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Object-based Temporal Dynamic Time Warping for Cropland Classification Using Multi-sensor Remote Sensing Data: A Comparative Analysis in Three Different Major Crop-growing Regions

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ABSTRACT: Cropland mapping is essential to ensure proper management of crop inventory and agricultural resources, and safeguarding food security for Earth's growing population. However, challenges remain as a result of smaller modern field sizes and diverse agricultural practices. Dynamic time warping (DTW) has seen increasing applications in recent agricultural monitoring studies, with its ability to match and classify crops using phenology characteristics, even under conditions of minimal sample data. In this paper, an Object-based Temporal Dynamic Time Warping (OTDTW) workflow using Sentinel-1 and TripleSat satellite imagery is proposed, incorporating current best practices of DTW in agricultural studies. OTDTW integrates various modifications into its workflow, allowing for comparative analyses of different local conditions and practices in different geographical contexts. The OTDTW crop classification algorithm is applied on three different major crop-growing regions: India, USA, and China. Different DTW methodologies were compared across these regions. Results show that the OTDTW crop classification workflow is able to achieve average accuracies of above 80% in most selected regions. The results have also shown how different parameters perform differently in these regions based on local practices and conditions. These results demonstrate OTDTW's ability to produce reasonably accurate classifications in regions with temporally-displaced cropping patterns, and this direction can serve as a useful step towards future crop studies with even more diverse local agricultural conditions.

1. INTRODUCTION

As the global population continues to grow unabated, it is predicted that by 2050, our food supply will have to be sufficient to sustain an estimated 9.7 billion people; more than a 20% jump within a timeframe of less than 30 years (UN, 2022). To properly manage our food productivity, it will require an efficient agricultural monitoring system to be put in place. Reliable crop maps are especially important in both providing measures of area and distribution of crops within management zones, accurate monitoring of individual crop growth statuses, and also for predictions of productivity and yield rates for the economy (Liu et al, 2019).

Satellite remote sensing technology, carried by many airborne satellite missions in the recent decades, provide continuous coverage and information of the Earth's surface, and serve as an essential database for many modern large-scale agricultural studies (Mani et al, 2018). Ranging from the high-revisit rates satellites like MODIS; 10m resolution Copernicus' optical and radar Sentinels; and various very-high resolution commercial satellite missions like the 0.8m TripleSat and Gaofen, satellite imagery comes in many different parameters to suit various research requirements. Satellite image time series (SITS) sequences in particular are often employed as signatures to identify crop types, as their relative temporal variations often reflect vegetative growth at different phenological stages (Schotten et al, 1995).

Different geographical conditions, compounded with different agricultural practices and schedules of individual landowners can, however, displace and distort standard phenological patterns of crops commonly assumed to be static and aligned within regions (Jin et al, 2019). This in turn handicaps time-series driven crop classification methodologies, and rather than a one-size-fits-all classification methodology based on assumptions that crops grow in temporally similar stages, a time-wise flexible classifier that takes into account temporal displacements between time series is more suitable. Dynamic time warping (DTW), a similarity measuring algorithm for temporal sequences through temporal distortions, serves as a stepping stone towards resolving this problem.

DTW was initially proposed as a time normalization and matching algorithm through warping time series data (Sakoe & Chiba, 1978). In situations whereby two time series are out of phase or unequally sampled, the DTW algorithm "warps" the time series, computes various elastic alignments between them independent of the temporal scale, and gives an optimal dissimilarity measure for the time series data. DTW, together with methods like K-means clustering, sees applications in multi-temporal remote-sensing based land-cover classifications (Petitjean et al, 2012). While the conventional DTW algorithm is suitable for finding matches between time series in general, however, when utilized for time series classification in the fields of agriculture, there is also a need to consider the temporal range when carrying out realignments. For example, while maize is sown both during the wet and dry seasons in India, a time series classification using the conventional DTW algorithm would likely have disregarded the temporal differences between the two seasons and resulted in excessive warping, causing erroneous classifications between wet and dry season maize fields.

Further DTW research has focused on two main methods in establishing a temporal limitation to the warping potential of the standard DTW algorithm. One of them, the temporal window method, restricts temporal warping to within specified temporal windows at each temporal location. Geler et al (2019) had compared the Sakoe-Chiba (S-C) band (Sakoe & Chiba, 1978), one of the most commonly used temporal window constraints, with other similar constraining methods, concluding that the S-C band being more advantageous in most scenarios. Concurrent with the temporal window method, another method instead chooses to assign temporal weights during the DTW calculations (Jeong et al, 2011; Maus et al, 2016; Guan et al, 2018). This method does not limit the warping path and keeps the DTW warp boundaries "open". However, cost weights are imposed through either linear or logistic functions of temporal differences during warping processes, as increasing temporal shifts are tolerated but penalized as the DTW algorithm considers further temporal warping while matching different time series.

The different modifications on the conventional DTW algorithm for remote-sensing time series classifications have seen various degrees of improvements, and are largely based on the context of what they are being applied on. While some research has concluded that a well-tested temporal window constraint works best for certain crop regimes (Csillik et al, 2019), weighted temporal warps imposed by phase functions may serve best in preserving shape similarity between two time series, by highlighting relative significances of temporal shifts (Jeong et al, 2011).

In this paper, the Object-based Temporal Dynamic Time Warping (OTDTW) algorithm, an integrated and flexible crop mapping workflow, is proposed, utilizing state of the art dynamic time warping research to better cater to the heterogeneous agricultural conditions. The proposed OTDTW seeks to explore and incorporate the varying DTW classification methodologies, including both forms of temporal constraints: the S-C band, and the temporal weight logistic function, and provide a platform on which classification results using different parameters can be compared and analyzed. Three regions of different agricultural characteristics were selected to evaluate the applicability of OTDTW and its various functions. The remaining sections of the paper is structured as follows: Section 2 describes the study regions, satellite imagery datasets, parameters and necessary inputs for the OTDTW workflow analysis. Section 3 covers the classification results and comparisons across the selected study regions. Section 4 rounds up the discussions and draws conclusions on the relative suitability of OTDTW and its different functions in future crop classification efforts.

2. MATERIALS AND METHODOLOGY

2.1. Study Regions

Three study regions were selected as case studies to test OTDTW's suitability as a flexible crop classification algorithm, and its transferability and flexibility across different regional conditions. The three study regions are situated in India's Lalitpur district, USA's state of North Dakota, and China's Heilongjiang province respectively (Figure 1). Small land ownerships remain prevalent in these regions, (FAO, 2005; Luo et al 2021), with heterogeneous crop varieties, management practices, and agriculture schedules.

Both North Dakota and Heilongjiang have a predominant single cropping season annually, between late spring in May, to late autumn in October, where rainfall is abundant with suitably warm temperatures. USA agricultural landscape has been traditionally divided into family units, giving rise to small-scale land ownerships. Studies have shown how with agricultural innovations, farmland ownerships have become more fractured and liquid, requiring improved monitoring top-down efforts to facilitate national-scale analyses (Keller et al, 2022). On the other hand, while similar smallholder farms are present in Heilongjiang, owned by either agricultural businesses or national stakeholders, there are regional efforts in place to connect and coordinate them to generate greater economies of scale (Cai et al, 2021). Unlike the other two case studies, India's Lalitpur agricultural system is divided into two major cropping seasons: the wet Kharif (June to

October), and dry Rabi (November to April). Different crops are grown during each season, and due to the presence of many small agricultural stakeholders, cropping schedules tend to vary relatively significantly within common crop calendar schedules.

2.2. Datasets

Two sets of satellite imagery data are used in the OTDTW workflow. Object-based analyses are generally more preferred over pixel-based equivalents, performing better in terms of overall accuracies and computational efficiency (Belgiu & Csillik, 2018). For crop classification purposes, optical imagery with suitably high resolutions are preferred when identifying and segmenting crop parcels, especially in regions with small crop fields that are not visible using images under coarser resolutions. The TripleSat satellite constellation is an optimal option for optical satellite imagery, carrying sensors capable of providing images with spatial resolutions up to 0.8 meters, and revisit frequencies on a daily basis. Image segmentation is performed on the TripleSat images, implemented on the eCognition Developer, a commercial software carrying various object-based image analysis (OBIA) tools and algorithms. The optical bands from the TripleSat imagery and available ancillary information, such as regional field boundary data, are used in conjunction with the multiresolution segmentation algorithm on eCognition to generate suitable objects for OTDTW analysis.

The Copernicus Sentinel-1 Ground Range Detected (GRD) Synthetic Aperture Radar (SAR) products provide SAR data at dual polarizations, used for ground-range studies. In most agricultural regions that rely on rainfall as water sources, cloud cover poses serious problems for optical satellite imagery. SAR data bypasses such issues, providing constant temporal coverage for specific regions. The Sentinel-1 SAR product has an approximate revisit rate of 12 days in most regions, and is suitable to be used as the time series data for the OTDTW algorithm. The Sentinel-1 time series data is preprocessed and obtained from the Google Earth Engine catalog. The segmented features derived from TripleSat imagery is used to sample the processed Sentinel-1 data, to obtain object-based Sentinel-1 time series for the subsequent steps.

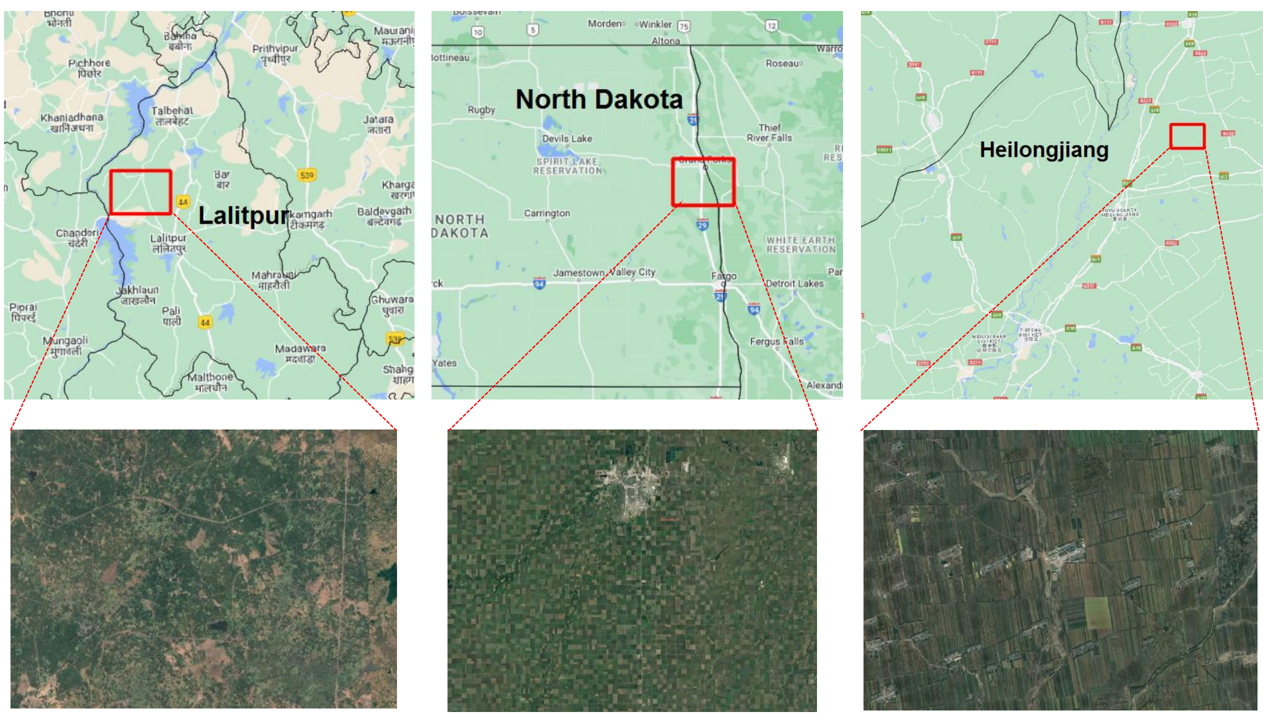

Figure 1. The three selected study regions, from left to right: Lalitpur (India), North Dakota (USA), and Heilongjiang (China).

2.3. OTDTW Workflow

Figure 2 summarizes the workflow and processes within the proposed OTDTW algorithm.

2.3.1. Crop Spectral Library

An accurate crop spectral library is required for the OTDTW algorithm to match time series data to their most likely crop class. The spectral library collects the most representative time series pattern for each crop class in the region through ground truth samples, and each input time series is matched against the collection to calculate their DTW distance with each present crop class. The primary advantage for a collection of representative spectral time series for individual crops is the greater emphasis on the quality of ground truth samples rather than quantity, a deviation from traditional classifiers' requirements. Rather than having a wide spectrum of samples setting the parameters for each crop class classifier, a handful of highly representative and accurate samples are preferred to provide a distinctive time series to carry out time series matching calculations. Each crop's representative time series is derived from the statistical mean of the ground truth crop sample time series values, after removing outliers.

2.3.2. Temporal Constraints

Two temporal constraints are installed in the OTDTW algorithm workflow.

The S-C band is used as the option for implementing a temporal limit in the OTDTW algorithm. Aside from the conclusions in Geter et al (2019), the S-C band is preferred over other options such as the Itakura parallelogram for its flexibility in accounting for misalignments along all of the time series, and not just within the growing stages (Figure 3). This is a common occurrence due to differences in growing conditions, such as shifting sowing or harvesting schedules of similar crops by different land owners. In the OTDTW algorithm, points along the two time series are given a specified temporal window to unbiasedly shift and match with each other, and the dissimilarity measure is calculated based on the optimal 'warping' within the temporal window.

The logistic weight function proposed in Maus et al (2016) is also adapted into the OTDTW. While their implementation of the proposed Time-Weighted Dynamic Time Warping (TWDTW) proposed both a linear and logistic weight equivalent, a logistic function provides a more realistic weight increment, with exponentially increasing cost over temporal displacements (Equation 1). An exponential weight gives allowances for smaller temporal shifts, while penalizing realistically incorrect larger warps. OTDTW offers two different parameters as proposed in Maus et al (2016)'s logistic weight function, α and β (Figure 4): the former setting the exponential weight slope increment over time, while the latter setting the "maximum" temporal shift allowed, after which the weight cost would approach the function's maximum asymptote value. The dissimilarity measure is then calculated after factoring in all the weights incurred during the shifts and obtaining the most likely time warp between the input time series.

$$\omega = \frac{1}{1+e^{-\alpha(g(t_1 t_2)-\beta)}} \tag{1}$$

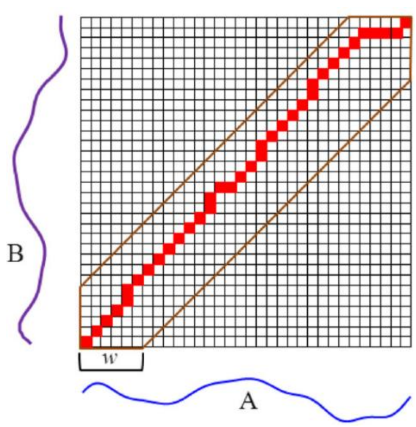

Figure 3. Example of a S-C band implementation between two time series (Jeong et al, 2011).

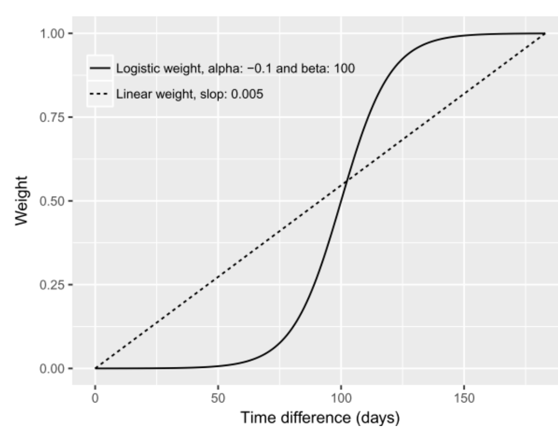

Figure 4. Linear and Logistic weight function curves (Maus et al, 2019).

Table 1. Results of OTDTW crop classification in all three study regions.

	Overall Accuracy		**Computational Efficiency**	
	S-C Band	Logistic Weight	No. of Objects	Duration (min)
Lalitpur	90.59%	88.74%	31,211	22
North Dakota	80.45%	85.75%	21,549	15
Heilongjiang	79.31%	78.30%	59,310	50

2.3.3. Class Assignment

The OTDTW takes in the input object features' time series and calculates the DTW distances with the crop classes within the crop spectral library, applying specified temporal constraints according to local conditions of regions being studied. Each crop class time series' dissimilarity measure with the object feature's is compared, and the class with the lowest dissimilarity measure is assigned to the object feature, providing a computation-lite classification at an object-based scale level.

3. RESULTS

3.1. Classification Accuracies

The crop classification results for all three regions are shown in Figure 5, and their respective error matrices in Figures 6 to 8. Table 1 shows the accuracy assessments of the OTDTW crop classification for all three study regions in the year 2019, using different temporal constraints on the DTW algorithm. OTDTW achieved different ranges of accuracies in each region, with India's Lalitpur having the most accurate accuracy assessment at around 90%, while China's Heilongjiang sees the lowest at just below 80%. From the results, most crop classification results in this study have demonstrated that OTDTW is capable of achieving respectable classification accuracy levels despite regional differences.

3.2. Results Discussion

Between the applications of the S-C band and the logistic weight function as temporal constraints for the OTDTW algorithm, there is no obvious lead between either method. North Dakota's study region has seen the logistic weight constraint improving the classification results by a significant margin; in Lalitpur and Heilongjiang, on the other hand, the S-C band performs slightly better as a temporal constraint.

The simplistic nature of the S-C band allows for time-series sequences to shift and match un-penalized within a specified temporal window, and this can be useful in catching crop classes with individual field patterns varying to an extent within the temporal limitation. Lalitpur's classification results benefit from the S-C band's more lenient approach: the region's highly-varied crop calendar had served as an indication on how local farmers have varying cropping schedules of their own, even among similar crops. In the case of Heilongjiang, the S-C band can also be beneficial for classifications with more generic "others" classes. Different crops of the same phenological family with similar growth patterns can potentially be identified and grouped together through temporal shifts using the S-C band as a limiting window; however, the results have also shown that these ambiguous crop classes have seen the highest misclassifications (Table 4), serving as the main factor for the region's overall lower accuracy assessment.

The logistic weight function as a temporal constraint, in regions with proper ground truth availability and crop class allocation, becomes the superior method over the S-C band, as seen in the results for North Dakota. The USA case study has a larger number of specific crop classes defined within the region, with some crops exhibiting similar time series patterns. In such scenarios, a constraint that penalizes unbiased temporal warping, more often than not, prevents similar-looking crops from being wrongly classified into other similar crop classes. A comparison can be drawn between the nature of Heilongjiang's generic classes and North Dakota's defined and varied crops: a more time-wise lenient constraint such as the S-C band can be useful when working on classes with high intra-class time series variations, but such considerations can be detrimental when classifying well-defined crop classes, and in such cases time-penalty based methods such as the logistic weight function fare better.

A

B

C

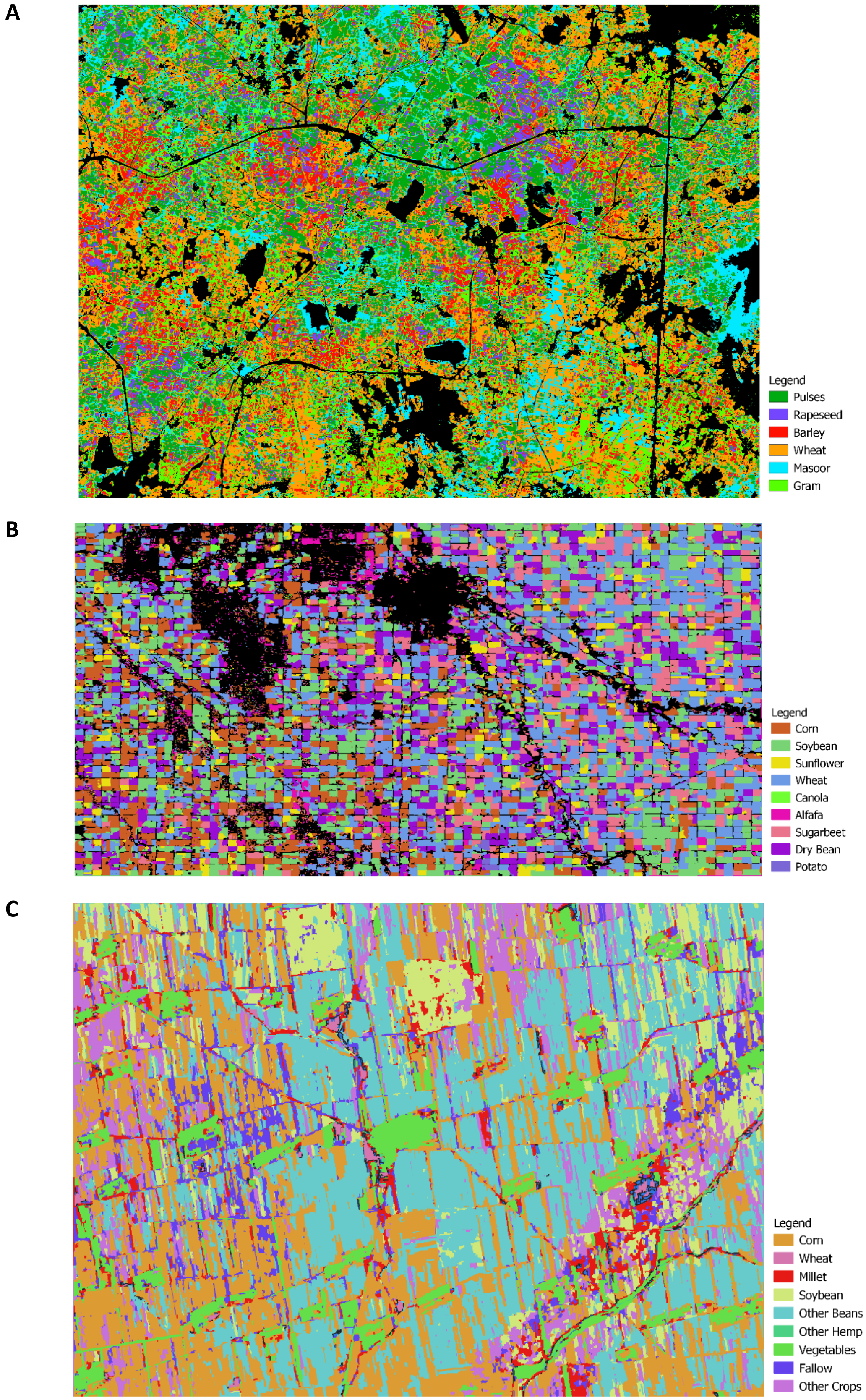

Figure 5. Classification results for (A) Lalitpur, (B) North Dakota, and (C) Heilongjiang.

Table 2. Error matrices for Lalitpur's crop classification results.

		Pulses	Rapeseed	Barley	Wheat	Masoor	Gram
S-C Band	Pulses	**199**	3	0	7	2	0
	Rapeseed	4	**153**	13	0	0	0
	Barley	0	1	**171**	0	0	20
	Wheat	0	0	0	**111**	0	0
	Masoor	0	0	0	1	**103**	0
	Gram	0	0	19	0	0	**65**
Logistic Weight Function		Pulses	Rapeseed	Barley	Wheat	Masoor	Gram
	Pulses	**190**	6	0	9	6	0
	Rapeseed	5	**149**	15	1	0	0
	Barley	0	3	**168**	0	0	21
	Wheat	0	0	2	**107**	0	2
	Masoor	0	0	0	1	**103**	0
	Gram	0	0	24	1	0	**59**

Table 3. Error matrices for North Dakota's crop classification results.

		Corn	Soybean	Sunflower	Wheat	Sugarbeet	Dry Bean	Canola	Alfafa	Potato
S-C Band	Corn	**123**	8	3	4	1	2	0	1	0
	Soybean	0	**134**	5	5	3	13	0	0	0
	Sunflower	0	37	**12**	3	12	1	0	0	1
	Wheat	0	1	0	**182**	0	0	0	0	0
	Sugarbeet	1	4	0	2	**130**	1	0	0	0
	Dry Bean	0	23	0	9	3	**73**	0	0	0
	Canola	0	0	0	0	0	0	**10**	0	0
	Alfafa	0	0	0	0	0	0	0	**9**	0
	Potato	0	3	0	0	1	9	0	0	**10**
Logistic Weight Function		Corn	Soybean	Sunflower	Wheat	Sugarbeet	Dry Bean	Canola	Alfafa	Potato
	Corn	**124**	4	1	2	1	0	0	1	0
	Soybean	0	**151**	3	5	6	12	0	0	0
	Sunflower	0	27	**16**	1	17	1	2	0	1
	Wheat	0	0	0	**194**	0	0	0	0	0
	Sugarbeet	0	1	0	0	**135**	1	0	0	0
	Dry Bean	0	20	0	6	1	**83**	1	0	1
	Canola	0	0	0	0	0	0	**7**	0	0
	Alfafa	0	0	0	3	0	0	0	**9**	0
	Potato	0	7	0	0	0	2	0	0	**9**

The advantages in terms of ground truth sample requirements have been discussed in the earlier sections: a highly representative time series for specific crops can improve identification and extraction within study regions. Heilongjiang's comparatively lower accuracy measurements can be attributed to the ambiguities in the region's general crop family classes. In comparison to traditional classifiers, OTDTW's approach in utilizing minimum distance for class assignment may not be as robust when classifying the "other" classes, where intra-class variability is inevitably higher. This is evident from the improvements in accuracies in the other two regions, where crop classes are much more specific and well-defined (Tables 2 & 3).

Table 4. Error matrices for Heilongjiang's crop classification results.

		Corn	Wheat	Soybean	Other Beans	Other Hemp	Vegetables	Fallow	Other Crops
S-C Band	Corn	**22**	0	1	17	0	17	6	6
	Wheat	0	**280**	0	10	5	6	2	1
	Soybean	6	12	**27**	20	1	0	2	2
	Other Beans	14	0	3	**204**	0	2	0	3
	Other Hemp	0	0	8	0	**291**	0	0	0
	Vegetables	0	0	0	1	0	**69**	0	0
	Fallow	2	5	5	14	3	14	**15**	6
	Other Crops	17	1	12	28	0	2	1	**12**
Logistic Weight Function		Corn	Wheat	Soybean	Other Beans	Other Hemp	Vegetables	Fallow	Other Crops
	Corn	**27**	0	1	15	0	14	6	6
	Wheat	0	**283**	0	8	3	7	2	1
	Soybean	6	12	**27**	20	1	0	2	2
	Other Beans	16	0	1	**207**	0	1	0	1
	Other Hemp	0	0	5	0	**294**	0	0	0
	Vegetables	0	0	0	0	0	**70**	0	0
	Fallow	2	6	4	13	3	14	**16**	6
	Other Crops	17	1	10	27	0	2	3	**13**

3.3. OTDTW Efficiency

Table X shows the number of segmented object features representing each study region, and the overall time taken for the OTDTW crop classification process. As compared to traditional classifiers like the Random Forest (RF) and Ordinary Least Squares (OLS), where time complexities are usually exponential to the number of input training and valid datasets, the OTDTW algorithm is a direct function of the number of input classes and object features. The time taken for each study region is shown to be approximately linear to the number of segmented objects in the region, under the conditions of largely similar crop class quantity. While the computation efficiency of the OTDTW algorithm can be further analyzed with more varied datasets in the future, the current workflow demonstrates how OTDTW can provide a relatively simple yet efficient classification alternative.

4. CONCLUSION

This paper proposed the OTDTW algorithm as an integrated workflow outlining dataset preprocessing, input preparations, DTW temporal settings, and classification output generation. The OTDTW algorithm provides two current leading approaches towards limiting temporal warping of the standard DTW: the S-C band and the logistic weight function, and serves as a platform to generate classification results using these functions for comparative analyses. The classification results generated from OTDTW suggest the time leniency of both temporal constraints can have different impacts in regions with different crop types and agricultural habits. The S-C band functions best in regions with crop classes with both temporal and spectral variabilities, as a result of differing agricultural decisions or environmental conditions. The logistic weight function instead performs better in regions with well-defined crop classes, and serves as a more accurate method in differentiating spectrally-similar crops while allowing temporal warping to take place. The OTDTW has also shown promising steps towards improving computational efficiency by adopting object-based approaches and other methodologies, and in future research, the proposed workflow can be expanded to incorporate more useful functions and parameters to allow for more flexible crop classification purposes with different datasets.

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