed as a percentage. The RMSECV and rRMSECV were computed as follows:

$$\text{RMSECV} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{n}} \quad (10)$$

$$\text{rRMSECV} = \frac{\text{RMSECV}}{\bar{x}} \times 100\% \quad (11)$$

where $x_i$ is the measured litter mass of sample $i$, $\hat{x}_i$ is the predicted litter mass of sample $i$ when linear regression model is developed without sample $i$, $n$ is the number of all samples and $\bar{x}$ is the mean value of litter mass of all samples.

**Results**

**Statistics of measured litter mass**

At the time of field surveys, vegetation had already dried out, and few green plants were observed in the study area. The NDVI (normalized difference vegetation index) (Rouse, Hass, Schell, & Deering, 1974), widely used for monitoring green plants, only varied between 0.11 and 0.19 with an average of 0.16 for 39 sampling fields. The statistics of the measured litter mass were calculated. As expected, a wide variation in litter mass was observed for the 39 sampling fields: the litter mass varied from 9.9 to 116.4 g m$^{-2}$ with an average of 66.8 g m$^{-2}$ and a standard deviation of 28.8 g m$^{-2}$. The litter mass of the 13 sampling fields collected in 2014 varied from 9.9 to 116 g m$^{-2}$ with an average of 65.8 g m$^{-2}$ and a standard deviation of 31 g m$^{-2}$. The litter mass of the 13 sampling fields collected in 2015 varied from 15.2 to 116.4 g m$^{-2}$ with an average of 68.4 g m$^{-2}$ and a standard deviation of 29.9 g m$^{-2}$. Finally, the litter mass of the 12 sampling fields collected in 2016 varied from 24.8 to 105.9 g m$^{-2}$ with an average of 66 g m$^{-2}$ and a standard deviation of 27.6 g m$^{-2}$. Further analysis of variance revealed that the means of litter mass measured in 2014, 2015 and 2016 were not significantly different ($P > 0.05$).

**Performance of soil-unadjusted vegetation indices for litter mass estimation**

The performance of the soil-unadjusted vegetation indices for litter mass estimation in the study area is shown in Figure 2 and Table 1. The NDTI ($R^2 = 0.63$, RMSECV = 17.74 g m$^{-2}$, rRMSECV = 26.6%) and STI ($R^2 = 0.63$, RMSECV = 17.79 g m$^{-2}$, rRMSECV = 26.6%) yielded far better estimation performances compared with those of NDI5, NDI7, NDSVI and CRC. The performances of NDTI and STI were similar, an expected result since both indices were calculated from the reflectance at Bands 6 and 7. The regression model based on NDI5 was not significant ($P > 0.05$). For NDI5, NDI7, NDSVI and CRC, the values of $R^2$ calculated from regression models were less than 0.3, which implied a weak capacity for litter mass estimation.

**Performance of soil-adjusted vegetation indices for litter mass estimation**

The performance of soil-adjusted SACRI and MSACRI for litter mass estimation in the study area is presented in Figure 3 and Table 1. The performance of MSACRI ($R^2 = 0.71$, RMSECV = 15.69 g m$^{-2}$, rRMSECV = 23.5%) for
Figure 2. Linear regression analyses between litter mass and soil-unadjusted NDI5 (a), NDI7 (b), NDTI (c), NDSVI (d), CRC (e) and STI (f).

Table 1. Linear regression analyses between litter mass and vegetation indices.

| Vegetation indices | Regression model | $R^2$ | RMSECV (g m$^{-2}$) | rRMSECV (%) | $P$   |
|-------------------|-----------------|-------|----------------------|-------------|-------|
| Soil unadjusted   |                 |       |                      |             |       |
| NDI5              | $y = -225.5x + 35.9$ | 0.03  | 28.76                | 43.1        | >0.05 |
| NDI7              | $y = 371.7x + 90.9$ | 0.24  | 25.43                | 38.1        | <0.01 |
| NDTI              | $y = 799.7x + 8.9$  | 0.63  | 17.74                | 26.6        | <0.01 |
| NDSVI             | $y = 501.7x - 80.5$ | 0.25  | 25.23                | 37.8        | <0.01 |
| CRC               | $y = 270.4x - 42.9$ | 0.64  | 17.14                | 40.6        | <0.05 |
| STI               |                 |       |                      |             |       |
| Soil adjusted     |                 |       |                      |             |       |
| SACRI             | $y = -227.8x + 14.6$ | 0.03  | 28.81                | 43.1        | >0.05 |
| MSACRI            | $y = 171.8x + 73.7$ | 0.71  | 15.69                | 23.5        | <0.01 |
| S_NDTI (0.6)      | $y = 1048.3x + 6.5$ | 0.66  | 17.11                | 25.6        | <0.01 |

$y$ represents litter mass and $x$ represents vegetation index.

NDTI: Normalized difference tillage index; NDSVI: normalized difference senescent vegetation index; CRC: crop residue cover; SACRI: soil-adjusted corn residue index; MSACRI: Modified Soil-Adjusted Crop Residue Index; S_NDTI: soil-adjusted NDTI; RMSECV: root mean square error of leave-one-out cross-validation; rRMSECV: relative RMSECV.
litter mass estimation was far better than that of SACRI ($R^2 = 0.03$, RMSECV = 28.81 g m$^{-2}$, rRMSECV = 43.1%). Comparing the algorithms for NDI5 (Equation (1)) and SACRI (Equation (7)), the SACRI was developed from NDI5 by integrating the soil line. Nevertheless, the SACRI had poor performance in the study area and did not provide any improvements over NDI5 for litter mass estimation. Both the MSACRI and the NDTI are based on Bands 6 and 7 and show good performances. In direct comparison, the MSACRI provided significant improvements over NDTI for litter mass estimation and appeared to be the overall best indicator of litter mass amongst the examined indices.

**Performance of S-NDTI based on different values of $L$**

We calculated different versions of S-NDTI with values of $L$ varying from 0 to 1 at an interval of 0.1. The values of $R^2$ and RMSECV calculated from linear regression analyses between litter mass and all S-NDTI versions are presented in Figure 4. Results showed that the values of $R^2$ decreased and the values of RMSECV increased with decreasing values of $L$ when the values of $L$ were less than 0.6, and the values of $R^2$ decreased and the values of RMSECV increased with increasing values of $L$ when the values of $L$ were more than 0.6. The maximum of $R^2$ (0.657) and minimum of RMSECV (17.11 g m$^{-2}$) was achieved with a value of $L = 0.6$. The performance of the optimal S-NDTI for estimating litter mass in the study area is presented in Figure 5 and Table 1. Although the accuracy of the S-NDTI ($L = 0.6$) for litter mass estimation was better than that of NDTI and STI, the accuracy of the S-NDTI ($L = 0.6$) was lower than that of MSACRI in the study area.

**Discussion**

The results of this study, which were consistent with those of Jacques et al. (2014) and Kergoat et al.
illustrated the better performance of NDTI and STI for litter mass estimation when comparing several soil-unadjusted vegetation indices (NDI5, NDI7, NDTI, NDSVI, CRC and STI). The improved performances of NDTI and STI may be attributed to the MODIS Band 7 (2105–2155 nm) which both indices apply and which is located in the spectral portion of the lignocellulose absorption feature.

Arid grasslands, including the examined desert steppe of Inner Mongolia, are characterized by low vegetation cover. Although the absorption feature near 2100 nm is absent for soils, the high bare soil cover may attenuate the absorption feature of litter (Bannari et al., 2000; Biard et al., 1995). This may reduce the estimation accuracy of litter mass in arid grasslands. Encouragingly, the soil-adjusted MSACRI ($R^2 = 0.71$, RMSECV = 15.69 g m$^{-2}$), a modification of the soil-unadjusted NDTI by incorporating the soil line, greatly improved litter mass estimation accuracy compared with the soil-unadjusted NDTI ($R^2 = 0.63$, RMSECV = 17.74 g m$^{-2}$). However, the soil-adjusted SACRI showed poor performance ($R^2 = 0.03$, RMSECV = 28.81 g m$^{-2}$) for litter mass estimation in the study. Similarly, the soil-unadjusted NDI5 (which is also calculated from B2 and B6 as SACRI) showed poor performance.

The MSACRI showed good estimation accuracy of litter mass but requires a specific soil line for the study area. In the given case, an appropriate soil line was available. However, this might cause additional work in other study areas. We hence proposed the S-NDTI to explore the potential of the NDTI for litter mass estimation in the study area by incorporating adjustment factors into NDTI instead of incorporating a soil line. Although the optimal S-NDTI had lower estimation accuracy ($R^2 = 0.657$, RMSECV = 17.11 g m$^{-2}$) than the MSACRI, the accuracy was better than that of the NDTI in the study area. Therefore, in case of an unknown soil line, the S-NDTI is a straightforward alternative to estimate litter mass by selecting optimal soil adjustment factor in arid grasslands.

It is important to note that the good performance of the NDTI, STI, MSACRI and S-NDTI ($L = 0.6$) in the study area was achieved during nongrowing seasons. During the growing seasons, the presence of photosynthetically active vegetation would significantly attenuate the reflectance signal from the absorption feature near 2100 nm due to high water content of photosynthetically active vegetation (Gao & Goetz, 1994; Murphy, 1995). In this case, the NDTI, STI, MSACRI and optimal S-NDTI are not only sensitive to the litter but also sensitive to the photosynthetically active vegetation. Making the distinction between litter and photosynthetically active vegetation during the growing seasons is therefore impossible using only the NDTI, STI, MSACRI or optimal S-NDTI. The combination of NDVI and NDTI, STI, MSACRI or optimal S-NDTI may be a promising avenue of litter mass estimation during the growing seasons (Jacques et al., 2014; Renier et al., 2015).

**Conclusions**

It has been demonstrated that the normalized difference between MODIS Bands 6 and 7, the NDTI, and the ratio of MODIS Bands 6 and 7, the STI, can be employed to estimate litter mass with good accuracy during nongrowing seasons in the desert steppe of Inner Mongolia. The MSACRI, the modification of NDTI by incorporating the soil line, can further improve estimation accuracy of litter mass over NDTI and STI. A new index, the S-NDTI, was proposed to estimate litter mass based on the algorithm
of NDTI in the study. The index is straightforward and efficient alternative to estimate litter mass in cases where a soil line has not been established by prior research. Further research is necessary to evaluate the potential of the NDTI, STI, MSACRI and S-NDTI for estimating litter mass in other arid grasslands.

Disclosure statement
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