Abstract

Hypertemporal image (HTI) is often used to exploit the seasonal characteristics of environmental phenomena such as sea ice concentration (SIC). However, it is difficult to analyse the long-term time series acquired at high temporal frequencies and over extensive areas. This study performed temporally mixed analysis (TMA), which is algebraically similar to spectral mixture analysis (SMA), but occurs in the time domain instead of the spectral domain. TMA was used to investigate the temporal characteristics of Antarctic sea ice. Because endmember (EM) selection is critical to the success of both SMA and TMA, it is important to select proper EMs from large quantities of HTI. In this study, a machine learning (ML) technique is incorporated in identifying EMs without prior information to address the limitations of previous research. A fully linear mixing model was then implemented in an attempt to produce more robust and physically meaningful abundance estimates. Experiments that quantitatively and qualitatively evaluated the proposed approaches were conducted. A TMA of high-temporal-dimensional data provides a unique summary of long-term Antarctic sea ice and noise-whitened reconstruction images via inverse processing. Furthermore, comparisons of regional sea ice fractions from experimental results enhance the understanding of the overall Antarctic sea ice changes.

1. Introduction

Although Piotrow, Peddle, and Ledrew (1988) first investigated TMA by analysing long-term remote temporal remote sensing (RS) data that were generated using 9 years of monthly Arctic SIC data, simple statistics (e.g. mean, median, maximum and minimum) are used to derive pure temporal EM spectra from a simple set of image spectra. However, this method can not properly capture spatial characteristics of sea ice because monthly data provide insufficient temporal information, and the temporal EMs generated by the purification process are not always collected on the same scale as the image data.

In this study, ML techniques are used for TMA of Antarctic SIC to provide unique and summarised information on the long-term time series in three steps.

1) Use daily SIC data, which are similar to hyperspectral image data but are different in domain, to better seasonally characterize the Antarctic sea ice.

2) Apply an ML-based endmember extraction (EE) algorithm to generate a collection of pure temporal EMs due to a lack of prior information on sea ice seasonality.

3) Conduct quantitative/qualitative evaluations, and discussed results to propose the evaluated approaches.

2. Methodology

2.1 Datasets

• Years of daily SIC data from 1979 to 2014 provided by NSIDC (National Snow and Ice Data Center).

• 25-km spatial resolution in the polar stereographic projection.

Linear interpolation was applied to SIC data from 1978 to 1987 to generate consistent daily time series throughout the time period.

2.2 Temporal mixture analysis (TMA)

• SMA assumes that the surface is dominated by a small number of such substances and can be modelled by representing the surface as a sub-pixel mixture of these substances.

• The main idea underlying TMA is rooted in SMA. TMA assumes that the time series consist of several temporal components that represent the seasonal characteristics of the substances.

• Two general steps were employed to address the mixture problems:

1) Identifying temporally unique signatures of pure components (temporal endmembers).

2) Unmixing each pixel in the time series as a linear combination of EM fractional abundances.

2.3 Linear mixing models for TMA

• Assumptions:

1) The temporal trajectories of seasonal sea ice are linearly independent.

2) The pixels in the image line in linear spaces.

3) Fully constrained least squares linear spectral mixture analysis (LICM) (Heinz and Chang 2001): To find the fractional abundances (v) that minimize the pixel reconstruction error: \( \text{RMSE} = |x - E(v)| \) where x is a daily trajectory of HTI, E is a temporal EM matrix. The least squares solution is \( v = (E^T E)^{-1} E^T x \).

2 Constraints for each HTI pixel to estimate physically meaningful abundances:

Non-negative: \( 0 \leq v \leq V \), \( \sum_{i=1}^{q} w_i = 1 \) where q is the number of EMs.

2 Sum-to-one: \( \sum_{i=1}^{q} v_i = 1 \)

• Mixing effects on the multi-temporal SIC using three temporal EMs (Figure 3): 1) Open sea: Sea ice free in both March and September. 2) Non-seasonal sea ice: 100% ice cover in both March and September. 3) Seasonal sea ice: 100% SIC in March and 0% in September.

Figure 1. Basic definition of the temporal EMs (Piotrowski, Peddle, and Ledrew 1998).

2.4 Endmember extraction

• The most crucial task in both SMA and TMA is identifying an appropriate set of EMs to use in the modelling of temporal HTI spectra or temporal trajectories through a linear combination of the EMs.

• Because image-derived EMs have the advantage of being collected under the same conditions as the RS data, an ML-based EE algorithm was typically used.

• Assuming that pure ore extreme signatures are EMs, the notion of geometric convexity is natural and logical. Thus, this approach is the most popular and is used to develop a wide range of algorithms.

• N-FINDR (Winter 1999):

1) Main idea: Use the simplex of maximum volume spanned by the EMs as a major criterion.

2) Assumption: The volume defined by a simplex spanned by the purest pixels is greater than any other volume defined by any other combinations of pixels.

3) Algorithm description:

Step 1: Arbitrarily select initial seed points (EM candidates) \( E_1, E_2, \ldots, E_t \).

Step 2: Compute the volume of the \( t \) simplex spanned by the seed points as follows: \( \text{Volume} = \frac{1}{t!} \text{det} \left( E_1, E_2, \ldots, E_t \right) \)

Step 3: Evaluate the volume for each pixel to replace each EM position as a new simplex vertex until no larger simplex is found, as follows:

\[ \text{arg max} \left( \frac{1}{t!} \text{det} \left( E_1, E_2, \ldots, E_t \right) \right) \]

N-FINDR requires dimensionality reduction because the matrix \( V \) must be a square matrix for its determinant to exist. In this study, the maximum noise fraction (MNF) transform was used.

3. Experimental results

3.1 Reconstruction image comparison

• The HTI can be reconstructed via the inverse process of pixel unmixing.

• Although a combination of the temporal EMs and the corresponding fractions does not perfectly reconstruct the HTI, it can be used, to a certain, to create reference images that do not contain anomalies from other unexpected environmental factors and that mitigates the impact of processing error and noise.

• The reconstructed images did not capture the detailed variability in the local areas as shown in Figure 5; however, they generally exhibited better visual consistency with the original images.

3.2 Regional comparison

While the Antarctic ice exhibits a long-term negative trend, the overall Antarctic sea ice has been changing for decades. However, SIC exhibit significant spatial variability in the Antarctic. The sea ice has significantly increased in the Ross Sea, while the Amundsen Sea sector exhibits a negative trend.

• The slopes of three trend lines over the extent of the whole of the Antarctic sea ice were less steep than those for the Ross Sea and Amundsen Sea, which indicates that none of the three temporal signatures was significantly affected by the overall sea ice increases in the Antarctic (Figure 6(Left)).

• Sea ice in the Ross Sea has exhibited a more significant change in annual average than the southern hemisphere average. Year-round SIC in the Ross Sea exhibits a positive trend; however, the area of open water has not changed significantly, and seasonal SIC exhibits a negative trend. These data indicate that sea ice growing in the Ross Sea sector is attributable to non-seasonal sea ice rather than open water or seasonal sea ice (Figure 6(Right)).

• Unlike the Ross Sea, the Amundsen Sea sector has exhibited statistically significant decreases in SIC. The TMA results show negative trends in both non-seasonal sea ice and open water in the Amundsen Sea. However, the trend for multi-year ice shows a significant negative trend compared with the southern hemisphere and Ross Sea, while the extent of seasonal sea ice exhibits a positive trend. Overall, these results indicate that a decrease in the non-seasonal sea ice fraction in the Amundsen sector affects the declining levels of sea ice, and considerable areas of multi-year ice and sea ice-free regions in the Amundsen have transitioned to areas of seasonal sea ice (Figure 6(Middle)).

4. Conclusions and future work

• Three conclusions were derived from this study:

1) TMA effectively provides a unique summary of long-term time series.

2) The reconstructed images did not frequently contain or minimize the impact of anomalies.

3) Changes in fractional abundances for each temporal EM in each region explained the overall changes in seasonal sea ice on the ice edge.

Several challenges remain to motivate future research:

1) NDSC's SIC data and retrieval algorithms should be evaluated for more scientific purposes.

2) Spatial information, which is distinguishing characteristics of image data, should be exploited to yield more accurate EM signatures.

3) An ensemble of the TMA results and other environmental factors might be used to better interpret sea ice dynamics in the Antarctic.

References


** This study was supported by the Korea Polar Research Institute [grant number PE15040].

Figure 3. Extracted temporal EMs showing the variation in sea ice concentration throughout the year.

Figure 4. Fractional abundance maps of temporal EMs (E1-E9).

Figure 5. Comparison of the original SIC with the reconstructed data. (Left) Best fit (RMSE 3.6%), (Middle) worst fit (RMSE 9.2%) and (Right) mean fit (RMSE 6.9%).

Figure 6. Regional comparison of non-seasonal sea ice, open water and seasonal sea ice in (Left) the eastern Antarctic, (Right) the Ross Sea and (Middle) the Amundsen Sea.

Figure 6. Regional comparison of non-seasonal sea ice, open water and seasonal sea ice in (Left) the eastern Antarctic, (Right) the Ross Sea and (Middle) the Amundsen Sea. The changes in fractional abundances for each temporal EM in each region explained the overall temporal characteristics of hypertemporal SIC data for each year.