An investigation of influencing factors of land surface temperature based on the iButton and MODIS temperature data

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Abstract: To clarify the effects on land surface temperature (LST), continuous LSTs of 19 rural and 9 urban sites in Nanjing are measured. Though the LST has a positive correlation with the air temperature, the diurnal surface temperatures ranging between 0°C and 4°C are far less than the diurnal air temperatures of 6°C–16°C. The rainfall made the LSTs and diurnal surface temperatures lower than those on sunny days. Despite that, the relationship between LST and humidity suggests that the average diurnal surface temperatures decreased with the increase in the humidity. Additionally, we employed a corrected method for Moderate Resolution Imaging Spectroradiometer (MODIS) temperature product and compared with the field-monitoring data collected from iButtons. The results demonstrate that the calibrated satellite temperatures have a better correlation with the measured values. MODIS temperatures and measured temperatures are different under different land types, and the MODIS temperature of a pixel is much closer to the LST of the dominated land type.

1. Introduction
The land surface temperature (LST) is an important factor in the physical processes on the surface and a key variable in climate and environmental research [1, 2]. In fact, the change of surface temperature has a great influence on the soil moisture content, which leads to the shrinkage strain of the soil and cause the geological disasters, such as the ground cracking and subsidence [3]. Generally, the surface temperatures can be acquired by field-monitoring and weather stations, but they are time-consuming and inefficient. Besides, it is nearly impossible to do a large-scale field monitoring due to lack of the means. Recently with a great deal of attention on the increasing global temperatures, thermal remote sensing development became a practical way to get spatially broad and continuous measurements of the surface temperature [4-5].
In the satellite inversion process, the radiating signals are received by the sensors on the satellite through
the atmosphere, and then the signals are processed and transformed into images [6, 7]. NASA’s Earth Observing System provides free, short time series of Moderate Resolution Imaging Spectroradiometer (MODIS) data products, which can acquire data four times in one day. Split window algorithm is used for temperature processing, however, the data quality of the LST products is affected by many factors, including the sensor, algorithm and parameter estimation [8, 9], causing insufficient processing of massive data and low precision. The aim of the remote sensing data reconstruction is to use a variety of statistical and numerical methods to simulate missing data, achieving the interpolation of missed observations.

There are many factors affecting the ground temperature distributions, such as the land covers, air temperature, weather (snowfall, wind, rainfall), global warming, seasons etc. For example, Popiel et al. [10] compared the effects of temperature distributions across two land covers, 6.9m and 17.3m deep, over 10 years, and found that the average ground temperature of the lawn was lower in summer and higher in winter in comparison to the bare soil. Tang et al. [11] compared the urban and rural surface temperatures at 600 locations in Nanjing and concluded that the urban soil temperatures are warmer, because with urbanization, the natural vegetation is gradually replaced by concrete and asphalt.

Many previous studies have verified the reliability of the MODIS temperature product data in comparison to the relatively accurate data form field-monitoring [12]. The ground infrared temperature radiation data are always applied to correct the districts with large lakes, grass and farmland, where the surface emissivity is corrected according to the land type. While for some areas without the infrared data or measuring instruments, the temperature can be obtained from the weather stations. Additionally, some data from high-resolution sensing sensors are synchronized with MODIS data, acquiring smaller scale data and more precise information of the surface [13, 14].

In this paper, based on the temperature data, the effects of air temperatures, rainfall and humidity on LST are discussed. Besides, according to the improved adaptive weighted Savitzky–Golay filtering method, the reconstructed time series of the MODIS data was verified by the measured surface temperatures of 9 urban and 19 suburban sites in Nanjing. Furthermore, the relations between measured LSTs under different land types and MODIS data per pixel were compared to explore the effects of land types. At the same time, the variation in the LSTs can affect the underground temperatures, and thus, it is of great engineering significance to study the influence factors of LSTs.

2. Material and method

2.1. Study area and sites

Nanjing lies in the southwest of Jiangsu Province, China. It stretches from 118°21’28” E to 119°15’57” E and from 30°13’39” N to 32°36’37”N. The width of Nanjing is 70 km, and the length is 150 km. The Yangtze River flows diagonally from the southwest to the northeast of the city. Nanjing is located in the northern subtropical monsoon climate zone with wet and cold winters, muggy summers, and long duration with large temperature differences throughout the year. Monitoring points of LSTs included 9 urban and 19 rural sites, which are described in Figure. 1.
2.2. Data acquisition

The iButton is a temperature sensor, shaped like a button sealed with stainless steel, with a diameter of about 16 mm and a thickness of about 5 mm. It contains a lithium battery and a temperature sensor, and the sensor is connected to a computer through a data cable to set and read data. For measurements, the time interval was set to 1 hour, and the iButton data were recorded continuously from 2019/8/1 to 2020/12/1. The data information of air temperatures, rainfall, and humidity were acquired from the China Meteorological Observation (free from http://data.cma.cn/).

The satellite data utilized here are the Terra-Aqua/MODIS products (MOD11A1 and MYD11A1) from NASA. However, the data had to be extracted by remote sensing images, which is nearly impossible when dealing with massive data. Google Earth Engine (GEE) is a good platform that can easily access high-performance computing resources and process large-scale geographic data sets conveniently. In addition, the GEE provides many algorithms for basic data format processing. The satellite collected the temperature data at 01:30, 10:30, 13:30 and 22:30.

2.3. The reconstruction of the surface temperature

The MODIS data products were inevitably affected by noise, such as cloud occlusion, resulting in partial data loss. Besides, MODIS products provide a Quality Control (QC) band value for each pixel to describe the reliability of the data, and the QC value description is shown in Table 1. Savitzky–Golay (S-G) smoothing algorithm is a polynomial smoothing algorithm based on the least square principle proposed by Savitzkg and Golay [15], also known as convolution smoothing algorithm. Due to the lack of unequal intervals in the LST time series obtained by remote sensing, the use of equal interval window widths is likely to cause a large range of data missing in the window. In this paper, first the null values were removed, then a certain weight coefficient was assigned to the data according to the QC value, and finally, the polynomial was fitted as the least square method, and all values in the window were
calculated based on the polynomial. Considering the QC values as 0, 2, 65 and 129 in the districts, the corresponding weight values were 1, 0, 0.6, and 0.4.

| QC   | Data description                                                                 |
|------|-----------------------------------------------------------------------------------|
| QC=0 | LST produced, good quality, not necessary to examine more detailed QC              |
| QC=2 or 3 | LST not produced due to cloud effects                                             |
| QC>3 | LST produced, other quality data                                                 |

Table 1. QC band corresponding bits and meaning.

3. Results

The surface temperatures were affected by many factors. Here ten sites of continuous LSTs in a year were chosen to investigate the effects of air temperatures, rainfall, and humidity. Combined with the MODIS data, the effects of land cover types were explored as well.

3.1. The relationship between surface and air temperatures

Comparing the daily mean air temperatures with the surface temperatures of ten sites over a year, the correlation between air and surface temperatures is depicted in Figure. 2, and was calculated as above 85%. Evidently, the overall temperatures of the former were higher than those of the latter. The diurnal temperature variations of the surface were between 0.5°C and 10°C, while it ranges from 2°C to 17°C for the air temperatures (Figure. 3). The bigger fluctuations mainly occurred in autumn and spring, especially for the air temperatures. Furthermore, the statistic results of diurnal temperature variation distributions are illustrated in Figure. 4, indicating that most of the diurnal surface temperature variations happened in the range of 0°C–4°C, with only a small part between 4°C–6°C. Inversely, the diurnal air temperature variations were mostly above 6°C, fluctuating around 10°C.

![Figure 2](image)

**Figure.2** Correlation analysis of the air and surface temperatures. Scattered plots represent the temperature value, and the fitted line represents the significant relationship between them (The first line from left to right: SG09, SG14, SG26, SG27, SG28; the second line from left to right: SG33, SG39, ...
SG44, SG45, SG49).

Figure 3 Diurnal temperature variations of air and surface temperatures in a year.

![Graph showing diurnal temperature variations](image)

Figure 4 Distribution characteristics of diurnal air and surface temperature difference.

![Bar chart showing frequency percentage](image)

3.2. The effect of rain and humidity

The rainfall from August 2019 to 2020 shows that 1/3 of this period was rainy while the rest of the days were sunny. The average diurnal temperatures were 1.54°C on rainy days and 2.3°C on sunny days with the standard deviations of 0.69°C and 0.77°C respectively. The average surface temperatures on rainy and sunny days were 17.49°C and 18.48°C, and the standard deviations were 7.38°C and 7.19°C respectively.

Average diurnal and surface temperatures of all sites were calculated in different range of humidity, as shown in Figure 5. The results suggest that the average diurnal temperature difference declined from 3.28°C to 1.38°C with the increase in the humidity. The average surface temperature was 16.3°C when the humidity was below 50%, and then it went up to 19.9°C, and down to 18.1°C with the increase of humidity, showing no obvious correlation between the two.
3.3. The effects of land cover types

3.3.1. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the relation coefficient before and after reconstruction

To evaluate the performance of the processing data, based on the average temperature of the measured data in a day, the differences between the observed and filled data were averaged for calculating the RMSE and MAE. In addition, the relation coefficients of average MODIS temperature data in a day and the average temperature data after the algorithm reconstruction are also compared in Table 2.

As shown in Table 2, the correlation coefficients between the surface temperatures before reconstruction and the measured values are between 0.1 and 0.8, and the correlation coefficients after reconstruction are generally higher than 0.9, indicating that the algorithm reconstruction can effectively improve the reliability of the data. In addition, the average value of MAE decreased from 4.70°C to 2.21°C, and the RMSE was decreased from 5.84°C to 2.76°C, indicating that the algorithm reconstruction can effectively supplement the null data, improve the accuracy of the original data, and reduce the data errors.

| Sites | RMSE/°C | MAE/°C | R²  | RMSE/°C | MAE/°C | R²  |
|-------|---------|--------|-----|---------|--------|-----|
| sg02  | 5.97    | 4.86   | 0.79| 2.36    | 1.77   | 0.96|
| sg03  | 6       | 4.86   | 0.78| 2.47    | 1.88   | 0.95|

Table 2. Comparison of remotely-sensed land surface temperature before and after algorithm reconstruction with the measured values.
### 3.3.2. The effect of different land types

There are usually multiple coverings distributed in a pixel with the area of 1 km × 1 km, and the MODIS data only represent the average value, so the real surface temperatures of different land types are different for every district. The surface temperatures with four land cover types were measured in one pixel located in the campus of Nanjing University. The results shown in Figure. 6 indicate that the surface temperatures of cement are also the largest, followed by grass, brush, and the tree. The temperature variations of cement are also higher than the other types, which can be explained by the following reasons. The cement has a lower specific heat capacity, thus it absorbs heat in the daytime and dissipates it in the nighttime. Therefore, the LSTs rise and decline quickly, causing large diurnal temperature difference.

|     |    |    |    |    |    |    |
|-----|----|----|----|----|----|----|
| sg06 | 6.87 | 5.65 | 0.78 | 3.79 | 3.15 | 0.95 |
| sg09 | 5.86 | 4.76 | 0.81 | 2.23 | 1.88 | 0.96 |
| sg11 | 4.21 | 3.47 | 0.88 | 1.98 | 1.55 | 0.98 |
| sg13 | 4.1  | 3.22 | 0.88 | 1.37 | 1.1  | 0.99 |
| sg14 | 5.32 | 4.26 | 0.84 | 2.55 | 2.1  | 0.95 |
| sg15 | 4.26 | 3.46 | 0.88 | 1.68 | 1.4  | 0.98 |
| sg16 | 5.31 | 4.28 | 0.87 | 2.14 | 1.77 | 0.98 |
| sg19 | 10.77 | 9.38 | 0.12 | 2.82 | 2.18 | 0.96 |
| sg26 | 6.18 | 4.96 | 0.8  | 3.71 | 3.11 | 0.95 |
| sg27 | 4.74 | 3.83 | 0.85 | 2.01 | 1.58 | 0.98 |
| sg28 | 5.62 | 4.42 | 0.83 | 2.55 | 2.06 | 0.96 |
| sg33 | 5.34 | 4.19 | 0.86 | 2.28 | 1.79 | 0.97 |
| sg39 | 5.52 | 4.46 | 0.84 | 2.04 | 1.59 | 0.98 |
| sg43 | 6.08 | 4.89 | 0.79 | 3.07 | 2.61 | 0.95 |
| sg44 | 6.62 | 5.35 | 0.8  | 2.94 | 2.4  | 0.94 |
| sg45 | 6.51 | 5.51 | 0.85 | 3.26 | 2.85 | 0.96 |
|     |    |    |    |    |    |    |
| c1  | 5.34 | 4.16 | 0.84 | 2.53 | 2.04 | 0.97 |
| c2  | 6.86 | 5.24 | 0.69 | 4.87 | 3.82 | 0.84 |
| c3  | 5.73 | 4.53 | 0.86 | 3.65 | 3.08 | 0.97 |
| c4  | 5.94 | 4.64 | 0.72 | 3.07 | 1.24 | 0.85 |
| c5  | 5.87 | 4.69 | 0.7  | 2.78 | 2.28 | 0.88 |
| c6  | 5.19 | 4.19 | 0.89 | 2.48 | 3.86 | 0.96 |
| c7  | 5.94 | 4.7  | 0.85 | 3.42 | 2.8  | 0.96 |
| c8  | 5.77 | 4.45 | 0.74 | 3.57 | 1.41 | 0.87 |
| c9  | 5.63 | 4.43 | 0.68 | 2.77 | 2.15 | 0.86 |
| Mean | 5.84 | 4.70 | 0.79 | 2.76 | 2.21 | 0.95 |
4. Discussion

The air temperatures are closely connected with the surface temperatures despite certain differences. There is enough sunshine in the day, but the wind flows non-uniformly, causing the non-homogeneous temperature distribution. Furthermore, the heat dissipates quickly in the night, causing large temperature differences in the entire day. On the contrary, the soil has higher volumetric heat capacity as compared to the air, so it can maintain relatively constant temperature.

The differences in surface temperatures depend on many factors, such as land cover, population density, weather conditions, and so on. The surface temperatures are often affected by the rainfall, and the average surface and diurnal temperatures on rainy days are lower than those on sunny days. This can be explained by the fact that the rain evaporates and absorbs the heat from the surface when the temperature rises, thus the surface temperatures fluctuate in a smaller range. In fact, because of the effect of rain, the humidity can reflect the rainfall to some extent. Diurnal temperatures decrease more with the increase in humidity than surface temperatures. Surface temperatures are often affected by many factors, especially the sun radiation, increasing the uncertainty in temperature fluctuations.

Comparing the MODIS data after reconstruction and the surface temperatures, the MODIS temperature is closer to the LST of cement, also the LST of the main land type. In addition, the relationships between MODIS data and LSTs under different land types are described in Figure. 7. The correlation coefficients are higher than 0.93, suggesting that the average value of the pixel can effectively represent the LST of each component in the range. Meanwhile, the liner functions can also be applied to adjust the LSTs for different surface types when using the MODIS temperatures to reflect the LSTs. However, the slope values of the fitting functions are below 1, and the comparisons of R² establishes that k_{Tree}<k_{Brush}<k_{Grass}<k_{Cement}. As a result, the nodes where the MODIS temperatures are equal to the actual LSTs under different surface conditions are also different: the node of shrub and tree are both close to about 15°C; the node of Grass is about 25°C; the node of cement ground is almost non-

![Figure 6 Land surface temperature under different surface covers and remotely-sensed temperature](image_url)
existent. These reflect the regulating effect of different surface coverings on the surface temperature. The overall aim of different surface materials is to maintain optimum LSTs throughout the day.

**Figure 7** The relationship between measured and remotely sensed land surface temperature under four surface types: (a) Cement; (b) Grass; (c) Brush; (d) Tree.

### 5. Conclusion

In this paper, the effect of air temperatures, rainfall, humidity and land cover types on the LSTs are discussed by measuring LSTs and the MODIS temperatures after reconstruction by the improved S-G algorithm. The main conclusions regarding the same are as following:

1. Compared with unprocessed satellite data, the S-G algorithm can increase the relation coefficients and decrease the MAE and RMSE, suggesting that the application of improved SG algorithm can not only supplement the missing data, but also improve the accuracy of the MODIS temperature data.
2. The air temperatures have a positive linear relation with the LSTs, while the rain can reduce them to some extent. The diurnal LST difference decreases with the humidity, and the relationship between humidity and LST is not specific.
3. The LSTs of vegetation are lower in comparison to the cement because of the shielding effect from the sunshine via the former. Though the adjusted temperatures have a close connection with the measured data, some differences still exist among different land types. A relatively simple linear function was proposed to correct the MODIS temperature data and acquire more accurate surface temperatures under different land covers in the study. Considering the corrected temperature data have some
differences with the measured data, thus it’s necessary to consider more factors to correct the MODIS temperature data in the future study.

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