

# Spatial Downscaling of MODIS Land Surface Temperatures Using Geographically Weighted Regression: Case Study in Northern China

Si-Bo Duan and Zhao-Liang Li

**Abstract**—Land surface temperatures (LSTs) at high spatial resolution are crucial for hydrological, meteorological, and ecological studies. Downscaling LSTs from coarse resolution to finer resolution is an alternative way to obtain LSTs at high spatial resolution. In this paper, we proposed a new algorithm based on geographically weighted regression (GWR) to downscale Moderate Resolution Imaging Spectroradiometer LST data from 990 to 90 m. Unlike previous LST downscaling algorithms, this algorithm built the nonstationary relationship between LST and other environmental factors (including the normalized difference vegetation index and a digital elevation model) using geographically varying regression coefficients. The uncertainty in this algorithm was evaluated with a sensitivity analysis. The results show that the total uncertainty in this algorithm is less than 2 K. The performance of the GWR-based algorithm was assessed using concurrent ASTER LST data as a reference LST data set. Moreover, this algorithm was compared against the TsHARP algorithm, which was widely used for LST downscaling. The results indicate that the GWR-based algorithm outperforms the TsHARP algorithm in terms of statistical results. The root mean square error (mean absolute error) value decreases from 3.6 K (2.7 K) for the TsHARP algorithm to 3.1 K (2.3 K) for the GWR-based algorithm.

**Index Terms**—Advanced spaceborne thermal emission and reflection radiometer (ASTER), downscaling, geographically weighted regression (GWR), land surface temperature (LST), moderate resolution imaging spectroradiometer (MODIS).

## I. INTRODUCTION

LAND surface temperature (LST) is a key parameter in the physical processes of surface energy and water balance at regional and global scales [2], [10], [28], [41], [45]. It is widely used in a variety of research fields including soil moisture

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S.-B. Duan is with the Key Laboratory of Agri-informatics, Ministry of Agriculture/Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, China (e-mail: duansibo@caas.cn).

Z.-L. Li is with the Key Laboratory of Agri-informatics, Ministry of Agriculture/Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, China, and also with the State Key Laboratory of Resources and Environment Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China (e-mail: lizhaoliang@caas.cn).

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estimation [5], [25], [35], surface urban heat island monitoring [39], [46], diurnal temperature variation modeling [8], [9], [16], [17], [19], surface longwave radiative estimation [44], [21], evapotranspiration studies [3], [23], [27], [31], and thermal inertia estimation [29].

Current satellite thermal sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), can provide LST images at various spatial and temporal resolutions [11], [15], [40]. Due to technical constraints, these current satellite thermal sensors reflect a tradeoff between spatial and temporal resolutions; thus, the sensors with high-spatial resolution possess low-temporal resolution, and *vice versa* [47]. An alternative and effective way to obtain LST images at high spatial and temporal resolutions is to perform LST downscaling.

Various algorithms have been developed to downscale LSTs from coarse resolution to finer resolution (e.g., [32], [36], and [49]–[51]). Detailed overviews of LST downscaling algorithms have been provided by Zhan *et al.* [52] and Chen *et al.* [6]. The most widely used approach is the DisTrad algorithm [24], which was renamed the TsHARP algorithm [1] and is based on the assumption that the relationship between the normalized difference vegetation index (NDVI) and LST is scale invariant. The performance of this algorithm was evaluated over different land cover types, including agricultural landscapes [20] and urban areas [12]. The main limitation of the TsHARP algorithm is that this relationship is not unique, which results in a wide range of LSTs for a given value of NDVI. Therefore, Merlin *et al.* [33] further improved the TsHARP algorithm by taking into account the effect of photosynthetically and nonphotosynthetically active vegetation within the spatial variability of LST. Furthermore, Bindhu *et al.* [4] proposed a nonlinear DisTrad (NL-DisTrad) algorithm based on the assumption that the polynomial relationship between NDVI and LST that is developed from the hot-edge pixels at coarse resolution is also valid at finer resolution.

Although great efforts have been made to advance the LST downscaling algorithms based on the relationship between LST and NDVI, certain issues still need to be investigated further. In previous studies, LSTs were predicted using univariate regression (i.e., NDVI, [1], and [24]) or multivariate regression (i.e., NDVI and albedo and [7]). These processes assume that the relationship between the dependent variable and the independent variables is stationary in space. In fact, the relationship