

Editorial

# Editorial for Special Issue: “Remote Sensing of Environmental Changes in Cold Regions”

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Received: 9 September 2019; Accepted: 16 September 2019; Published: 18 September 2019



Cold regions, characterized by the presence of permafrost and extensive snow and ice cover, are significantly affected by changing climate. Of great importance is the ability to track abrupt and longer term changes to ice, snow, hydrology and terrestrial ecosystems that are occurring within these regions. Remote sensing allows for measurement of environmental variables at multiple spatial and temporal scales, providing key support for monitoring and interpreting the environmental changes occurring in cold regions. The recent advances in the application of remote sensing for the analysis of environmental changes in cold regions are documented in this Special Issue.

Theoretical modeling—For improving the current understanding of L-band microwave emissions from snow-covered soil, the Wave Approach for LOW-frequency MICrowave emission in Snow (WALOMIS) model, initially developed for semi-infinite snow-firn conditions, was adapted and parameterized for seasonal snow. Evaluations of the model simulations against ground-based radiometer measurements show that the WALOMIS model can well reproduce the observed brightness temperature (T<sub>b</sub>) with overall root-mean-square error (RMSE) between 7.2 and 10.5 K and have higher performance over larger incidence angles and H-polarization. The wave approach of WALOMIS also enables better quantification of the effects of interference and snow layering [1].

Ice—Satellite-based sea ice concentration (SIC) products have been widely used in monitoring global warming and navigating ships but are difficult to validate over the remote Arctic regions. For assessing the performance of satellite products and algorithms, SIC data sets were derived from ship-borne photographic observations acquired along cruise paths and compared with six passive microwave remote sensing products. The comparisons suggest that satellite products likely over/underestimate SIC under low/high SIC conditions mainly due to the presence of melt ponds; and the Special Sensor Microwave Imager Sounder (SSMIS) NASA Team algorithm has the overall best accuracy [2].

Ice-jam flood is one of the major hazards threatening riverine communities in the sub-arctic regions. Early forecasting of ice-jam flood can benefit from accurate locating and discriminating different types of ice. A novel method of differentiating ice runs from intact ice covers was developed using spaceborne synthetic-aperture radar (SAR) observations and the Freeman–Durden decomposition technique. The method was demonstrated using RADARSAT-2 imagery acquired along the Athabasca River for the spring of 2018, showing the distinct scattering signatures of ice runs and intact ice and its potentials in flood monitoring [3].

**Snow**—Snow properties including snow cover area and snow water equivalent (SWE) are vital inputs for numerical weather predictions and hydrologic model simulations. The quantification of global snow depth (SD) and SWE distributions generally relies on the observations from multi-frequency satellite microwave radiometers such as the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) and China's FengYun-3D (FY-3D) Microwave Radiometer Image (MWRI). For developing FY-3D SD algorithm for regions of China, five operational algorithms were first evaluated using in-situ measurements. Considerable underestimate for deep snowpack (>20 cm) or persistent overestimate of SD by these algorithm outputs are mainly caused by inaccurate representation of snowpack characteristics in China. The FY-3D SD algorithm was then built using an empirical retrieval formula calibrated by weather station measurements. The refined algorithm shows improved retrieval accuracy over the baseline products with a RMSE of 6.6 cm and bias of 0.2 cm [4].

**Frozen soil**—One of the key issues in satellite microwave sensing of frozen soil is the determination of microwave radiation response depth (MRRD). A parameterized model to estimate MRRD was developed using the combination of theoretical model simulations and field measurements. According to the model, MRRD can be accurately determined from soil temperature, soil texture and microwave frequency. The estimated errors of MRRD of frozen loam soil at 6.9 GHz, 10.65 GHz, 18.7 GHz and 36.5 GHz were about 0.537 cm [5].

**Surface water**—Near-nadir interferometric imaging SAR techniques are well suited for measuring terrestrial water body extent and surface height at relatively fine spatial and temporal resolutions. The concept of near-nadir interferometric measurements was implemented in the experimental Interferometric Imaging Radar Altimeters (InIRA) mounted on Chinese Tian Gong 2 (TG-2) space laboratory. Both theoretical simulations and InIRA imagery showed that water and surrounding land pixels can be well distinguished by near-nadir SAR and the intensity of radar signals is determined by surface dielectric properties, roughness and incidence angles. A dynamic threshold approach was developed for InIRA and tested over Tibetan lakes where in-situ observations are sparse. Validations using a 30-m LandSat water mask suggest that high accuracy (>90%) of water and land classification can be achieved by InIRA [6].

Alternatively, optical remote sensing enables surface water mapping at sub-meter to meter scales. For mitigating the risks of glacier lake outburst flood, multi-resolution satellite imageries from LandSat (30-m resolution), Sentinel-2 (10-m resolution), WorldView and GeoEye (0.5–2 m resolution) were synergistically used to analyze the dynamics of supraglacial ponds in the Himalayan region. The analyses showed a continuous increase in the area and number of supraglacial ponds from 1989–2017, consistent seasonal patterns and a great diversity of pond features. The satellite images also revealed high persistency and density of the ponds (>0.005 km<sup>2</sup>) near the glacier terminuses; and a fast expanding of spillway lakes on the Ngozompa, Bhote Koshi, Khumbu and Lumsamba glaciers [7].

Landsat imageries (1985–2015) and higher resolution aerial photographs were used to quantify surface water changes in the high Arctic pond complexes of western Banks Island, Northwest Territories. Analysis based on remote sensing, field sampling and geostatistic approaches showed an overall drying trend of high Arctic lakes mainly driven by climate factors and also affected by intensive occupation by lesser snow geese [8].

**Vegetation**—Multi-year Landsat and MODIS (Moderate Resolution Imaging Spectroradiometer) data sets were examined to reconstruct vegetation recovery from wildfire disturbances in Alaska. Breakpoint analysis using the BFAST (Breaks for Additive Seasonal and Trend) approach was able to capture the wildfire-related structural change in the MODIS normalized difference vegetation index (NDVI) time series. Further analysis of the change detection results suggested that vegetation cover density in the Alaskan wetlands likely recovers to pre-fire levels in less than 10 years [9].

In summary, continuous warming has altered the hydrologic and ecologic conditions across the cold regions, resulting in a myriad of changes including glacier melting, active layer deepening, permafrost degradation, snow and ice phenology changes, water body shrink and expansion, and regional greening and browning. Remote sensing is essential in tracking and understanding the environmental

changes and revealing the underlying physical mechanisms. Multi-source data fusion approaches, emerging techniques such as microsatellites and artificial intelligence, light detection and ranging (LIDAR) and structure from motion photogrammetry, and next generation satellite missions will enable unprecedented remote sensing performance in cold land studies [10].

**Conflicts of Interest:** The authors declare no conflict of interest.

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