

An Observation of Arctic Melt Ponds Based on Sentinel-2 and ICESat-2



Xiaoyi Shen

Nanjing University

(shenxy@nju.edu.cn)



Background

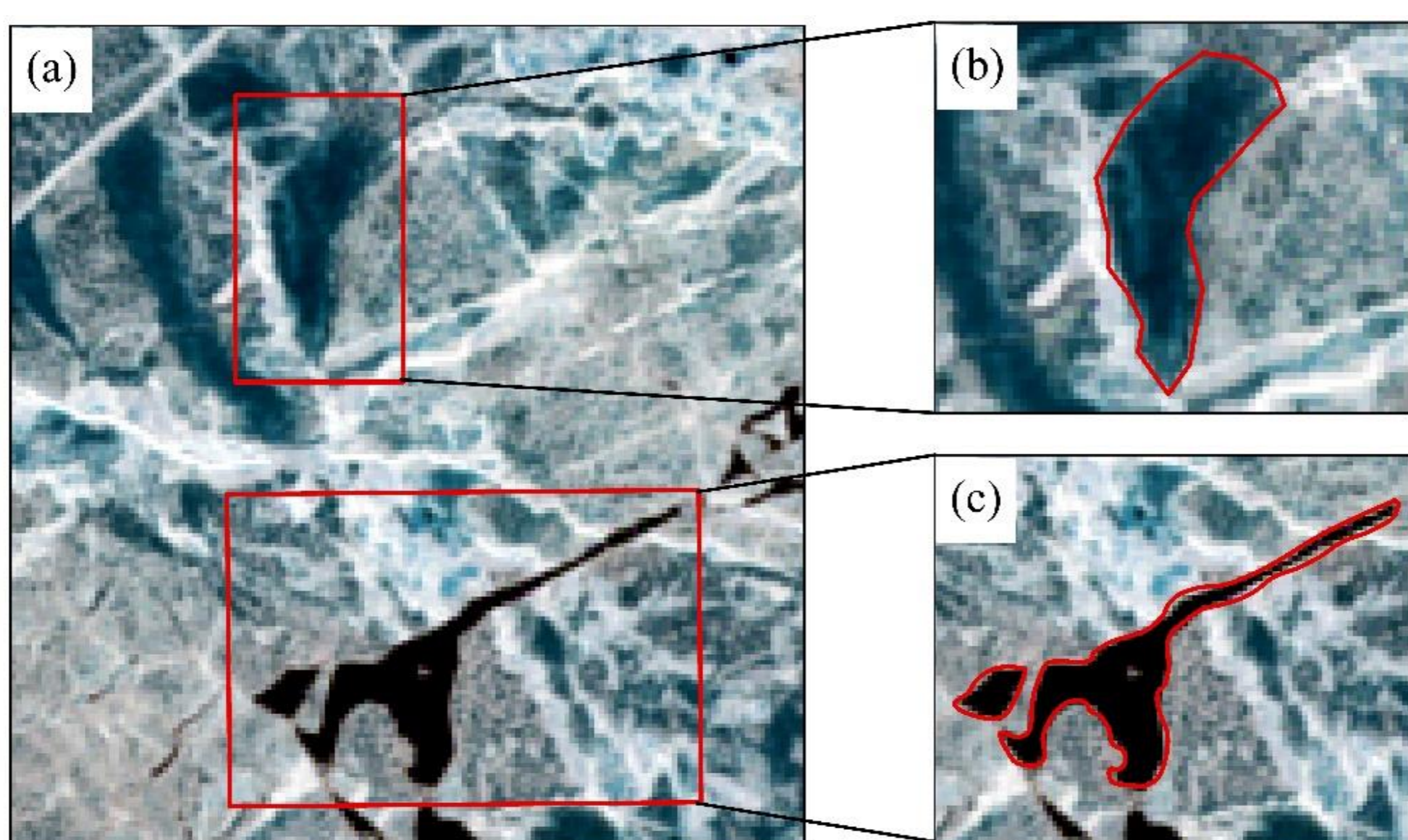
- Sea ice plays a significant role in the Earth's climate system, and its changes impact the exchange of energy and matter between the ocean and the atmosphere, thereby influencing global climate change. In recent years, the melting speed of Arctic sea ice, which serves as one of the sensitive indicators of global climate change, has been accelerating continuously, drawing widespread international attention. When the surface of sea ice begins to melt, the melted water gathers in depressions, forming small water bodies known as melt ponds. The formation and evolution of these melt ponds accelerate sea ice melting, altering the morphology and distribution of sea ice. By identifying and analyzing parameters such as melt pond area, quantity, and distribution, it is possible to understand the rate of sea ice melting and its spatiotemporal distribution characteristics. This provides essential data support for research on marine ecosystems and global climate change. Therefore, conducting large-scale and long-term dynamic monitoring of melt ponds holds great significance.

Data

- Using Landsat-8 Top of Atmosphere (TOA) data from the period between May and August from 2016 to 2021, melt ponds were identified and their interannual variations were monitored. Additionally, melt pond depths were estimated by combining Landsat-8 TOA data and ICESat-2 data from May to August during the years 2019 to 2021.

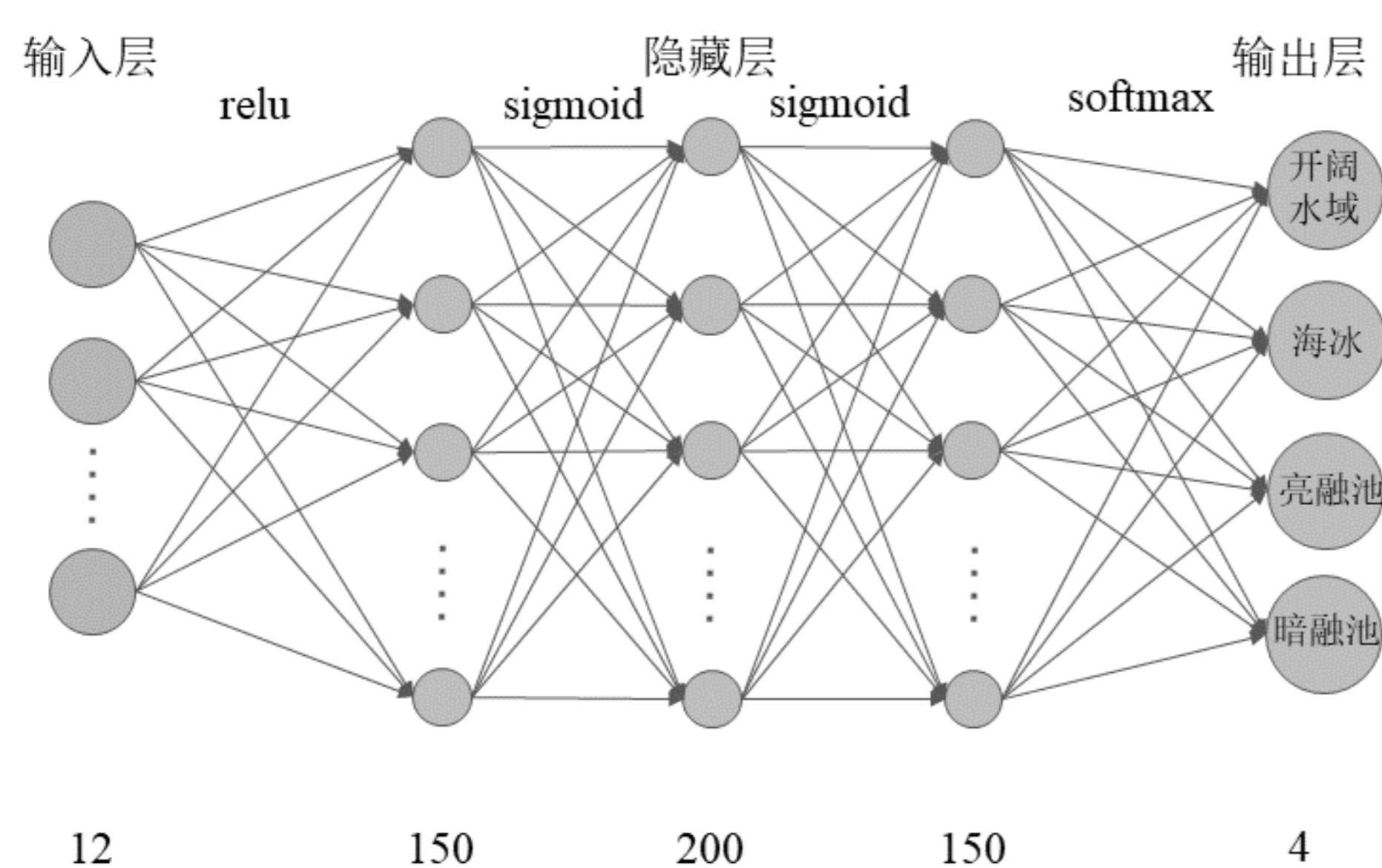
Melt pond identification using a multi-layer neural network

- Quality control: Removing the influence of clouds and shadows
- Construction of object samples: A total of 45 scenes of images from the years 2017 and 2019 were selected for sampling, spanning the period from May to August, and covering a geographical range between 68°N to 81°N latitude. During the selection of sample points, a total of 16,796 points were chosen, including 6,506 points representing open water, 5,918 points representing sea ice, 2,273 points for bright melt ponds, and 2,099 points for dark melt ponds.



Example of melt ponds

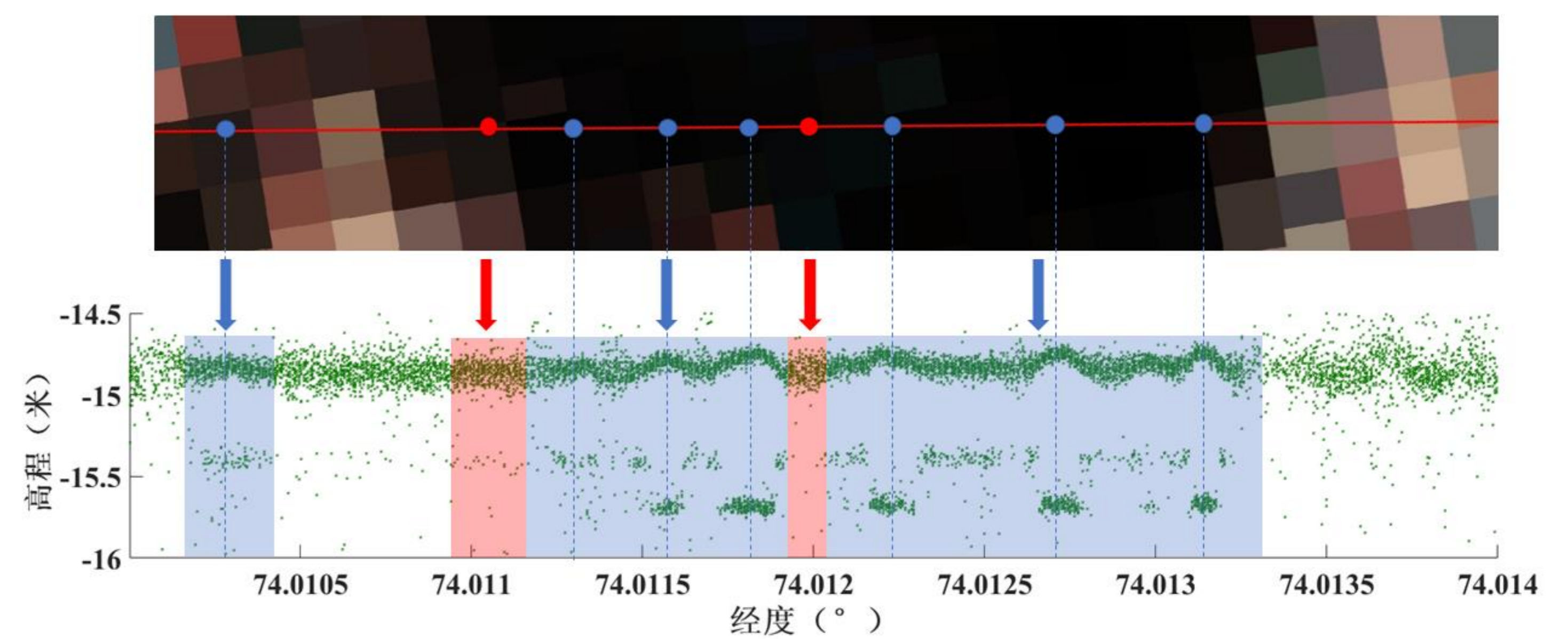
- Construction of multi-layer neural networks



- After multiple rounds of testing, it was observed that increasing the number of hidden layers and neurons has a negligible impact on accuracy improvement and significantly reduces data processing speed. Therefore, only three hidden layers were configured, containing 150, 200, and 150 neurons respectively. Additionally, the parameters that yielded the highest accuracy during several rounds of testing were chosen as the final settings.

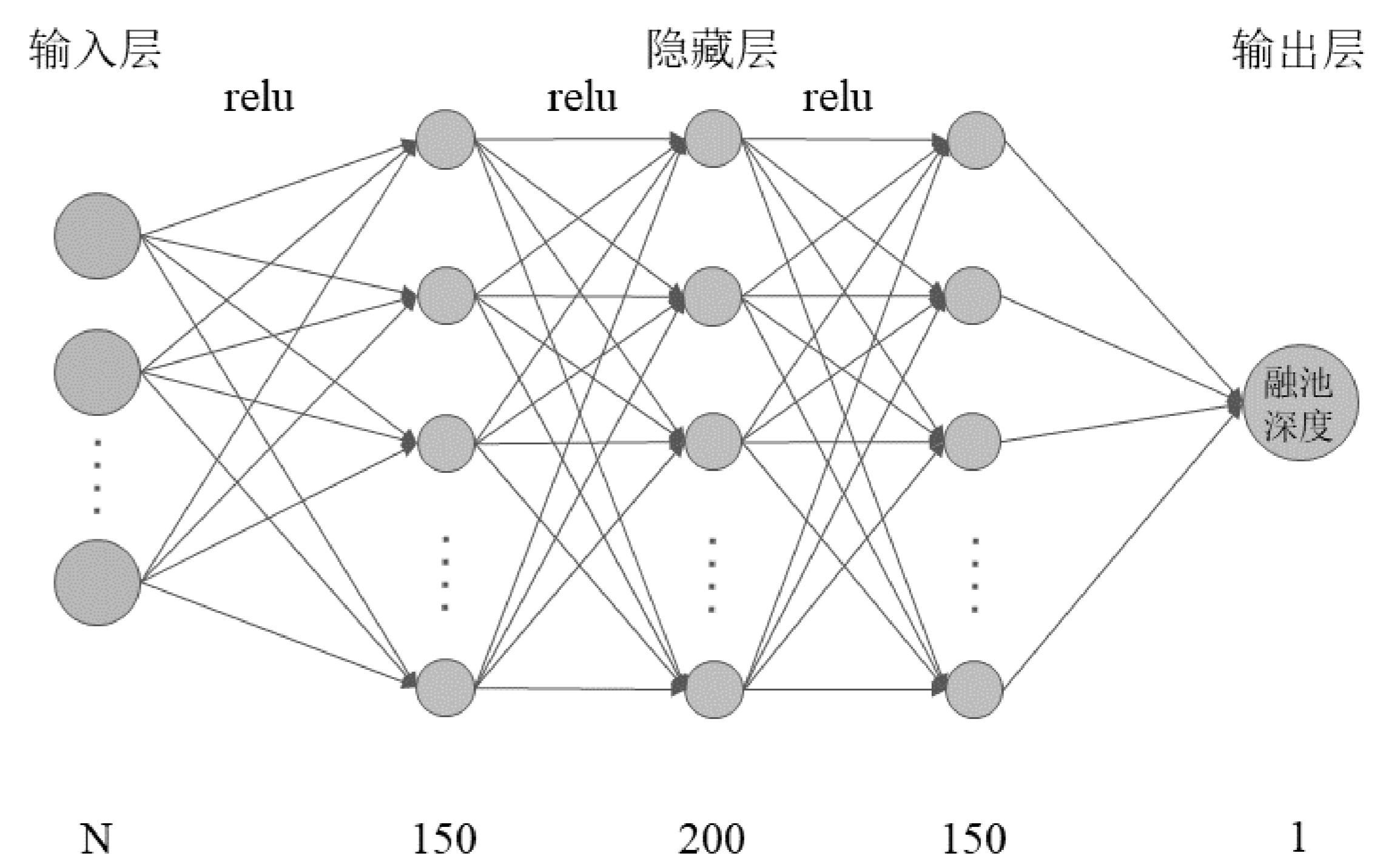
Melt pond depth estimation based on a multi-layer perceptron

- Spatial and temporal match of ICESat-2 and Landsat-8
- Construction of melt pond depth sample dataset: Using ICESat-2 ATL03 photon data as input, employing adaptive kernel density estimation to determine the top three maximum values of photon elevation. Subsequently, the photons are classified into categories including lake surface, surface ice, subsurface ice, and lake bottom based on their relative height and intensity. Moreover, it is capable of capturing minor surface undulations, enabling small-scale lake depth estimation without prior knowledge of the lake's location. Thus, utilizing ICESat-2 ATL03 data, depth values estimated by this algorithm serve as reference values for melt pond depth assessment.

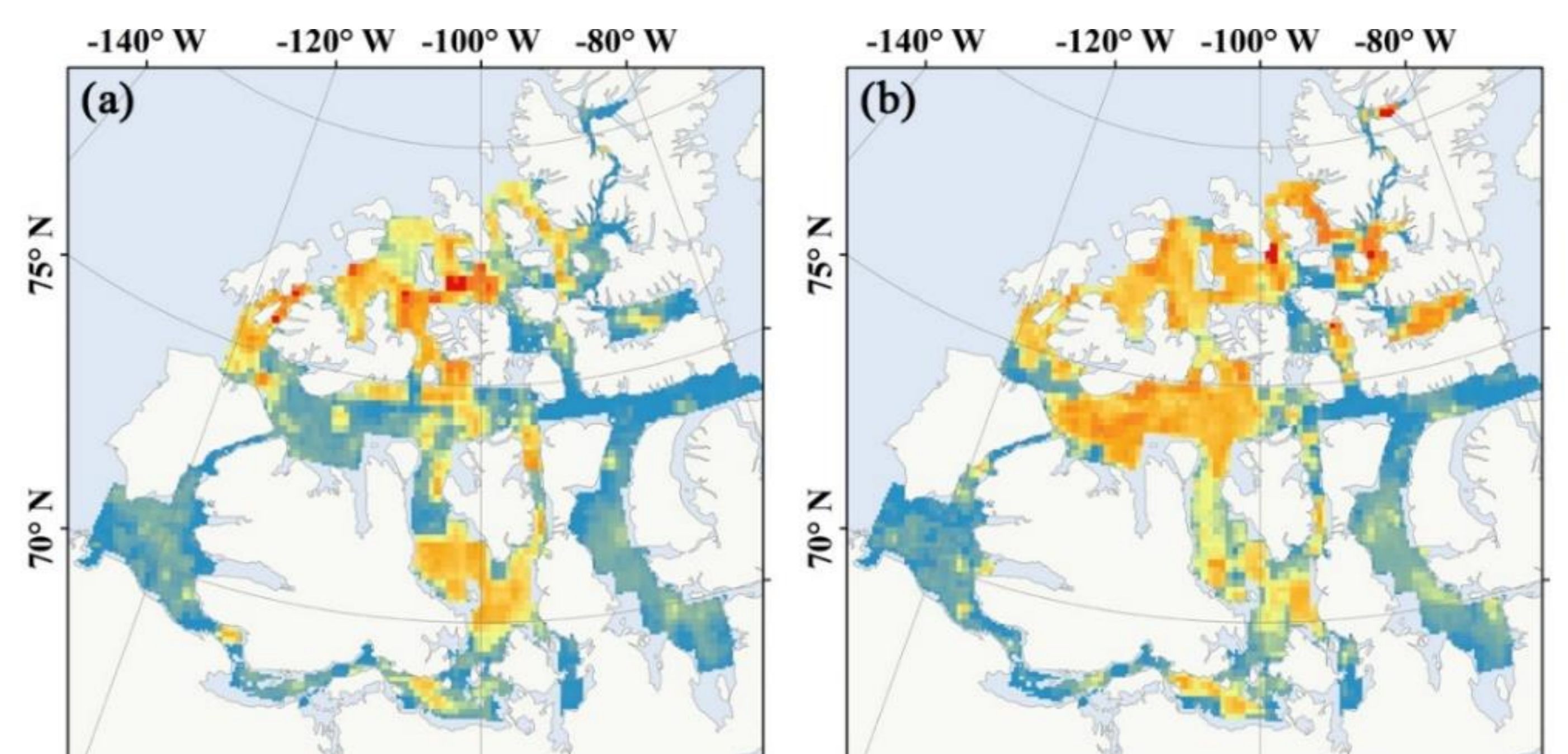


Example of ICESat-2 photon elevations

- Melt pond depth estimation: A Multi-Layer Perceptron (MLP) model was constructed using the TensorFlow framework. This model comprises an input layer, multiple hidden layers, and an output layer. The input layer receives various Landsat 8 feature data from the training set, while the output layer generates predictions for melt pond depth. During model training, hyperparameters are adjusted using a validation set to choose the optimal ones. Simultaneously, the training process is halted when the model's performance plateaus to prevent overfitting. By utilizing the selected optimal feature combinations, the MLP model is further refined, leading to the optimal model. Ultimately, the optimal MLP model is applied to the estimation of melt pond depths in the Canadian Arctic Archipelago region.



Results



Spatial distribution of averaged melt pond volume from 2016 to 2021 in 15 km grids