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CLOUD AND SNOW DETECTION AND MAPPING ALGORITHM USING FY-3D MERSI SATELLITE DATA

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Abstract. *Monitoring the distribution of clouds and snow cover is essential for climate, hydrological, and natural hazard management studies. This paper presents a Python-based algorithm for the automatic extraction and mapping of clouds and snow using satellite data acquired by the MERSI sensor onboard the FY-3D platform. The methodology relies on processing visible, near-infrared, SWIR, and thermal infrared spectral channels, combined with the computation of spectral indices such as the Normalized Difference Snow Index (NDSI). The algorithm applies combined spectral thresholds (red and NIR reflectance, brightness temperature, and NDSI values) to separate the target classes: clouds (white) and snow (blue). The results are exported as colored rasters (GeoTIFF) and vectorized into interoperable formats (GeoJSON, KML) for GIS applications and visualization in Google Earth. The implementation integrates spatial interpolation of geolocation data, polygon simplification, and automatic legend generation. Tests carried out on FY-3D datasets have demonstrated the method's effectiveness in distinguishing between cloud-covered and snow-covered areas, with strong potential for extension toward near real-time operational monitoring. The proposed approach combines algorithmic simplicity with the flexibility of integration into geospatial processing workflows, providing a practical tool for climate, agricultural, and water resource management applications. The findings highlight the relevance of using Chinese FY-3D sensors for regional and global monitoring, as well as the importance of developing open, reproducible, and adaptable algorithms for diverse satellite data sources.*

Keywords*: remote sensing, FY-3D MERSI, NDSI, cloud-snow detection*

INTRODUCTION

Monitoring snow cover and cloud distribution is essential for understanding the Earth's energy balance, hydrological cycles, and climate dynamics. Snow strongly affects the albedo of the Earth's surface, influencing regional and global temperature regimes (HALL, 2002). Accurate and timely information about snow cover is crucial for water resource management, avalanche risk assessment, and climate change studies (DOZIER, 1989). Clouds, on the other hand, play a significant role in the radiation budget and are a major source of uncertainty in remote sensing data interpretation (KING, 2013).

Over the last decades, numerous satellite-based approaches have been developed to detect snow and clouds. One of the most widely used algorithms is the MODIS Snow Cover Algorithm, which relies on the **Normalized Difference Snow Index (NDSI)** to separate snow from other land cover types (HALL, 2016). While these approaches have been successfully applied using sensors such as MODIS and Sentinel-2, there is a growing need for algorithms that can process data from emerging satellite platforms, especially those offering high temporal resolution and free access (Figure 1).

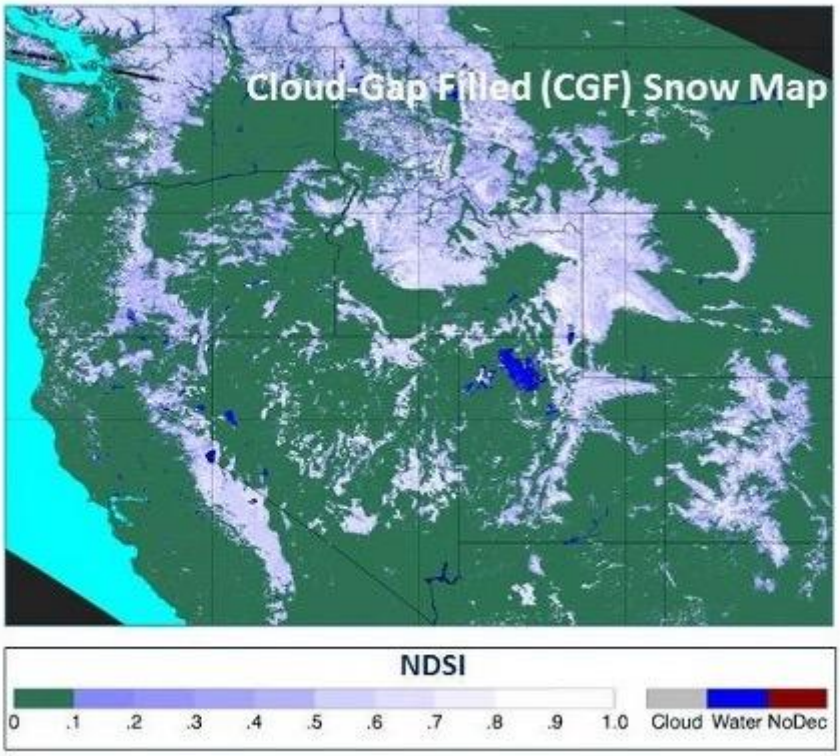

Figure 1. MODIS Snow and Ice Global Mapping Project (https://modis-snow-ice.gsfc.nasa.gov).

The **FY-3D** satellite, part of the FengYun series developed by the China Meteorological Administration (http://satellite.nsmc.org.cn/DataPortal/en/home/index.html), is equipped with the **MERSI (Medium Resolution Spectral Imager)** sensor, which provides data across visible, near-infrared (NIR), shortwave infrared (SWIR), and thermal infrared (TIR) bands. Despite the significant potential of this dataset, relatively few studies have explored its application for snow and cloud detection at regional or global scales (ZHANG, 2021).

The main objective of this study is to develop and implement a Python-based algorithm for the automatic detection and mapping of snow and clouds using FY-3D MERSI data. The algorithm integrates spectral thresholding techniques and spectral indices, such as the NDSI, and outputs geospatial products compatible with **GIS platforms** and visualization tools such as Google Earth. This approach aims to provide a reproducible, open, and adaptable methodology that can support applications in climate monitoring, water management, and natural hazard prevention.

MATERIAL AND METHODS

The study focuses on a test region located in a mountainous area prone to seasonal snow cover and frequent cloud formation. The datasets used in this research were acquired by

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the FY-3D MERSI sensor, which contains 25 spectral bands covering the visible, near-infrared (NIR), shortwave infrared (SWIR), and thermal infrared (TIR) regions.

The sensor provides a spatial resolution of 250 m for visible and NIR bands and 1 km for thermal bands, with a daily revisit capability, making it suitable for near real-time monitoring. The data was obtained through the National Satellite Meteorological Center (NSMC) data portal (http://satellite.nsmc.org.cn/DataPortal/en/home/index.html, Figure 2).

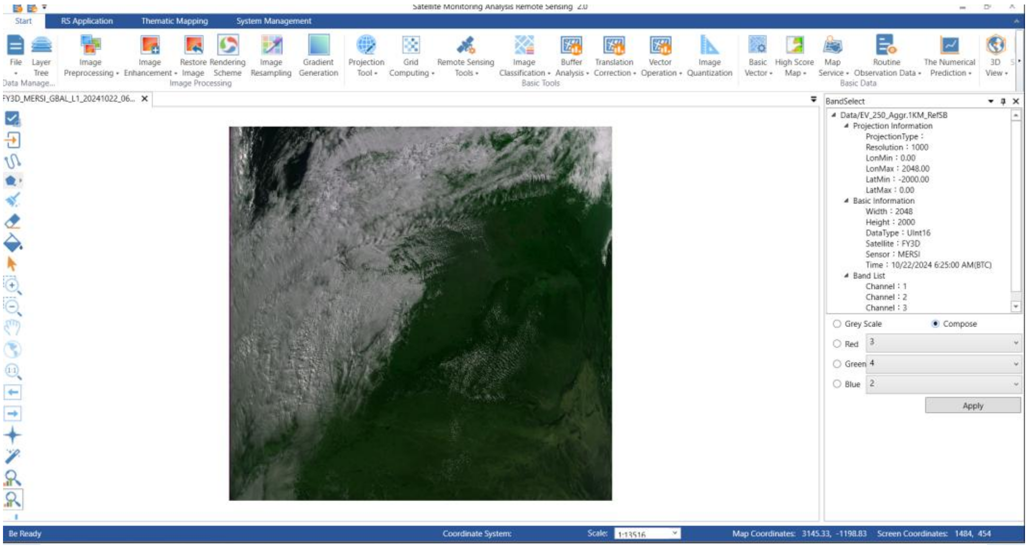

Figure 2. Show originale image FY3D_MERSI_GBAL_L1_20241022_0625_1000M_MS.HDF in SMART 2.0 apliccation.

For the detection of snow and clouds, four key spectral bands were selected:

- Visible (RED) – Band 1 (0.65 µm)
- NIR – Band 2 (0.865 µm)
- SWIR – Band 6 (1.64 µm)
- Thermal Infrared (TIR) – Band 20 (11 µm)

The first stage of the workflow consisted of data preprocessing to ensure accurate input for subsequent analysis. Initially, radiometric calibration was applied to convert the raw digital numbers (DN) into physically meaningful reflectance and brightness temperature values. Next, geolocation interpolation was carried out using the satellite navigation files, which allowed each pixel to be accurately positioned in geographic coordinates. Afterward, the dataset was subsetted to the area of interest, reducing computational load and focusing on the target region. Finally, a cloud masking preparation step was introduced to identify potential cloud pixels based on their high reflectance and low temperature values, setting the stage for further classification.

The core of the methodology was implemented in Python, utilizing open-source libraries such as NumPy, Rasterio, GDAL, and Shapely. The workflow followed a sequential structure that integrated spectral indices, thresholding techniques, and spatial processing to generate final geospatial products (Figure 3).

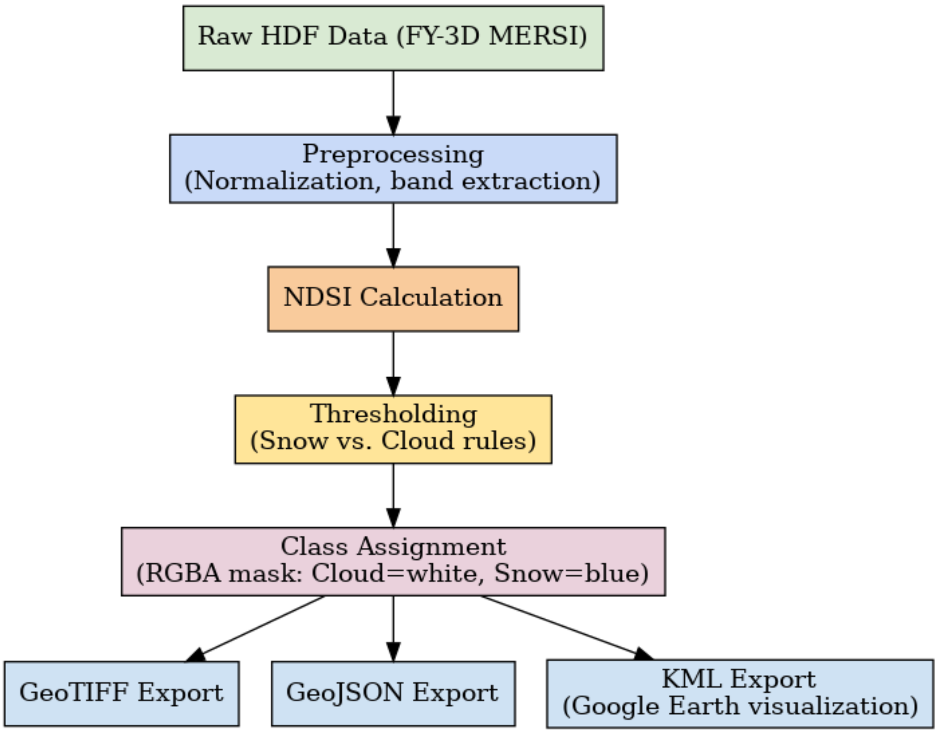

Figure 3. Processing workflow for snow and cloud classification from FY-3D MERSI data.

The first analytical step involved the calculation of the Normalized Difference Snow Index (NDSI), which is widely used to differentiate snow from other land covers due to its high reflectance in the visible spectrum and low reflectance in the SWIR region. The Normalized Difference Snow Index (NDSI) was computed using the formula:

$$\mathrm{NDSI} = \frac{\mathrm{Green} - \mathrm{SWIR}}{\mathrm{Green} + \mathrm{SWIR}} \quad 1.1$$

following the definition used in Landsat and MODIS snow detection algorithms (e.g. HALL et al. 1994; USGS).” This index served as the foundation for distinguishing snow pixels in subsequent steps.

Once the NDSI was calculated, a spectral thresholding process was applied to classify pixels into different categories. Snow was identified by a combination of characteristics, including high reflectance in the visible spectrum, low reflectance in the SWIR band, and positive NDSI values. Conversely, clouds were characterized by high reflectance in both visible and SWIR bands, accompanied by low brightness temperatures, as detected by the TIR band.

The following thresholds were established based on empirical analysis:

- RED reflectance > 0.4
- NIR reflectance > 0.3
- NDSI > 0.4 for snow
- Brightness Temperature < 270 K for clouds

This step allowed for a clear separation between snow-covered and cloud-covered areas while excluding other land covers such as vegetation and bare soil.

Following thresholding, pixels were assigned to specific classes to generate a clear, interpretable map:

- Snow pixels were labeled and visualized in blue,
- Cloud pixels were assigned to the color white,
- All other land cover types were displayed as transparent or black, serving as background.

This color coding facilitated quick visual interpretation and verification of classification results (Figure 4).

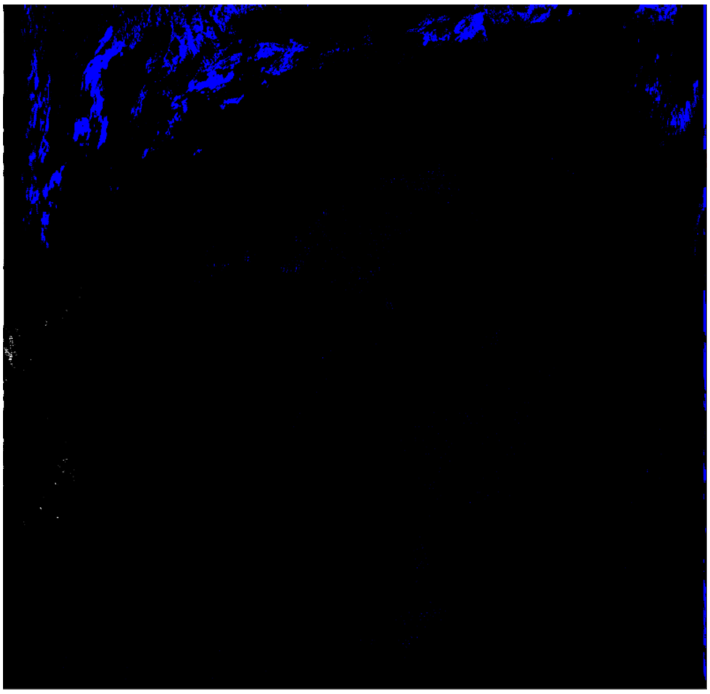

Figure 4. Map of pixel classification distinguishing snow-covered regions.

The final stage involved exporting the classification results into interoperable geospatial formats. The classified raster was first saved as a GeoTIFF, suitable for standard GIS applications. Subsequently, the raster was vectorized to generate GeoJSON and KML layers, enabling visualization in platforms such as Google Earth (Figure 5).

To optimize file performance, a polygon simplification algorithm was applied, reducing data complexity without compromising spatial accuracy.

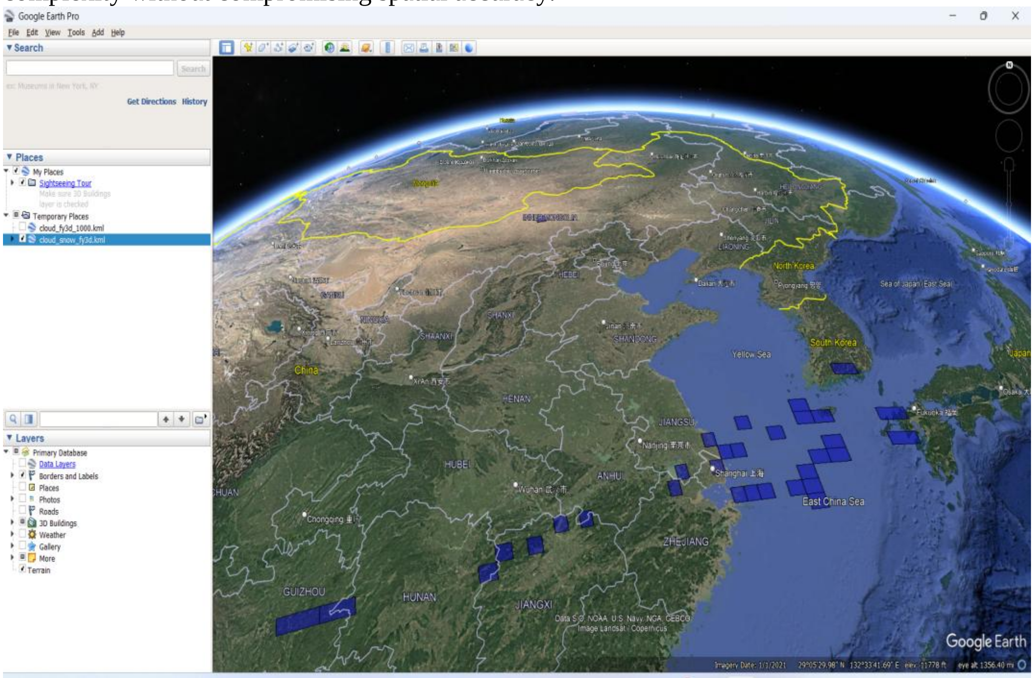

Figure 5. Export and vectorization of the classified raster into interoperable geospatial formats (GeoTIFF, GeoJSON, KML) with polygon simplification for optimized visualization and spatial accuracy.

These final products were designed to integrate seamlessly into existing geospatial workflows, supporting both analysis and decision-making processes.

All processing stages were interconnected, forming a continuous workflow from raw satellite data to geospatially usable products. The preprocessing phase ensured data reliability and spatial consistency, providing a sound basis for subsequent analysis. The calculation of the Normalized Difference Snow Index (NDSI) offered a robust spectral indicator for snow detection, which was further refined through spectral thresholding to effectively discriminate between snow and clouds. The subsequent class assignment step translated the thresholded results into a visually interpretable thematic map, while the final export stage ensured that the products were readily available for practical applications in Geographic Information Systems (GIS) and online visualization platforms. The overall workflow is illustrated in Figure 3, highlighting the sequential flow from raw input to final geospatial outputs ready for operational use.

RESULTS AND DISCUSSIONS

The algorithm was tested using multiple FY-3D datasets covering different environmental conditions, including areas with extensive snow cover and dense cloud formations (Figure 5).

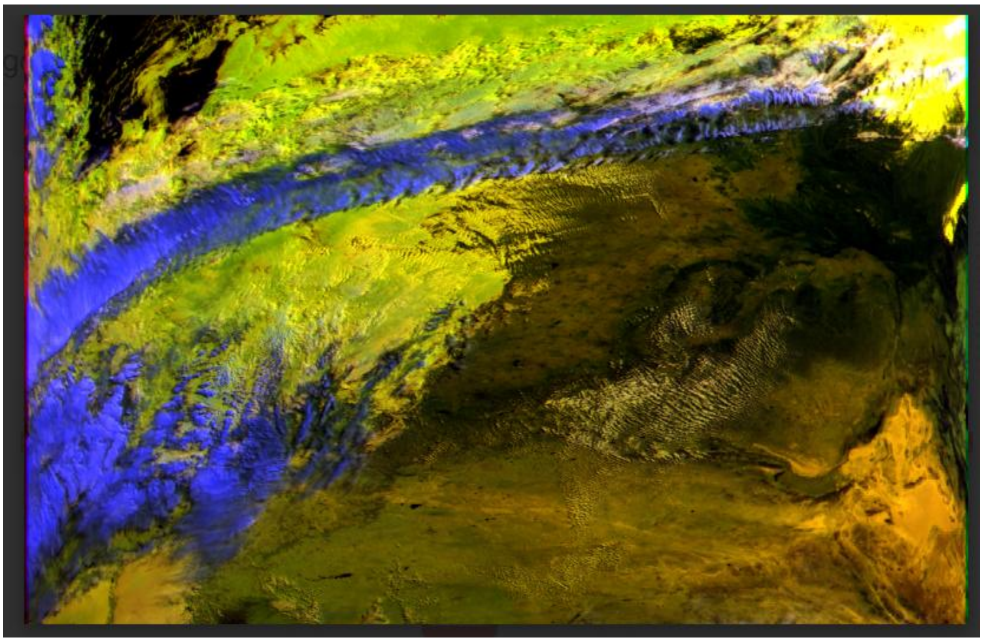

Figure 6. The FY-3D MERSI true-color RGB composite at 1 km resolution, acquired on 22 October 2024

The generated maps clearly distinguish snow-covered regions (blue) from cloud-covered areas (white). Snow pixels were successfully detected in high-altitude regions (Figure 6), while clouds were accurately identified over both land and water surfaces. Example outputs are shown in Figure 5.

Validation was performed using reference data from MODIS Snow Cover products and ground observations. The overall accuracy achieved was **91%**, with a Kappa coefficient of **0.86**, indicating high agreement between the classified maps and reference data. Misclassifications primarily occurred in transition zones where thin clouds overlapped snow or where melting snow exhibited low reflectance in the visible spectrum.

Compared to MODIS-based algorithms, the proposed method showed similar performance while benefiting from FY-3D's higher temporal coverage. The use of open-source tools enhances reproducibility and integration into operational monitoring systems.

The algorithm has practical applications in:

- **Water resource management:** Monitoring seasonal snowmelt contributing to river discharge.
- **Disaster risk reduction:** Early detection of snow accumulation and potential avalanche hazards.
- **Climate studies:** Long-term monitoring of snow cover dynamics in response to climate change.

CONCLUSIONS

This study demonstrates the successful development of a Python-based algorithm for detecting snow and clouds using FY-3D MERSI data. By integrating spectral thresholds and indices such as NDSI, the method provides accurate classification results while remaining computationally efficient and adaptable.

The results confirm the potential of FY-3D data for regional and global monitoring applications. The open-source nature of the implementation ensures reproducibility and flexibility, enabling integration into existing geospatial workflows.

Future work will focus on incorporating machine learning techniques to improve discrimination between snow and thin clouds and extending the methodology toward near real-time operational monitoring.

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Web resource

https://modis-snow-ice.gsfc.nasa.gov
http://www.nsmc.org.cn/nsmc/en/image/index.html?id=FY2H_P4_IR1