ETWatch: calibration methods

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Abstract: Satellite imagery provides an unprecedented spatial distribution of critical land surface parameters. Numerous physical and empirical remote sensing-based models, in conjunction with ancillary surface and atmospheric data, have been developed to estimate evapotranspiration (ET) in the quantitative thermal remote sensing field. ETWatch is an operational scheme for watershed ET monitoring, which is designed to integrate with various types of remote-sensed ET models to obtain continuous ET maps. To reduce the errors from modeling, we improved ETWatch to carry out calibration on key variables such as surface temperature, ground temperature difference, short-wave and long-wave radiation, water heat flux, and sensible heat flux, using ground measurement data. The validation results show that the calibration greatly improved the accuracy of ET products, and the importance of calibration cannot be overemphasized in applications used in watershed water management.

Key words: evapotranspiration, quantitative remote sensing, energy balance, Hai Basin, ETWatch, PEST

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1 INTRODUCTION

Evapotranspiration (ET), including evaporation from bare soil and vegetation transpiration, is an important parameter for determining water and energy balance on the Earth’s surface, which is also the most difficult part to estimate in the land surface water cycle. In a water-saving irrigation project, ET estimation for large areas is essential for the planning and allocation of water rights. For decades, surface evaporation in the water cycle has been a hot topic among water managers and researchers. Ground measurements show that the spatial-temporal distribution of ET are influenced by various factors related to water and heat conditions, such as weather, terrain, and vegetation and soil types. Field observations of ET are the basis for accurate estimates, which can be cataloged into two types: the first is a direct measurement of the water loss rate from a land surface; the second is a measurement of water vapor transmission to the atmosphere. Ground measurement methods such as the Bowen ratio, eddy covariance, and soil water depletion can provide only the point value of the ground. Satellite imagery provides an unprecedented spatial distribution of critical land surface parameters, such as surface albedo, leaf area indices, and land surface temperatures, among other data, as input for a surface energy balance model to retrieve ET information without precipitation and soil moisture information (Bastiaanssen et al., 1998; Gillies, et al., 1997; Norman, et al., 1995; Su, 2002). In addition, the complementary correlation approach also can provide actual ET information with potential ET (Craco & Crowley, 2005; Liu, et al., 2004).

Empirical equations used in ET models were established based on limited ground measurement; the applicability depends mainly on the calibration process by using local data and scaling approach. Although researchers carried out a series of observations in the Qinghai-Tibet Plateau, extremely dry areas, dry desert regions, semi-arid grasslands, transitional zone, and Loess Plateau region (Wu, et al., 2005; Wang, et al., 2007), few of these observations data were used to optimize current parameterization schemes in satellite retrieval algorithms. Teixeira, et al. (2009) applied the SEBAL model in the São Francisco River basin, Brazil, using four local flux sites’ observations to calibrate albedo and land-surface temperature while calculating emissivity, roughness, and sensible heat flux by using an indirect approach. The research shows that the emissivity of the atmosphere has the largest uncertainty in the modeling. The method of calibration is mainly an empirical formula using linear regression. After model’s calibration (including daily ET), the correlation coefficient ($r^2$) of calibrated values and observed ET was 0.91 and RMSE was 0.38 mm/d. Yin, et al. (2008) used radiation records from 81 weather stations in China to optimize responding equations from the FAO56 algorithm, calibrating the coefficients of short-wave and long-wave radiation equations separately, which eliminated the previous ET0 overestimation of 27%.

McCabe et al. (2005) presented a multi-objective optimization matrix which could lower the joint error of LE, H, and LST, assuming that the parameters from this approach would be more stable. Raymond and Jongstchaap (2007) proposed a real-time calibration method for...
LAI in combination with remote sensing and ground measurements to improve the simulation precision of a crop-growth model. Wang, et al. (2009) proposed a hierarchical analysis method of the Biome-BGC model for model calibration, which divided the model into different layers, then liked layers with key parameters (LAI) and achieved rapid calibration of the model results through calibrating the LAI parameter. Li, et al. (2008) promoted a framework to develop scaling methods, taking aviation remote sensing for bridges and improving the satellite retrieval algorithm and indirect estimation methods of various components in the water cycle.

We used ETWatch to divide the calibration into land surface variables’retrieval, flux calculations, and temporal-scaling to calibrate each separately, using ground measurements in application to the Hai Basin.

2 STUDY AREA

The Hai Basin in North China, as the political, economic, and cultural center of China, has been suffering from a water shortage since the 1970s. The Hai Basin is one of the seven largest river basins in China, with 10% of the country’s population, including mega cities such as Beijing and Tianjin (Fig. 1). However, the water availability in the basin in only 305 m³ per capita, which is 14% of the national average and 4% of the world average. Agricultural irrigation relies mainly on groundwater pumping. Net reduction of groundwater is about 9 billion m³ per year. Eco-environmental problems, owing to water shortages and over-exploitation, also have become increasingly pressing.

Mountainous areas, accounting for 58.4% of the whole area, stretch from north to south like a belt along the western section of the southern part of the Hai Basin. Plains, accounting for 41.6%, are spread from piedmonts along the Taihang Mountains eastward to the coast of the Bohai Sea. Four river nets—Yongding, Daqing, Zeya, and the Nanyun—traverse the plains area and flow into the Bohai Sea.

The land use in the plains area is dominated by an intensive dual-cropping system based on winter wheat and summer crops, including maize, millet, soybean, cotton and sorghum. Winter wheat is sown in early October and harvested in early or mid-June of the next year, and the summer maize is planted in early to mid-June and harvested at the end of September. Annual precipitation is about 500 mm, more than 50% of which arrives during the summer monsoon between July and September. Due to the limited and variable precipitation, in Spring, the winter wheat production is guaranteed only by irrigation; otherwise, the production will be low, with no grain being yielded in extreme drought conditions. The intensive cropping systems have increased the irrigation water requirements from 100 mm/year in the 1950s to 300 mm/year in the 1980s for winter wheat (Wang, et al., 2001). Because of the low annual precipitation and a shortage of surface water, the intensive agricultural systems rely mainly on the irrigation water extracted from the ground aquifers. Continuous over-extraction of regional groundwater has resulted in the aquifer levels decreasing in some areas by as much as a 1 m/year over a prolonged 40-year period (Liu, 2001).

3 MODEL AND DATA

3.1 ETWatch approach

ETWatch has been established as an operational data processing chain for regional ET monitoring (Wu, et al., 2008). Firstly, SEBAL and SEBS are combinations of the energy balance theory and the mass transfer method and are used to compute the evaporation from the cropped surfaces based on the standard climatological records of sunshine, temperature, humidity and wind speed, by introducing the resistance factors, and the Penman-Monteith (P-M) model determines the spatio-temporal variability of the regional evaporative condition. Secondly, we chose available surface resistance (RS) as a temporal-scaling factor (Xiong, et al., 2008). While bulk surface resistance is properly defined, the P-M equation is valid for both soil and vegetation canopy for calculating daily ET and then aggregating daily ET to monthly and annual ET (Fig. 2).
3.2 Observational data

3.2.1 Flux sites

We had verified the ET algorithm at four eddy covariance tower sites during 2006 and 2007. These flux towers (Fig. 2, Table 1) covered two typical land cover types and a wide range of climates.

### Table 1 Flux sites in the Hai Basin

<table>
<thead>
<tr>
<th>Site</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Crop</th>
<th>Instrument</th>
<th>Height/m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daxing</td>
<td>116.427°E</td>
<td>39.614°N</td>
<td>Maize</td>
<td>EC, AWS</td>
<td>4</td>
</tr>
<tr>
<td>Guantao</td>
<td>115.127°E</td>
<td>36.515°N</td>
<td>Wheat/Maize</td>
<td>EC, AWS</td>
<td>15.6</td>
</tr>
<tr>
<td>Luancheng</td>
<td>114.683°E</td>
<td>37.883°N</td>
<td>Wheat/Maize</td>
<td>EC, AWS</td>
<td>4</td>
</tr>
<tr>
<td>Miyun</td>
<td>117.324°E</td>
<td>40.632°N</td>
<td>Fruit Trees</td>
<td>LAS, EC, AWS</td>
<td>35.6</td>
</tr>
<tr>
<td>Yucheng</td>
<td>116.6°E</td>
<td>36.95°N</td>
<td>Wheat/Maize</td>
<td>EC, AWS</td>
<td>Wheat: 2, Maize: 3.3</td>
</tr>
</tbody>
</table>

These sites have similar instrument installations with little variances. For example, in the Yucheng site, the soil type in the experimental area was silt loam. Latent heat and CO₂ fluxes were measured with an eddy covariance system installed at a height of 2.10 m above the soil surface for winter wheat and 3.30 m for summer maize. Average values were calculated and recorded every 30 minutes. A net radiometer (CNR1, Kipp & Zonen, Delft, The Netherlands) also was installed at a height of 2.10 m for winter wheat and 3.30 m for summer maize to measure incoming, reflected, and emitted components of short-wave and long-wave radiation. Air temperature and relative humidity were measured with a temperature/humidity probe (HM-P45C, Vaisala, Helsinki, Finland). Wind speed was measured with an anemometer (A100R, Vector Instruments, Rhyi, United Kingdom). Two soil heat flux plates (HFP01SC, Hukselux, Delft, The Netherlands) were installed at 1.0 m below the soil surface at row and inter-row positions. The Lysimeter (1 m length × 1 m width × 2.4 m depth) was located in the middle of 6.25 ha fields and measured daily ET based on measurement of soil water depletion.

For the site observations of ET and meteorology, we aggregated the half-hourly observation into daily data without using additional quality control. Because the sensors in the eddy correlation system were greatly influenced by rainy weather, the data obtained during these anomalous days were excluded before evaluations. To maintain the integrity of the observations, no gap-filling was performed for these data.

The Miyun LAS site is located in Miyun County, Beijing (116°37’ 51” N, 117°19’ 24” E). The land cover mainly consists of fruit, cropland, and residential areas. Instruments equipped inside the site include a large aperture scintillometer (LAS), an Eddy correlation meter (EC), and automatic weather stations (AWS). The transmitter and receiver of the LAS are installed on the tops of two hills with optical paths of 2400 m and 36.5 m high. The AWS and eddy covariance system are installed on a 31.5 m high tower, and the tower is about 900 m from the receiver. The AWS has two layers of wind, temperature, humidity, radiometers, surface temperature, soil heat flux, multi-layer soil moisture, precipitation, and air pressure observations. The eddy covariance system consists of an ultrasonic anemometer (CSAT3, Campbell) and an H₂O/CO₂ infrared analyzer (LI-7500, LI-COR). The continuous observation data has been post-processed, according to Lu, et al., (2009), and then gap-filled and interpolated to monthly data (Xu, et al., 2008).

3.2.2 Meteorological data

Daily data from 83 meteorological stations administrated by the Chinese Bureau of Meteorology were collected; the network of agro-meteorological stations used in this study is shown in Fig. 1. All selected stations have good quality daily records from 2002 to 2008, including sunshine duration, relative humidity, wind speed, and daily maximum and minimum temperatures. The solar radiation was estimated with clear-sky radiation and relative sunshine duration. Except for sunshine duration, all variables were corrected for elevations above sea level. Then variables were interpolated into a daily map at 1 km resolution. The inverse-distance-squared method was used for air temperatures and air pressure in combination with DEM data, whereas the thin-plate-spline method was employed for other variables. The approximate instantaneous maps of air temperature were calculated from daily maximum air temperatures by using a sinusum conversion.

3.2.3 Remote sensing data

The MODIS data used in this study are the MOD021KM, MOD02QKM, MOD02HKM and MOD03 product files provided by the NASA Goddard Space Flight Center (GSFC) Distributed Active Archive Center (GDAAC) (http://edcimswww.cr.usgs.gov/). The MOD02QKM and MOD02HKM products, including the 250 m and 500 m resolution bands, were aggregated to 1 km resolution TOA radiances and reflectance. The MOD03 products were the geolocation fields’ data calculated for each 1 km MODIS Instantaneous Field of View (IFOV) for all daytime orbits. The geolocation fields included geodetic latitude, longitude, solar zenith and azimuth angles, satellite zenith and azimuth angles as well as a land/seamask for each 1 km sample. Both solar and satellite zenith and azimuth angles were used to estimate the net short-wave radiation in this study. The MODIS 2.1-μm band was used to detect dark targets, estimating their reflectance in the blue and red channels and using them for remote sensing of aerosol based on Kaufman’s (1997) study. Using the aerosol optical thickness as input, a lookup table was established, based on the 6S model, to carry out the atmospheric correction (Vermote, et al., 1997). A practical split-
window approach was used to retrieve LST from MODIS data (Mao, et al., 2005). The DEM data was a processed result, the source of
which is SRTM 90 m elevation.

4 CALIBRATION RESULT

4.1 Parameter estimation algorithm

PEST (Parameter Estimation) tool package was used for model parameter calibration and optimization in ETWatch. PEST is a
powerful independent parameter estimation procedure for model
calibration and predictive analysis, which is now widely applied to
underground water and surface hydrological geology, geophysics,
chemistry and the other fields. The core of nonlinear parameters
estimation algorithm in PEST is Gauss-Marquardt-Levenberg
steepest descent algorithm (Marquardt, 1963).

The steps of actual evapotranspiration process includes: the extrac-
tion of key land surface parameter (surface temperature, emissivity
and the vegetation coverage); calculations of land surface energy balance
(net radiation, soil heat flux); sensible heat flux (roughness length and
and aerodynamic resistance); evaporation ratio and daily evapotranspi-
ration. A group of parametric and empirical equations are collected
through literatures. And initialization values are calculated by using
PEST and local measurement. PEST-based automatic calibration
module implemented into ETWatch can be customized according to
the remote sensing images, the underlying structure and the climatic
regions. Parameters can also be pre-calculated by simulation as part
of the lookup table to speed up the calculations. Limited by the avail-
able ground observation, the main calibrated variables focuses on the
surface temperature and net radiation, and the improved results mainly
includes the evaporation ratio and the evapotranspiration.

4.2 Surface temperature and air temperature

The LST estimation over the 3×3 MODIS pixels surround-
ing the Miyun site was compared with the ground observations,
together with the MODIS daily LST product (MOD11) in 54 days
of 2007. The results, shown in Fig. 3, demonstrate clearly that the
calibrated split-window estimation performs better than the MODIS
global LST product, especially records a reasonable magnitude and

![](image1)

Fig.3 Calibrated results of temperature compared with the measured
data, Miyun site, 2007

The correlation coefficient between the LST observations and split-
window estimation are \( R^2 = 0.86 \) (\( p < 0.01 \)) and \( R^2 = 0.82 \) (\( p < 0.01 \)) by us-
ing the MODIS 11 product. However, RMSE increases from 5.02 K to
10.53 K, indicating that even a simple calibration of the MODIS LST
product is necessary in agricultural ecosystems in North China.

In the remote sensing ET model, the air temperature of bound-
ary layer is another important non-remote sensing input. The
inconsistency of observation time with land surface temperature
is usually ignored. Therefore, the air temperature in the boundary
layer (12:00 a.m.) was adjusted to the MODIS / Aqua transit time
(13:30 p.m.), assuming that the change of such air temperature was
according to the sine function, as follows.

\[
T_{13:30} - T_0 = A \sin \left( \frac{\pi x}{4} \right)
\]

where \( A \) is the amplitude of daily air temperature.

4.3 Radiation

The daily solar radiation (\( R_{dn} \)) is calculated using the Angstrom
equation:

\[
R_{dn} = \left(a + b \times \frac{n}{N} \right) R_d
\]

where \( R_{dn} \) is solar or shortwave radiation (MJ m\(^{-2}\) day\(^{-1}\)), \( n/N \) is
relative sunshine duration; \( R_d \) is extraterrestrial radiation (MJ m\(^{-2}\) day\(^{-1}\)), and \( a, b \) is regression constant, expressing the fraction
of extraterrestrial radiation reaching the earth on overcast days
(\( n = 0 \)). Depending on atmospheric conditions (humidity, dust)
and solar declination (latitude and month), \( a, b \) will vary.
In that case, based on a regressive analysis of long-term daily
radiation records (2000—2009) of seven meteorological sites,
including Taiyuan, Beijing, Tianjin, Leting, Jinan, Fengqu, and
Donglingshan, the regional daily solar radiation is estimated by
using monthly empirical coefficient by spatially interpolated daily
meteorological data. Fig. 4 shows good correlation coefficients
between the observed and estimated solar shortwave radiation at
the Yucheng site, 2008.

![](image2)

Fig.4 Comparison of the observed and estimated solar short-wave
radiation in Yucheng site, 2008
Long-wave radiation was calculated by using the following equation:

\[
R_a = \frac{T_{\text{max}}^4 - T_{\text{min}}^4}{2} \left(0.34 - 0.14 \sqrt{e_a} \right) \left[1.35 \frac{R_s}{R_{so}} - 0.35 \right]
\]

where \( \sigma \) is the Stephen-Boltzmann constant; \( T_{\text{max}}, K \) and \( T_{\text{min}}, K \) are maximum and minimum absolute temperature (K) during the 24-hour period, respectively, \( e_a \) is actual vapour pressure (kPa), \( R_s/R_{so} \) is relative shortwave radiation, and \( R_s \) and \( R_{so} \) are solar radiation and clear-sky radiation, respectively. Fig. 5 shows good correlation coefficients \( R^2 = 0.854 \) between observed and estimated solar long-wave radiation at the Daxing site, 2008.

4.4 Heat flux of water body

In order to estimate actual evaporation in large water bodies, in ETWatch, we used the pan evaporation data measured in the Miyun Reservoir from 2002 to 2004 to establish a daily empirical relationship between \( R_n \) and \( G_0 \) of the water body.

\[
G_{0,\text{water}} = 0.225 R_n
\]

The calibrated result is in good agreement with observed data, the relative deviation is about 14.9%, and the correlation coefficient is 0.91. During the flood season (June to August), the yearly relative deviation is within 1.5%, as shown in Fig. 7.

4.5 Sensible heat flux

Sensible heat flux (H) is also determined by aerodynamic resistance, together with the difference between surface temperature and air temperature. The parameterization of aerodynamic resistance is also calibrated by using ground data to make sure that the output of sensible heat flux was consistent with LAS observations at the Miyun site (Fig. 8).

4.6 Evaporative fraction

As an evaluation of calibration of model parameters, the output evaporative fraction was selected to compare with eddy covariance observations, which was calculated using this equation:

\[
EF = \frac{\sum E_j}{\sum H_j + \sum E_j}
\]
The observed EF is averaged by using half an hour’s H and LE data, which were obtained 1.5 h prior to and 1.5 h after the time of the satellite overpass (13:30 local time). Researchers found that observation of flux around noon was stable (Xu, 2008), thus this average value can provide a good estimation of actual daily EF.

Fig. 9 shows the comparison of the evaporative fractions at the four flux sites of Daxing, Luanchen, Miyun, and Yucheng. The correlation coefficient $R^2$ is 0.65, 0.86, 0.78, and 0.74, respectively.

5 CONCLUSION

In this paper, calibration methods and modules in ETWatch are developed. Land surface variables, such as radiation temperature, net radiation and other outputs are calibrated based on the ground truth observation at 5 sites located in Hai basin. The verification result shows that the calibration module has effectively enhanced the consistency between remote-sensed value and ground observation. The average correlation coefficient of model output and ground measurement can achieve round 0.7.

Remotely-sensed ET is calculated by pixels, which is a statistics-average value of a range of underlying surface, while ground observation is available at a point scale. Therefore, the scaling method will play a particularly important role on the further comparative analysis of parameters in ET estimation. It is a very complex procedure from the theoretical algorithm to operational system; the limited ground observations rarely provide a convincing evaluation of the heterogeneous underlying surface. The combination of a flux towers network and sub-basins could provide a meaningful calibration framework for dynamic, comprehensive evaluation in the near future.

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daily meteorological data and rainfall gauge measurement in the Hai Basin for 2002 to 2008. Special thanks are given to the three anonymous reviewers for providing their so many good and kind comments.

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ETWatch中的参数标定方法

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摘 要: ETWatch 是用于流域蒸散遥感监测、针对遥感应用而设计的集成框架。方法集成了具有不同应用优势的遥感蒸散模型, 并以Penman-Monteith方法为基础建立时间扩展方法, 利用气象数据与晴好日的通量遥感估算结果, 获得逐日连续的蒸散分布图。所生成的从流域级到地块级的数据产品能动态反映区域蒸散发的时空变化规律。为深入了解遥感蒸散量估算中的不确定因素, 本文将其通量计算过程分为地表温度、地气温差、短波与长波辐射、水体热通量、显热通量等环节与地面数据进行对比和逐项的标定。利用站点地面观测资料对模型输入的蒸发比的比较表明参数标定可有效提高遥感与地面蒸散观测的吻合程度。

关键词: 蒸散发, 定量遥感, 能量平衡, 海河, ETWatch, PEST

1 引 言

蒸散发（Actual ET）是通过土壤蒸发和植被蒸散发过程将水汽输送到大气中的过程。ET是地表与大气间能量转换的重要组成部分，同时也是陆地表层水循环过程中的重要估算的分量。在节水灌溉项目实施中，量化估算大面积的ET对于水权制定与分配具有重要意义。几十年来，地表水循环中的蒸散发一直是水管理者和研究人员的关心热点。地面测量表明，ET的时空格局与诸多因子有关，如气象水热条件、地形、植被状况以及土壤类型。

蒸散发的实地观测是准确估算的基础，根据测量原理的不同，实地测定方法主要分为两种：一是直接测定下垫面的失水速率，称为液态水分消耗测量；二是测定大气中得到水分的速率，称为水汽传送测量。地面蒸散发测量方法如波文比，涡度相关仪和土壤耗水法等，都只能提供点尺度的地面观测量。遥感方法具有空间上连续和时间动态变化的特点，可以向地表能量模型提供如地表反照率、叶面指数和地表温度等重要的输入，可以在缺乏降雨和土壤湿度输入的情况下获得地表蒸散蒸发的状况，此类的模型代表有地表能量平衡系统SEBS（Su, 2002），陆地表面能量平衡算法SEBAL（Bastiaanssen 等，1998），TS/VI三角法（Gillies等，1997），双源能量平衡模型（TSEB；Norman 等，1995）等。此外，潜在蒸散与实际蒸散之间的差异也能在一定程度上反映土壤水分信息，如互补相关法，Crago将遥感反演的地表辐射温度作为输入，利用多套实验样地比较了不同复杂程度的互补相关模型，刘绍民（2004）检验了几种互补相关模型在不同时间尺度、不同气候类型上的计算精度。

遥感应用中的参数化方案往往是在有有限的地面观测的基础上建立起来的，如何结合地面实测资料进行定标则是应用中的难点，其核心问题是参数化方案的适用性评价与优化，关键技术则是地面观测的尺度转换方法，目前这方面研究较少。中国虽然已在青藏高原、极端干旱地区、干旱荒漠地区、半干旱草原地区、农牧交错带、黄土高原等典型区域开展了一系列以陆面过程为主的陆面过程试验（宋霞 等，2004；张一平等，2005；李英年等，2003；吴家...

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通信作者：吴炳方。E-mail:wubf@irsa.ac.cn。
兵等，2005；王春林等，2007），但很少把这些观测结果转化为陆面过程或卫星遥感反演模式中所需要的参数，而仍是以典型下垫面单点试验研究为主。Teixeira等人（2009）在巴西圣弗朗西斯科流域应用SEBAL模型计算区域蒸散，基于4个地面通量站的观测数据对地表反照率和地表温度，由于缺乏直接观测量，比辐射率和粗糙度、显热通量等则通过间接的方法得到。其中大气的表观比辐射率的不确定性最大。标定方法主要是通过对经验公式进行线性纠正。最后的日蒸散量也通过类似的方法相对于地表观测值进行了线性回归，标定后的日蒸散量与观测值的决定系数$R^2$为0.91，RMSE为0.38 mm/d。Yin（2008）利用中国地区81个气象站的观测数据对FAO56式中的辐射计算方法进行了优化，分别纠正了短波辐射中的直射和散射系数以及长波辐射的经验系数，结果说明纠正后的净辐射量可大大提高ET0的计算精度，而未经纠正的方法会引$ET_0$约27%的高估。相对于单一参量的标定与优化，McCabe等人（2005）提出了多目标优化通量结果的标定思路，使得LE，H和LST的联合误差矩阵最小，认为这样得到的纠正参数在大范围应用时更为稳定。Raymond和Jongschaap（2007）针对作物生长模型模拟结果对于叶面指数LAI的高敏感性，提出了联合遥感与地面观测对LAI进行实时标定，从而提高模拟精度的方法。又有研究者提出了先将模型分层（Wang，2008），用关键参量（如LAI）来链接各层，再通过对关键参量的标定来实现对模型结果的快速标定。李新等人在黑河流域开展的航空-卫星遥感与地面观测同步试验中，则提出以航空遥感为桥梁，发展尺度转换方法，改善从卫星遥感资料反演和间接估计水循环各分量的模型和算法（李新等，2008）。

ETWatch是面向水资源管理和农业节水管理的实用需求，针对遥感应用设计的业务化遥感蒸散监测系统，可用于计算流域地表净辐射、感热、潜热（ET）的空间分布图及其时间过程，在海河流域应用时，结合多点地面实测数据开展了模型标定工作，为形成持续监测能力，开发了模型参数的自动标定与分区管理模块。本文在简述其主要方法的基础上，介绍模型标定的研究工作。

2 研究区

海河流域是中国七大流域之一，流域人口占全国的10%，包括了北京、天津等大型城市（图1）。然而，人均利用水资源仅为305 m$^3$，约为全国平均水平的14%，或世界平均水平的4%。长期以来，由于对水资源的过度开发，“有河皆干，有水必污”几乎成为海河流域水资源现状的写照，农业用水主要依赖于地下水抽取，地下水超采量达到了每年90亿m$^3$。如果能获得流域尺度上的ET估值，则可以极大地降低流域水平衡中的不确定性，为水管理者提供重要信息，主要包括真实耗水量，即不能作为地下水回补和下流用户的水资源量，以及水分生产率，即每单位生物量的耗水量。
海河流域的山区约占总面积的58.4%，山前平原主要为两季作物，即冬小麦与夏季的玉米、小米、大豆、棉花和高粱。冬小麦一般在10月初播种，次年6月上中旬收割；夏玉米在6月中播种，9月底收割。流域年均降雨量约为500 mm，半数以上降雨都发生在6月—9月之间的汛期。因此，冬小麦在春季主要依赖地面灌溉。由于集约型农业的不断发展，流域灌溉水需求量已经从20世纪50年代的100 mm/a增长到了1980年以后的300 mm/a。由于降雨与入流的不足，农业部门主要依靠地下水的超采，由此也超成了这一地区含水层40年来以每1 m/a的速率降低的恶果（Liu等，2001）。

3 方法与数据

3.1 区域遥感蒸散模型ETWatch

ETWatch采用余项法与P-M公式相结合的方法计算蒸散（吴炳方等，2008）。方法应用能量平衡余项式模型估计晴好日的蒸散量：面向高分辨率遥感数据时应用SEBAL模型和METRIC，面向低分辨率遥感数据时应用SEBS模型，均采用地面观测数据对模型参数进行了标定；并以Penman-Monteith公式为基础建立下垫面表面阻抗模型，使用遥感监测的晴好日的表面阻抗估算连续的表面阻抗（熊隽等，2008），获得逐月、季、年的蒸散量产品（图2）。

3.2 观测数据

3.2.1 通量观测

在海河流域选择了中国科学院禹城站、栾城站、北京师范大学密云、馆陶LAS站和水科院大兴实验基地等站的观测数据进行模型验证与参数优化（表1）。

各通量站的观测仪器主要由自动气象站和涡度相关仪构成，以禹城站为例：对于冬小麦地块，涡度相关系统安装在距地面2 m高处，对于玉米地块则安装在3.3 m高处，仪器输出每半小时的通量平均值。CNR1净辐射仪可分别测量短波和长波辐射的入射、反射和辐射部分。温湿使用HMP45C探头（法国）测量。风速使用A100R风速计（英国）测量。土壤热通量使用安装在0.1 m深度的两个HFP01SC（荷兰）热流板测量。考虑到涡度相关仪受降雨的影响较大，在数据处理时去除降雨量的数据，在标定时只采用晴日地面数据和遥感数据的交集。

LAS地面观测站位于北京市密云县新城子镇（40°37' 51" N，117°19' 24" E），下垫面主要为果树、耕地和居民地。观测站通量仪器主要包括大孔径闪烁仪（LAS）、涡动相关仪（EC）以及自动气象站（AWS）等观测。一套LAS装置在南北两座小山顶，光程2420 m，有效高度为35.6 m。自动气象站和涡动相关仪安装在高为31.5 m的铁塔上，铁塔与LAS接收端约900 m处。自动气象站包括两层风、温、湿以及四分量辐射仪（向上、向下短波辐射，向上、向下长波辐射）、地表辐射温度、土壤热通量、多层土壤温度、多层土壤湿度、降雨量以及气压等观测。

<table>
<thead>
<tr>
<th>站名</th>
<th>经度</th>
<th>纬度</th>
<th>下垫面</th>
<th>仪器</th>
<th>架高/m</th>
</tr>
</thead>
<tbody>
<tr>
<td>大兴站</td>
<td>116.427°E</td>
<td>39.6144°N</td>
<td>小麦</td>
<td>EC, AWS</td>
<td>2</td>
</tr>
<tr>
<td>馆陶站</td>
<td>115.127°E</td>
<td>36.515°N</td>
<td>小麦、玉米</td>
<td>EC, AWS</td>
<td>15.6</td>
</tr>
<tr>
<td>栾城站</td>
<td>114.683°E</td>
<td>37.883°N</td>
<td>小麦、玉米</td>
<td>EC, AWS</td>
<td>4</td>
</tr>
<tr>
<td>密云站</td>
<td>117.324°E</td>
<td>40.6321°N</td>
<td>果树</td>
<td>LAS, EC, AWS</td>
<td>35.6，光程2420</td>
</tr>
<tr>
<td>禹城站</td>
<td>116.6°E</td>
<td>36.95°N</td>
<td>小麦、玉米</td>
<td>EC, AWS</td>
<td>冬小麦2,3,玉米3.3</td>
</tr>
</tbody>
</table>
涡动相关仪包括超声风速仪（CSAT3, Campbell），H2O/CO2红外分析仪（LI-7500, LI-COR）等。地面观测获取了2007年的数据（卢俐等，2009），并经数据补插，剔去无效数据观测后插补到逐月（徐自等，2008）。

3.2.2 气象数据

收集了包括日照时数、相对湿度、风速、最高气温、最低气温、近地大气压在内的气象数据，在海河流域共83个台站（图1），并通过空间插值方法生成1 km的栅格数据。在空间插值过程中考虑了地形因子的影响。气温和气压使用的插值方法是反距离权重，日照、湿度、风速等使用的是样条函数方法。为使下午2点气温与MODIS过境时刻地温尽可能接近，对气温数据还进行了基于正弦函数的时间变换。

3.2.3 遥感数据

从NASA的MODIS数据发布网站（http://ladsweb.nascom.nasa.gov）上下载了所需的中分辨率遥感数据，包括MOD021KM、MOD02QKM、MOD02HKM和MOD03产品。MOD02QKM和MOD02HKM产品中的250 m和500 m分辨率波段被空间聚合到1 km分辨率上，生成大气层顶的辐照度和反射率。MODIS2.1μm波段用于探测影像暗目标，并使用Kaufman的方法（Kaufman等，1997）来计算红、蓝波段的气溶胶光学厚度，并将其作为输入，使用了6S模型进行大气校正（Vermote等，1997）。劈窗算法则用于从MODIS1B数据的27, 32波段计算地表温度LST（Mao等，2005）。

4 参数标定

4.1 模型参数估计方法PEST

ETWatch应用PEST软件进行模型参数标定与优化。PEST（Parameter Estimation）工具包由澳大利亚Watermark Numerical Computing公司开发，是功能强大的独立参数估计程序，可用于模型校正和预测分析。目前广泛应用于地下与地表水文地质学、地球物理、化学以及其他许多领域的模型校正和数据插值。PEST中的核心非线性参数估算方法是Gauss-Marquardt-Levenberg算法（Marquardt等，1963），是一种最速下降算法。

实际蒸散的计算过程包括：重要参数的提取（地表温度，比辐射率，植被覆盖度）、地表辐射平衡计算、土壤热通量计算、粗糙度长度和阻抗计算、显热通量和蒸发比率计算。通过文献调研，收集输入不同、复杂程度不等的各种参数式，并将其经验参数初始化，计算模型值，利用PEST自动标定程序与实测值比较并调整参数大小。基于PEST实现的自动标定模块，可以根据所用的遥感影像和地面数据生成参数集，可以对于不同的传感器数据、不同的气候区域，设置不同的参数集。某些参数也可预先通过模拟计算得出，作为查找表的一部分以加快计算的速度。受地表观测数据的限制，标定步骤主要以地温及净辐射为主，标定对模型的改进结果则体现于蒸发比和日蒸散量上。

4.2 地表温度与地气温差

将2007年密云测站周围3×3个MODIS像元的平均地表温度与测站地表辐射温度作了比较，共54例数据（图3）。选择相关系数 R和标准化误差RMSE作为统计指标，标定后的劈窗算法（R²=0.91，RMSE = 5.02 K）要优于MOD11全球地温产品（R²=0.91，RMSE=10.53 K）。结果表明，尽管密云站的下垫面比较复杂（果树），但简单的线性标定也可显著地提高季节温度变幅的估算精度，这一点对于全年蒸散量的准确估算是非常重要的。
后，即与地表辐射温度取得地气温差，而两者之间由于观测时间的不一致性造成的误差则往往被忽略掉。因此，需要将12点的边界层空气温度调整到MODIS/Aqua 13:

$$T_{12} - T_0 = \frac{A}{2} \sin\left(\frac{\pi}{4}\times \frac{3}{4}\right)$$

$$T_{13:30} - T_0 = \frac{A}{2} \sin\left(\frac{\pi}{2}\times \frac{3}{4}\right) + \frac{A}{2}$$ (1)

式中，$A$为气温日变幅，脚标为时刻。

### 4.3 短波辐射与长波辐射

日太阳短波辐射 ($R_{so}$) 用包括天文辐射和相对日照的Angstrom式计算，如下式：

$$R_{so} = \left(\frac{n}{N}\right) R_s$$ (2)

式中，$R_{so}$为太阳短波辐射 (MJ·m$^{-2}$·d$^{-1}$)；$n/N$为相对日照时间；$R_s$为天文辐射 (MJ·m$^{-2}$·d$^{-1}$)，$a_s$和$b_s$为经验常数。因大气条件不同（混浊/干洁）和日倾角的不同，$a_s$和$b_s$的取值会发生较大的变化。基于海河流域七个甲级辐射台站（太原、北京、天津、乐亭、济南、封丘、东灵山）2000年以后的观测，对该$a_s$和$b_s$的取值进行了逐月的空间化，再根据(2)式计算太阳短波辐射结果，达到标定的目的。图4显示了禹城站2008年的估算结果与实测结果的比较 ($R^2=0.869$)。

长波辐射 ($R_{nl}$) 使用式(3)计算：

$$R_{nl} = 0.34 - 0.14 \sqrt{e_a} \times \left[\frac{1.35 R_s}{R_{so} - 0.35}\right]$$ (3)

式中，$\sigma$为斯蒂芬—波尔兹曼常数；$T_{max,k}$和$T_{min,k}$分别为24h最高和最低气温（K）；$e_a$为实际的水汽压（kPa）；$R/R_{so}$为相对太阳短波辐射；$R_s$为太阳短波辐射 (MJ·m$^{-2}$·d$^{-1}$)；$R_{so}$为晴空太阳辐射 (MJ·m$^{-2}$·d$^{-1}$)，其余为经验系数。图5显示了在大兴站2008年的长波估算结果与实测结果的比较 ($R^2=0.723$)。在太阳短波辐射和长波辐射的基础上，进一步对日净辐射量进行标定，图6为馆陶站2008年净辐射估算结果与实测结果的比较 ($R^2=0.889$)。
4.4 锚点通量的内部标定

对于余项式单层模型，极端干湿材料（冷热点）的通量由有效能量的计算结果得出，并不受当地的气象条件制约，在迭代计算的过程中达到的平衡状态可能与实际情况差别较大。原SEBAL模型中假设热点处无蒸散（LE=0），H为最大值（Rn-G）；冷点处无显热（H=0）。参考METRIC模型的做法，ETWatch利用本地的参考蒸散信息对冷热点的初始通量给出了一个更优的初值：将冷点处的显热情况修正为：

\[ H_{\text{cold}} = R_n - G - LE_{\text{cold}} \]

其中 \( LE_{\text{cold}} = 1.05 \times ETr \)（H_{\text{cold}} 为冷点处显热，LE_{\text{cold}} 为冷点处潜热，ETr 为参考蒸散），这一做法通常可以有效减少迭代次数，使通量结果更快收敛。

4.5 水体热通量

为准确估算华北地区大型水体的水面实际蒸散，ETWatch利用2002年—2004年密云水库的水面月蒸发数据（由E601型蒸发器和20 cm型蒸发器获取，通过水面蒸发折算系数作了归一）。在日时段的尺度下，建立了 \( G_{\text{water}} = 0.225 R_n \) （4）

应用这一关系后，密云水库的估算蒸散量与观测数据具有较好的一致性，逐月相对偏差在14.9%左右，相关系数达到0.91，汛期（6月—8月）相对偏差在年尺度上的误差在1.5%以内（图7）。

4.6 显热通量

余项式单层模型中的核心反演量显热通量H除受地气温差的直接影响外，空气动力学阻抗可能存在的系统误差也可能造成结果的低估，因此利用4.1节的参数估计方法订正了模型中空气动力学阻抗计算时的系数值，使得模型输出的显热通量与密云LAS站显热观测值吻合（如图8）。在图7中，实测显热为卫星过境前后3 h的平均值（上午12：00—下午3：00），而遥感显热其实质是一个瞬间量，两者之间存在一定的差异；同时空气动力学阻抗的计算与订正方法是遥感蒸散方法中最为复杂和困难的部分，因此必须借助参数估计方法，才能将显热通量的误差控制在一定的范围内。

4.7 蒸发比

作为对模型参数标定结果的评价，选择模型输出的蒸发比与涡度相关观测值进行比较，观测蒸发比由下式给出：

\[ EF = \frac{\sum E_j}{\sum H_i + \sum E_j} \]  （5）

地面观测数据包括涡度相关仪的每0.5 h的H和LE数据，选择遥感卫星过境时刻（地方时13：30）前1.5 h和后1.5 h的数据求平均值，观测表明午后的蒸发较为稳定（徐自为等，2008），因此这一平均值应对全天的蒸发比较有一定表征能力。图9是蒸发比输出在大兴、栾城、密云和禹城四通量站上与实测蒸发比的对比，相关系数分别达到了0.65、0.86、0.78和0.74。其中禹城站的有效记录最多（共147例），蒸发比结果在1：1等值线左右分布得也较均衡。

5 结 论

本文基于ETWatch模型，在参数化选择的基础上发展了模型参数自动标定方法，并选择了遥感地表辐射温度和日净辐射进行了模型参数标定，发展了基于实时监测数据之间的参数化数据集，标定后，模型输出蒸发比与实测的时段平均蒸发比的相关系数可达到
参数标定可有效提高遥感与地面蒸散观测的吻合程度，是提高数据精度和应用水平的关键环节。

遥感计算ET是基于像元的，像元上的数值反映的是一定空间范围内的地表要素的平均信息，而地面观测往往基于单点进行。因此地面观测结果与遥感监测ET结果对比分析时要特别注意到由空间尺度造成的差异，需要进一步开展与遥感尺度相吻合的尺度转换方法研究。从概念性的遥感算法到成熟的产品处理平台是非常复杂的过程，有限的地面单点验证无法提供对差异性极大的下垫面的整体评价，大量的地面验证有助于算法改进和参数化，但在统计意义上也是有限的。建立区域适用的遥感监测与评估系统，还需要将通量塔点联网观测、小流域水文资料，以及与其他遥感面上资料、模型模拟结果相结合，发展基于动态过程的，点面结合的综合评价思路。

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