Reconstruction of multiple climate variables at high spatiotemporal resolution based on Big Earth data platform

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Certificate of Original Authorship

I, Mingxi Zhang declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Life Sciences/Faculty of Sciences at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by an Australian Government Research Training Program.

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Glossary

EO	Earth Observation
PB	Petabytes
GEE	Google Earth Engine
ODC	Open Data Cube
SH	Sentinel Hub
API	application programming interface
DEM	Digital Elevation Model
HPC	High-Performance Computing
CNN	convolutional neural network
DL	Deep Learning
STMSR	Spatial and Temporal Mountain Solar Radiation Modelling
SSR	Surface Solar Radiation
GSR	Global Solar Radiation
ТР	Tibetan Plateau
LST	Land Surface Temperature
GWTR	geographically and temporally weighted regression
RF	Random Forest
XGBoost	eXtreme Gradient Boosting
LLTO	Leave-Location-Time-Out
LLO	Leave-Location-Out
LTO	Leave-Time-Out
FFS	Forward Feature Selection
EHF	Excess heat factor
HWN	Heat Wave Number
HWD	Heat Wave Duration
HWF	Heat Wave Amplitude
HWM	Heat Wave Magnitude
HWT	Heat Wave Tracker
GEV	Generalized Extreme Value
NEVA	Non-stationary Extreme Value Analysis
CMIP5	Coupled Model Intercomparison Project 5
WEPP	Water Erosion Prediction Project
SWEEP	Single-Event Wind Erosion Evaluation Program
RUSLE	Revised Universal Soil Loss Equation
RWEQ	Revised Wind Erosion Equation
GPM	Global Precipitation Measurement
GLDAS	Global Land Data Assimilation System
ERA5	European Centre for Medium-Range Weather Forecasts Reanalysis 5
SLGA	Soil and Landscape Grid of Australia
FVC	Fractional Vegetation Cover

Abstract

Reconstruction of climate variables with high spatio-temporal resolution is important when the meteorological observations required for environmental monitoring and modelling do not cover the study area. In addition, climate model reanalysis datasets suffer from coarse spatio-temporal resolutions, which fails to capture the complex variability of climate at fine scales. This thesis mainly reconstructed four climate datasets including: mountainous solar radiation, near-surface air temperature datasets over rugged terrain, five distinct metrics of long-term heat wave datasets, an updated database of water and wind erosion. For further use in practice, these datasets are freely accessible and online web application has been developed for academic research on climate change under accelerated global warming. The main findings of this thesis are: (1) A GIS-based solar radiation model that incorporates albedo, shading by surrounding terrain, and variations in cloudiness was developed to address the spatial variability of these factors in mountainous terrain. (2) The Tibetan Plateau has been undergoing accelerated warming over recent decades, and is considered an indicator for broader global warming phenomena. However, our understanding of warming rates with elevation in complex mountain regions is incomplete. The most serious concern is the lack of high-quality nearsurface air temperature (Tair) datasets in these areas. To address this knowledge gap, we create new near-surface air temperature datasets to understand elevation-dependent warming in the Tibetan Plateau. (3) Under ongoing global warming due to climate change, heat waves in Australia are expected to become more frequent and severe. A Google Earth Engine-based toolkit named heat wave tracker (HWT) is developed, which can be used for dynamic visualization, extraction, and processing of complex heat wave events. The datasets, toolkit, and findings we developed contribute to global studies on heat waves under accelerated global warming. (4) Soil erosion caused by water and wind is a complicated natural process that has been accelerated by human activity. This erosion has resulted in increasing areas of land degradation which threaten the productive potential of landscapes. Consistent and continuous erosion monitoring will help identify the trends, magnitude, and location of soil erosion. We apply the water-wind erosion model to produce monthly and annual water, and wind erosion estimation at high spatial resolution (up to 90 m, 500 m) for Australia from 2000 to 2020.

Keywords: Big data; solar radiation; near-surface air temperature; heat wave; water and wind erosion; climate change; Cloud computing; China, Australia