Crop Coefficient Simulation and Evapotranspiration Estimation for Sand Dunes and Meadows in Semi-Arid Regions: Postprint

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Abstract

Crop coefficient (Kc) is of great significance for improving the estimation accuracy of actual evapotranspiration and regional water resources regulation. Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Simple Ratio vegetation index (SR) were calculated from Landsat 8 data, combined with ground-measured soil moisture (SM) and leaf area index (LAI) in 2017. Stepwise regression analysis was employed to establish crop coefficient estimation models for meadow and sand dune experimental sites in the Horqin region. The simulated Kc values for 2018 were multiplied by potential evapotranspiration (ET0) calculated using the FAO 56 Penman-Monteith model to obtain estimated values of actual evapotranspiration (ETa), which were then validated against actual evapotranspiration measured by eddy covariance systems. The results indicated that: (1) The variation trends of crop coefficients in both meadow and sand dune experimental sites during the growing season were consistent with vegetation indices and SM, demonstrating the feasibility of establishing Kc estimation models based on these indicators; (2) In the correlation analysis, the correlation between Kc and SR in the meadow experimental site was not significant (P>0.05), while the correlation between Kc and SR in the sand dune experimental site was relatively low (0.46), thus this factor was excluded; (3) After further excluding non-significant factors in the stepwise regression analysis, crop coefficient estimation models for meadow and sand dune sites were established, with root mean square errors and adjusted coefficients of determination of 0.06, 0.84 and 0.12, 0.71, respectively; (4) Validated by eddy covariance data, the ETa calculated based on the Kc estimation models achieved good simulation performance in both meadow and sand dune experimental sites.

Full Text

Crop Coefficient Simulation and Evapotranspiration Estimation for Dune and Meadow in a Semiarid Area

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Abstract

The crop coefficient (Kc) is crucial for improving the accuracy of actual evapotranspiration (ETa) estimation and regional water resource regulation. Using Landsat 8 data, we extracted three vegetation indices: Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Simple Ratio Vegetation Index (SR). Combined with ground-measured soil moisture (SM) and leaf area index (LAI) data from 2017, we established crop coefficient estimation models for meadow and dune experimental areas in the Horqin region through stepwise regression analysis. The simulated Kc values for 2018 were multiplied by potential evapotranspiration (ET_0) calculated from the FAO 56 Penman-Monteith model to obtain ETa estimates, which were validated against actual ETa measured by eddy covariance systems. Results showed that seasonal variation trends of Kc in both meadow and dune areas were consistent with vegetation indices and soil moisture, confirming the feasibility of establishing Kc estimation models based on these indicators. Correlation analysis revealed that the relationship between Kc and SR was not significant in the meadow area ($P > 0.05$), while the correlation was weak in the dune area. Stepwise regression analysis further eliminated non-significant factors, establishing final Kc estimation models for both areas. The models achieved root mean square errors of 0.84 and 0.71, and modified coefficients of determination of 0.89 and 0.83 for meadow and dune areas, respectively. Validation using eddy covariance data demonstrated that ETa calculated from the Kc estimation models produced good simulation results in both experimental areas.

Keywords: Horqin Sandy Land; evapotranspiration; remote sensing; crop coefficient; vegetation index; eddy covariance

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1. Study Area Description

The study area is located at the Agula Eco-hydrological Experimental Station in Horqin Left Wing Rear Banner, Tongliao City, Inner Mongolia Autonomous

Region [Figure 1: see original paper], covering approximately 30 km^2. The region has a multi-year average precipitation of 389 mm, concentrated between June and September, with an average annual temperature of approximately 6.6°C and average relative humidity of 55.8%. The terrain is high in the north and south and low in the middle, forming a typical dune-meadow landscape. The area belongs to a temperate semiarid continental monsoon climate zone, with main natural vegetation including *Artemisia halodendron*, *Caragana microphylla*, *Artemisia sieversiana*, *Salix gordejevii*, and *Populus* species.

The meadow experimental area is situated in the lower-lying central region adjacent to a lake, with flat terrain, shallow groundwater depth, and consistently moist sandy loam soil. Dominant vegetation includes *Phragmites communis*, *Leymus chinensis*, and *Juncus effusus*. The dune experimental area is located in the northern dune zone with low vegetation coverage, where natural vegetation consists mainly of *Artemisia halodendron* and *Agriophyllum squarrosum*.

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2. Data and Methods

2.1 Data Collection and Processing

2.1.1 Meteorological, Soil, and Eddy Covariance Data Both meadow and dune experimental areas are equipped with open-path eddy covariance systems and meteorological observation towers. The eddy covariance systems include open-path infrared gas analyzers, three-dimensional ultrasonic anemometers, four-component net radiometers, and photosynthetically active radiation sensors, measuring fluxes and meteorological elements at a sampling frequency of 30 Hz. Bowen ratio meteorological and soil environmental monitoring systems measure air temperature and humidity, wind speed and direction, precipitation, soil heat flux, soil temperature, and soil moisture .

Eddy covariance data were processed using Eddy Pro software, including secondary coordinate rotation correction, frequency loss correction, trend correction, and WPL correction. Quality control procedures included removal of data during precipitation periods, screening and removal of nighttime data, threshold testing and outlier removal, and data removal under atmospheric stability conditions. Missing data gaps less than 2 hours were interpolated using linear interpolation, while longer gaps were filled using the mean diurnal variation method to obtain accurate flux data. Energy balance closure rates were 0.85 and 0.83 for meadow and dune areas, respectively, indicating high reliability of flux data.

2.1.2 Vegetation Data Within the eddy covariance source areas, LAI was measured using an Li-2200 plant canopy analyzer. In the meadow area, which has dense and uniform vegetation, 15 herbaceous quadrats (0.5 m × 0.5 m) were established centered on the meteorological station. In the dune area with low vegetation coverage, 5 large quadrats (3 m × 3 m) were established, with

3 semi-shrub quadrats (1 m × 1 m) selected along diagonal lines within each large quadrat. All quadrats represent average vegetation conditions within the eddy source area, surveyed monthly during the growing season with vegetation height recorded.

2.1.3 Remote Sensing Data Landsat 8 OLI images with 30 m spatial resolution were selected based on image quality, acquisition time, and cloud cover conditions. Data were obtained from the USGS Earth Explorer and the Geospatial Data Cloud. ENVI 5.3 software was used for geometric correction, radiometric calibration, histogram equalization, and image cropping to improve vegetation index calculation accuracy.

2.2 Methods

2.2.1 Crop Coefficient Calculation The crop coefficient (Kc) is the ratio of actual evapotranspiration (ETa) to reference evapotranspiration ($\mathrm{ET_0}$), comprehensively reflecting the effects of crop type, growth status, and soil water and fertility conditions on crop evapotranspiration. $\mathrm{ET_0}$ was calculated using the FAO 56 Penman-Monteith model with meteorological data, and Kc was then calculated as the ratio of latent heat flux measured by eddy covariance towers to $\mathrm{ET_0}$:

$$K_c = \frac{ET_a}{ET_0}$$

where $\mathrm{ET_0}$ is calculated as:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where Δ is the slope of the saturation vapor pressure curve ($\mathrm{kPa \cdot {}^\circ C^{-1}}$), R is net radiation at the canopy surface ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$), T is mean air temperature (°C), G is soil heat flux ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$), $\mathrm{u_2}$ is wind speed at 2 m height ($\mathrm{m \cdot s^{-1}}$), e is saturation vapor pressure (kPa), e is actual vapor pressure (kPa), and γ is the psychrometric constant ($\mathrm{kPa \cdot {}^\circ C^{-1}}$).

2.2.2 Vegetation Index Calculation Vegetation indices are linear or nonlinear combinations of different remote sensing spectral bands that reflect differences between visible and near-infrared reflectance and soil background, quantitatively describing vegetation growth status. To identify the vegetation index most correlated with Kc, we selected NDVI, SAVI, and SR, calculated as the mean of all pixels within the eddy covariance source areas .

2.2.3 Model Evaluation Using 2017 growing season meteorological, soil, and vegetation data, Kc estimation models were established. Landsat 8-derived vegetation indices, ground-measured LAI, and SM data were input into the models to simulate Kc values, which were multiplied by ET_0 from the FAO 56 PM model to obtain ETa estimates. Model feasibility was evaluated by comparing simulated ETa with eddy covariance measurements. Four statistical metrics were used: relative error (RE), mean bias (bias), Nash-Sutcliffe efficiency (NSE), and coefficient of determination (R^2):

$$RE = \frac{\sum_{i=1}^{N} |P_i - O_i|}{\sum_{i=1}^{N} O_i}$$

$$bias = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2}$$

where N is the number of observations, P is the simulated ETa value ($mm \cdot d^{-1}$), O is the measured ETa value ($mm \cdot d^{-1}$), and $\bar{O}$ is the mean of measured values.

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3. Results and Analysis

3.1 Dynamic Analysis of Related Factors

To determine the feasibility of using various factors as independent variables, we first analyzed the dynamic changes of vegetation indices (NDVI, SAVI, SR), soil moisture (SM), actual evapotranspiration (ETa), potential evapotranspiration (ET_0), and crop coefficient (Kc) throughout the 2017 growing season in both experimental areas [FIGURE:2, FIGURE:3].

In the meadow area, NDVI showed no significant variation throughout the growing season, as it is primarily used for dynamic monitoring of high-density vegetation. Daily ETa ranged from 0.99 to 6.47 mm, with a seasonal total of 825 mm. ET_0 showed similar variation trends, with small changes during early growth (early May), rapid increase during the vigorous growth period as vegetation cover expanded, and a slight decrease in late July due to less precipitation. After mid-August, vegetation entered the late growth stage with declining indices. Kc showed similar patterns to vegetation indices, being higher during the vigorous growth period than in early and late stages, consistent with previous research. SM showed small fluctuations, generally not exceeding $0.25\ m^3 \cdot m^{-3}$, with increases following precipitation events.

Comparison between meadow and dune areas revealed that precipitation affects both soil moisture and Kc. Precipitation impacts vegetation indices primarily through reduced indices after prolonged drought, with studies confirming positive correlations between vegetation indices and precipitation. The meadow area, adjacent to a lake with shallow groundwater, maintained high soil moisture, and its Kc was mainly influenced by vegetation growth stage. In contrast, the dune area' s Kc was more sensitive to precipitation, showing fluctuating increases after rainfall and declining trends during continuous drought due to water deficit in both soil and vegetation.

In the dune area, ETa showed a bell-shaped distribution with a seasonal total of 247 mm, accounting for 12.15%, 69.26%, and 18.61% of the total during initial, vigorous, and late growth stages, respectively. Vegetation indices and Kc showed similar increasing then decreasing trends, while SM remained below $0.10\ \mathrm{m}^3 \cdot \mathrm{m}^{-3}$ with minimal variation.

3.2 Kc Estimation Model Development

Correlation analysis was performed to further identify suitable independent variables for Kc estimation models . In the meadow area, Kc showed significant correlations with NDVI, SAVI, LAI, and SM ($P < 0.01$), but not with SR ($P > 0.05$). In the dune area, Kc was significantly correlated with all variables except SR, which showed weak correlation. Therefore, we selected the three most correlated variables for model development.

Using 2017 growing season data, stepwise regression equations were developed. The stepwise regression principle introduces variables sequentially, testing each for significance and removing non-significant variables until no further significant variables can be added or removed. In the meadow area, the non-significant factor SR was removed ($P > 0.05$), while in the dune area, SR was also removed. The final regression equations are presented in .

Model performance improved with additional variables. For the meadow area, Case 1 (using NDVI only) and Case 2 (using NDVI and SM) both performed well, with simulated Kc means of 1.21 and 1.18 compared to the measured mean of 1.17. For the dune area, Case 1 (using LAI only) and Case 2 (using LAI and SM) produced simulated means of 0.62 and 0.59 compared to the measured mean of 0.58. Case 2 results were closer to measured values, and R^2 increased from 0.82 to 0.89 in the meadow area and from 0.71 to 0.83 in the dune area with additional variables.

Crop evapotranspiration involves complex processes influenced by local climate conditions (temperature, vapor pressure deficit, wind speed) and environmental factors including soil and vegetation characteristics. Vegetation indices reflect phenological features such as vegetation density, growth stage, and height, effectively describing Kc variation trends. Soil moisture is the direct water source for soil evaporation and plant transpiration, affecting water vapor pressure differences at the soil-plant-atmosphere interface and stomatal conductance. Previous studies often established simple linear relationships between single vegetation indices and Kc, but this study integrates comprehensive crop and soil information using Landsat 8 data, making the models more reliable.

3.3 Model Validation

To evaluate model feasibility, 2018 simulated Kc values were multiplied by ET_0 to obtain ETa estimates and compared with eddy covariance measurements. Due to data gaps in the meadow area during 2018, 2017 data were used for validation. Linear regression analysis showed that simulated and measured ETa followed similar seasonal trends, with slight deviations during rainfall periods when eddy covariance data quality was lower [Figure 4: see original paper].

Statistical analysis showed good agreement between simulated and measured values. In the meadow area, measured total ETa was 372 mm ($3.38\ mm \cdot d^{-1}$) while simulated total was 404 mm ($3.66\ mm \cdot d^{-1}$), representing an 8.28% overestimation. In the dune area, measured total ETa was 236 mm while simulated total was 261 mm, a 10.59% overestimation. Scatter plots showed concentrated distributions near the 1:1 line, with R^2 values of 0.84 and 0.71 for meadow and dune areas, respectively . NSE values of 0.82 and 0.71 indicated high model reliability.

This study demonstrates that integrating satellite remote sensing data with ground measurements can effectively establish Kc estimation models for both meadow and dune ecosystems in arid regions. However, the study did not consider Kc variations during different crop growth stages. Future research will incorporate multi-year data to further optimize the models and investigate Kc variation patterns and influencing factors during specific growth stages.

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4. Conclusions

Using Landsat 8 satellite data, this study investigated the feasibility of estimating crop coefficients (Kc) for meadow and dune areas in the Horqin region using NDVI, SAVI, SR, ground-measured LAI, and surface soil moisture (SM). The main conclusions are:

1. Dynamic analysis of Kc during the 2017 growing season showed high consistency between Kc variation trends and vegetation indices and soil moisture, confirming the feasibility of establishing Kc estimation models based on these indicators.
2. Correlation analysis eliminated variables with poor correlation (SR), and stepwise regression further removed non-significant variables. The final models integrated soil moisture information with ground-measured LAI and Landsat 8-derived vegetation indices, demonstrating high reliability with modified R^2 values of 0.89 and 0.83 for meadow and dune areas, respectively.

3. Validation using 2018 data showed that simulated and measured ETa values were distributed near the 1:1 line with high R^2 values (0.84 and 0.71). Statistical metrics indicated close agreement between simulated and measured values, with relative errors of 8.28% and 10.59%, and NSE values of 0.82 and 0.71 for meadow and dune areas, respectively, demonstrating good simulation performance in both ecosystems.

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Note: Figure translations are in progress. See original paper for figures.