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MultiSat4Slows system for detecting and assessing potentially active landslide regions – initial results from an ongoing interdisciplinary collaboration

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Abstract

Landslides represent one of the major threats worldwide to human life, settlements, and infrastructure. Their occurrence is increasing due to anthropogenic activities and environmental changes. Detecting slow-moving landslides in geographical space, monitoring their kinematic behavior in time, and correlating their changes in displacement to potential influencing factors (i.e., precipitation, land use change detection, and earthquakes) can contribute to forecast possible future landslide collapses. Satellite Earth Observation (EO) technology, such as Multi-temporal Synthetic Aperture Interferometry (MTI), provides millions of ground displacement time series that enable EO data scientists to detect slow-moving landslides in geographical space. In this short paper, we discuss our current Visual Analytics (VA) concept and system that supports EO data scientists to analyze ground displacement time series in a semi-automatic and exploratory manner. The goal is to derive helpful information for landslide hazard assessment, such as the location of slow-moving landslides, main kinematic parameters, changes in displacement trend, and possible correlation with external triggering factors. This paper presents the initial results of our VA system in supporting displacement classification and clustering, depicting detected clusters in the cluster overview visualization, and enabling exploratory data analysis and interactive steering.

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;***

1. Introduction

Satellite Earth Observation (EO) technology has revolutionized the way scientists collect information about the processes occurring on the Earth's surface (e.g. [HPM*13]). Remote sensing systems mounted on satellite platforms orbiting the Earth register the reflected radiation from ground targets produced by sunlight (i.e., optic or passive sensors) or by a transmitter (i.e., radar or active sensors) [Ric22]. EO data platforms such as the Copernicus Open Access Hub [ESA23a] and NASA Earthdata [NAS23] provide the final accessible as images (matrix), in which each pixel corresponds to a specific ground area on the Earth's surface [Ric22]. The increasing number of free accessible satellite EO missions, which acquire global images (e.g., weekly) at a medium resolution (pixel size equivalent to 10-30 m on the ground), poses new challenges to scientists in dealing with large in time and/or space EO data sets. Adopting state-of-the-art computer science concepts and methods to EO data sets, such as Visual Analytics (VA) systems combining semi-automatic analytic techniques with interactive visualizations, are among the solutions to analyze and interpret such big EO data sets.

In 2014, the European Space Agency (ESA) launched the Synthetic Aperture Radar (SAR) Sentinel-1 mission [ESA23b], allowing scientists to assess bi-weekly radar images over almost the entire world. Multi-temporal SAR Interferometry (MTI) techniques (e.g., [BGB21]) are a family of advanced processing methods that extract temporal ground displacement information for each pixel based on the phase shift of the back-scattered microwave signal between two consecutive in time SAR acquisitions. The output is a time-series of ground displacements in line-of-sight (sensor-ground target) direction in the form of raster or vector stored data sets containing millions of measurements.

MTI offers new and exciting opportunities for studying and monitoring geological hazards (geohazards) such as landslides over long periods of time and large geographic areas. Landslides, defined as the movement of rock, earth, or debris down slopes along hillsides, represent one of the major threats worldwide to human life, settlements, and infrastructures. Anthropogenic activities and global weather extremes due to climate change considerably contribute to increasing landslide hazards worldwide. In order to mitigate their impact on human life and activities, it is fundamental to address the following analytical questions: a) where in geographic space can slow-moving landslides be observed? b) what is their kinematic behavior (linear, quadratic, bi-linear)? c) does the trend

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change in time, and if yes, when? and d) what are possible external triggering factors influencing landslide kinematics? In order to answer these questions, EO data scientists need to analyze and interpret a large amount of MTI displacement time series measurements.

In this short paper, we discuss the initial results of an ongoing interdisciplinary collaboration between computer and EO data scientists. Our interdisciplinary collaboration aims to develop a VA system that supports users in answering the analytical questions involved in landslide hazard assessment (as mentioned earlier). To address these analytical questions, scientists need to detect slow-moving landslide regions over large geographic areas with high-resolution MTI displacement data, estimate the average displacement trend, detect changes in the average displacement trend, and correlate landslide kinematics to possible external triggering factors. However, analyzing high-resolution MTI displacement data sets is challenging because EO scientists must assess many pixels/observations. We adopted a user- and task-based design approach (e.g., [HR98, Mun14] to thoroughly understand the landslide assessment scenario of our scientific collaborators, eliciting the challenges in detecting slow-moving landslide regions and assessing their kinematic behavior, and taking the first steps toward an appropriate VA concept and solution. Our VA concept aims to support users in analyzing and interpreting large amounts of high-resolution MTI ground displacement time over landslide-prone areas series in a semi-automatic and exploratory manner.

The discussions in our interdisciplinary collaboration show that VA can play a vital role in enabling users to understand landslide processes and triggering factors of specific geographic regions. A better understanding of landslide processes will contribute to proper landslide mitigation measures, which will help to reduce the devastating impacts of landslide events. Hence, the capacity of a VA system for detecting and analyzing slow-moving landslide regions using MTI ground displacement time series introduces a unique contribution to the Earth science domain. The subsequent research and development activities in our ongoing collaboration will focus on supporting additional crucial steps of the landslide assessment workflow: to assess ground displacement spatiotemporal patterns of detected landslide regions for predicting potential collapses and assess the correlation structure between landslide kinematics to additional external data streams for identifying potential external triggering factors of landslide events.

2. Design requirements and VA concept

In this section, we discuss the current status of our VA concept to support users in detecting active landslide regions and analyzing their displacement trends using MTI ground displacement data sets in a semi-automatic and exploratory manner. From the discussions in our interdisciplinary collaboration, we derived several requirements that the VA concept needs to address:

R1 Semi-automated detection of potentially active landslide regions and classification of their kinematic behaviours. The semi-automated analysis should support users in detecting potentially active landslide regions. Therefore, the VA system should associate, in the first step, a unique label (i.e., stable, linear, quadratic, and bi-linear) to each pixel based on a statistical classification algorithm of the MTI ground displacement time-series (Figure 4 shows representative time series for each of the four classes from our application scenario). In the second step, the VA system should group the pixel according to their displacement labels and additional information i.e., utilizing geological maps, digital elevation models, and other domain-specific information characterizing the landslide kinematics and geometry into distinct spatial clusters. The spatial clusters represent potentially active landslide regions with specific kinematic behaviors (Figure 1 depicts the detected spatial clusters of our application scenario).

R2 Cluster overview visualization for assessing the spatial distribution of detected landslide regions. The cluster overview should be the analytical component that helps users in assessing the spatial distribution of detected landslide regions. It should provide a visual representation of the ground displacement clusters, combined with other data such as geological maps, digital elevation models, enabling users to assess the results of the semi-automated detection step. The cluster overview visualization should be tightly coupled with the semi-automated detection step, supporting users to refine the detected landslides and to make further analytical decisions.

R3 Analytical interaction and visual queries to understand the displacement characteristics of landslide regions. The analytical interaction in the cluster overview visualization should support users in querying each pixel's or cluster's MTI ground displacement time series. By selecting specific pixels or clusters of interest in the cluster overview visualization, the VA system should immediately create a line plot depicting the selected time series and additional time-series variables such as precipitation. The VA system should also depict overall statistics such as velocity and acceleration values to users, supporting users to assess the detected landslide regions and make further analytical decisions.

R4 Interactive steering for refining detected landslide regions. Users usually consider the associated displacement labels and detected spatial clusters by automated data analysis methods as proposals for slope instabilities and, under specific conditions, potential locations for future landslide collapses. Therefore, the analytical interaction in the cluster overview visualization should support users in adjusting the algorithmic parameters based on their knowledge of the region and landslide processes.

From the design requirements, we developed the following current twofold VA concept for supporting users in detecting active landslides regions and assessing their displacement trends:

- **Semi-automated classification and clustering step.** Our VA system combines the widely-used classification algorithm for MTI ground displacement time-series proposed by [MWN*22] and the k-means clustering algorithm (e.g., [HTF09, HKP12]) to group the pixels into distinct spatial clusters, which **addresses R1**. The MTI ground displacement time-series classification algorithm [MWN*22] associates a unique displacement trend label (i.e., stable, linear, bi-linear, and quadratic) to each pixel of the MTI displacement data. The k-means algorithm then groups the pixels according to their displacement trend labels and ad-

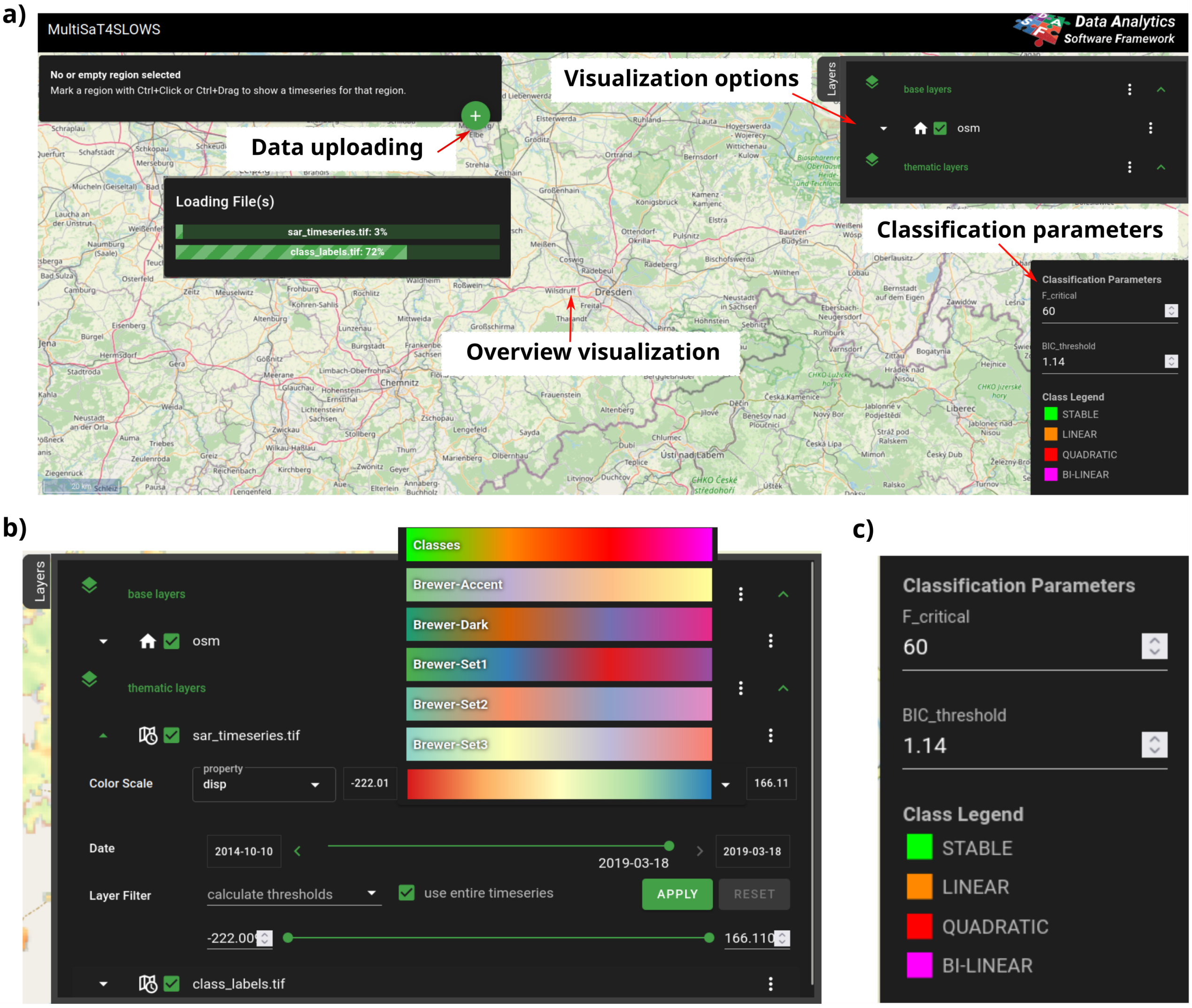

Figure 1: ***The exploration interface of the MultiSat4Slows System*** *– a) overview of the exploration interface of the MultiSat4Slows System, b) visualization and exploration options of the interactive exploration and c) interactive specification of algorithmic parameters of the semi-automated detection step*

ditional physical parameters such as overall velocity, cumulative displacement, and topographic slope into distinct spatial clusters.

- **Exploratory analysis and interactive steering step.** Our VA system allows users to explore the detected landslide regions from the semi-automated classification and clustering step in the cluster overview visualization, **which addresses R2**. Users assess the detected landslide regions by exploring the displacement time series and their computed displacement trend (**addressing R3**). Users can also adjust the parameters of the algorithms used in the classification and clustering step to steer the semi-automated classification and clustering step and refine the detected landslide regions based on their domain knowledge of the region and landslide processes (**addressing R4**).

3. MultiSat4Slows System

This section discusses the current status of our VA system. We begin this section by briefly discussing the semi-automated classification and clustering step and continue with the discussion of the exploratory analysis and interactive steering step. Figure 1 shows the cluster overview visualization and exploration interface of the MultiSat4Slows system.

3.1. Semi-automated classification and clustering step

We use the MTI ground displacement time-series classification algorithm proposed by [MWN*22] to associate a unique displacement trend label to each pixel of the MTI displacement data set. We present briefly the issues that are relevant to the discussions

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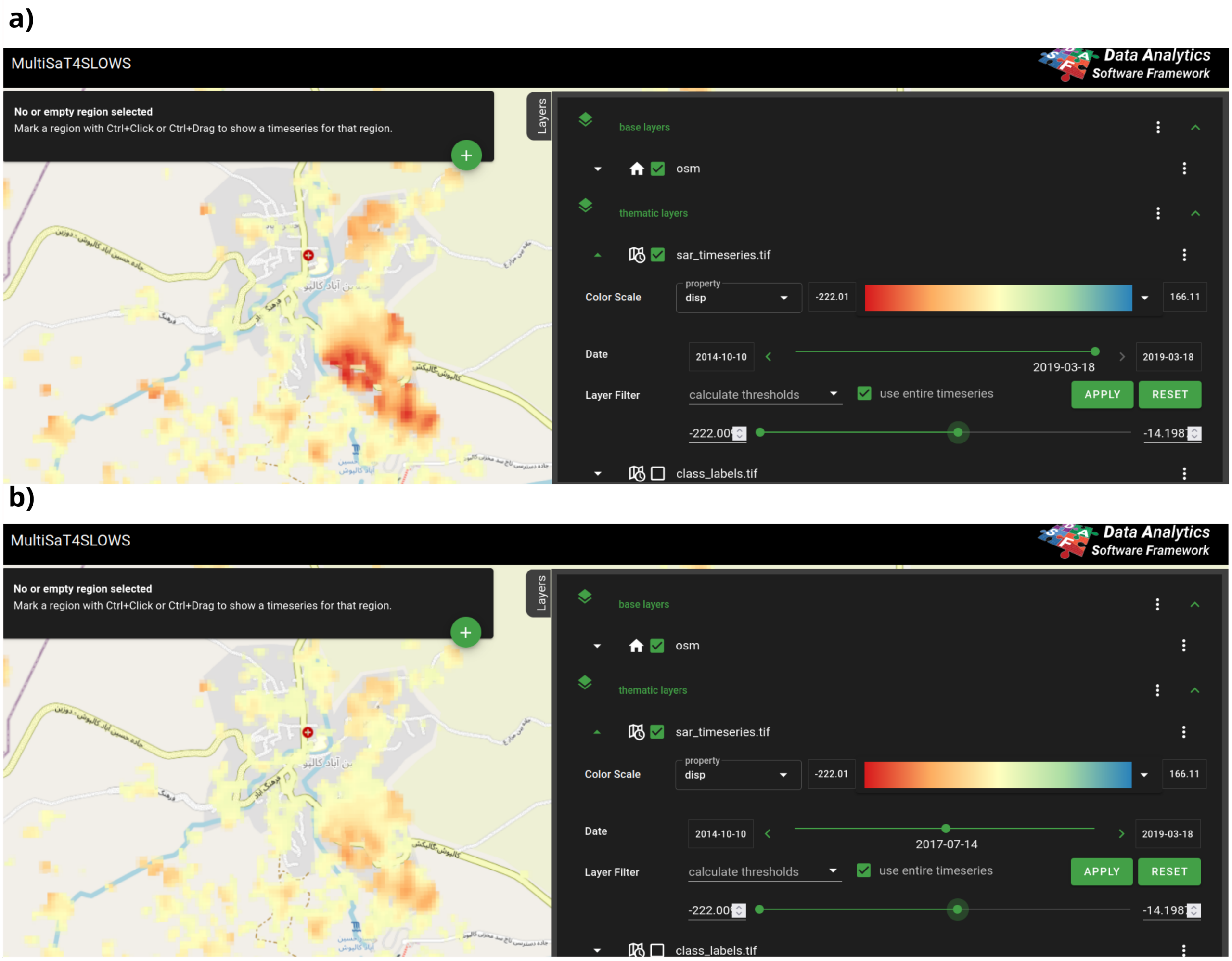

Figure 2: ***Interactive Exploration of the MTI data*** *– users explore the MTI data through interactive visual queries (exploration path goes from a) to b))*

of our VA system. The basic idea is to determine the main displacement trend based on the MTI ground displacement time series data through a series of statistical tests. First, we test whether the data fit a constant function with a slope close to zero (i.e., stable trend, which means no displacement). We fit a linear regression function to the MTI ground displacement time series and implement an ANalysis Of VAriance (ANOVA) Fisher test to calculate the F-score of the R^2 metric (e.g., [HTF09]). We conclude that the pixel has a stable trend if the F-score is lower than a certain threshold. Second, we continue with the time series not associated with the stable trend and differentiate them further into linear, quadratic, and bi-linear based on the Bayesian Information Criterion (BIC) (Berti and collaborators [BCFI13] provide details about the computation of the BIC for displacement time series data). In the case of the bi-linear class, the second test automatically determines the so-called breaking point, e.i. the time at which the ground displacement trend changes.

Finally, we group the pixels into distinct clusters using the k-means algorithm. We use the previously obtained displacement labels and additional physical parameters derived from the MTI ground displacement time series and auxiliary data (i.e.digital elevation models) in the clustering process. Figure 1 depicts the detected spatial spatial clusters of our application scenario.

3.2. Exploratory analysis and interactive steering step

The cluster overview visualization is the starting point of the exploratory data analysis in our VA system. The cluster overview visualization depicts the detected types of displacement clusters on a map (Figure 1). We use a qualitative color scheme from ColorBrewer [Cyn23] to differentiate the clusters. Users can formulate visual queries against the MTI ground displacement time series to explore the displacement trend. Our VA system provides an intuitive mechanism to formulate visual queries by allowing users to select specific pixels or clusters in the cluster overview visualization. The VA system provides immediate visual feedback to users

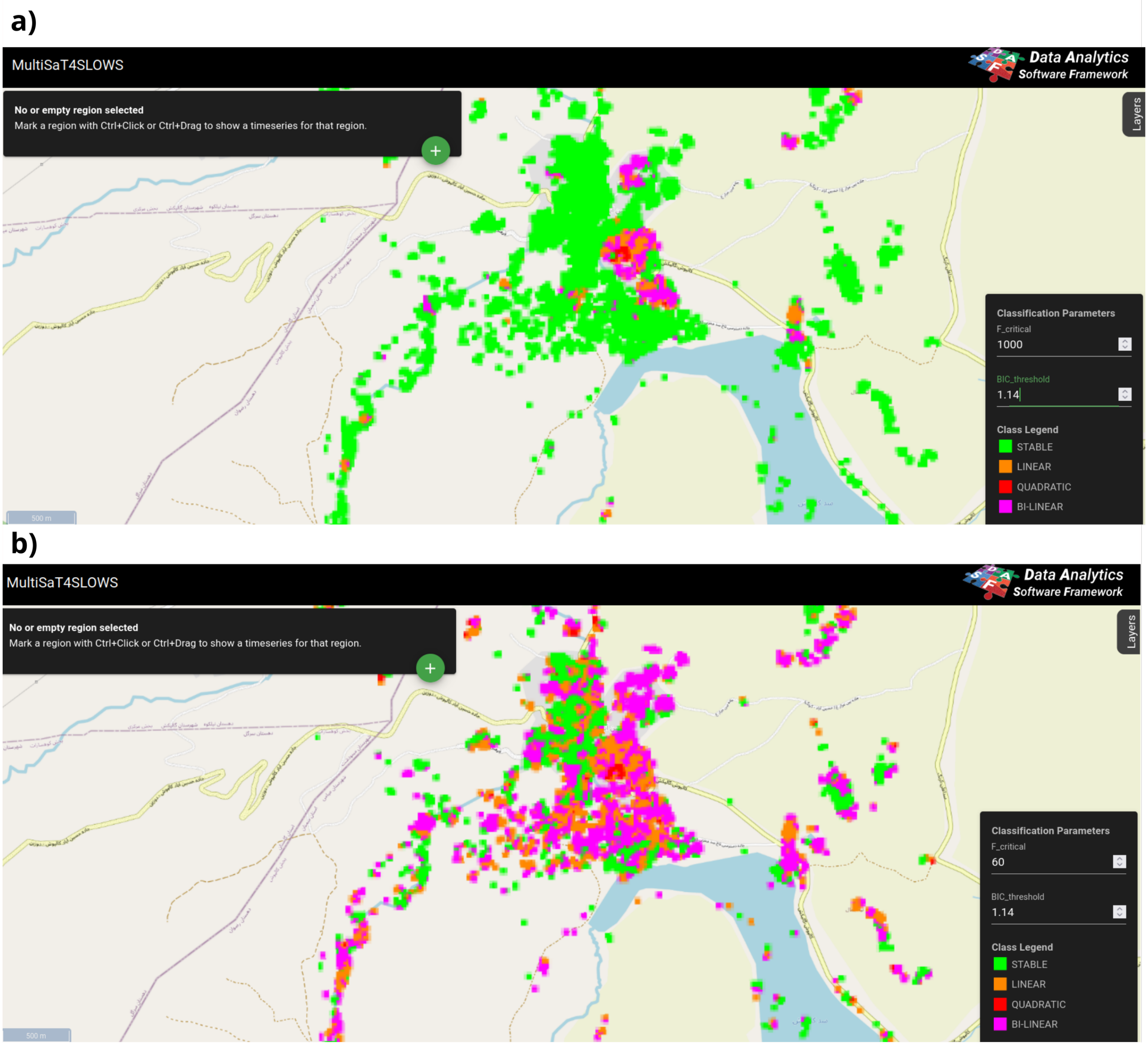

Figure 3: ***Assessment of the the detected landslide areas*** *– users interactively explore the results from the semi-automated detection step and revise the algorithmic parameters to improve the detection results; a) and b) present the detection results for different classification parameter settings*

by depicting the MTI ground displacement time series of the selected pixels or clusters in a line plot where the x-axis represents the observation time, and the y-axis represents the displacement (Figure 4). The line plot also depicts the regression model (linear, bi-linear, quadratic) computed in the classification and clustering step to users. The cluster overview visualization enables users to detect active landslide areas and, thus, direct users' attention to potentially interesting landslide regions.

Our VA system provides an intuitive mechanism to steer the classification and clustering step by refining the F-score and the BIC-score (Figure 1). The system performs the classification and clustering step with the refined parameters. Users can refine the parameters of the classification and clustering step until the detected clusters and their average displacement trend (i.e., the displacement trend of selected pixels) matches their domain knowledge.

4. Application Scenario

We demonstrate the versatility of our VA system by using the MTI ground displacement time-series dataset of the Hoseynabad-e Kalpush landslide area in northeast Iran. We used a small subset of 98x83 pixels of the original data for this initial experiment. The

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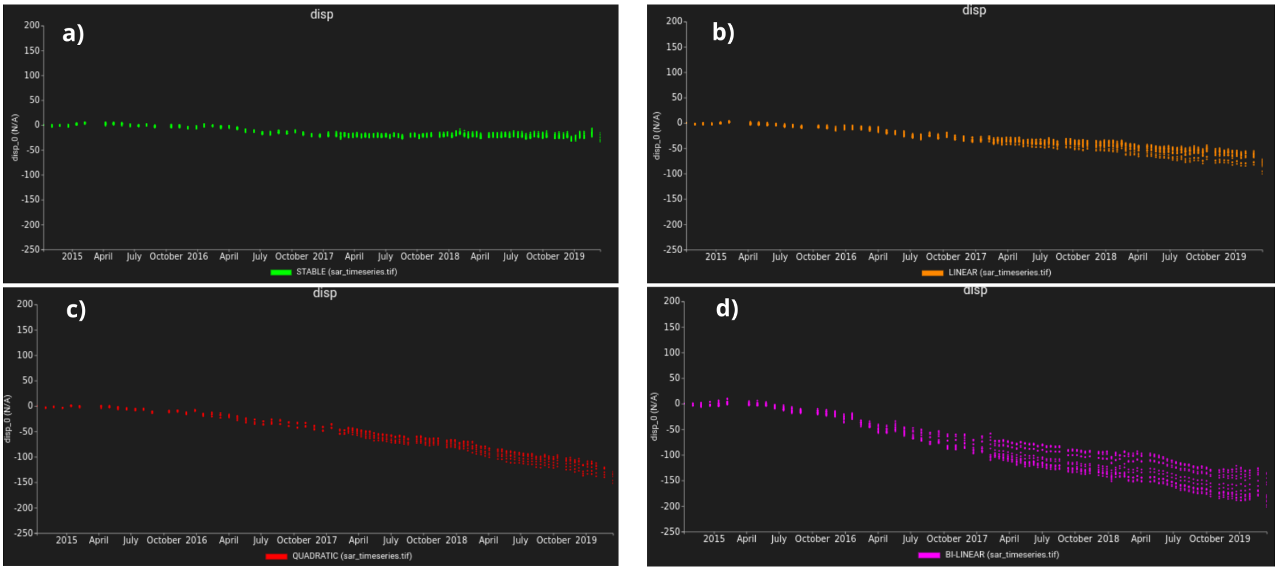

Figure 4: ***Representative MIT ground displacement time series of the Hoseynabad-e Kalpush dataset*** *– the figure presents a representative time series with a) stable, b) linear, c) quadratic, and d) bi-linear displacement trend.*

dataset covers the period between October 2014 and March 2019, with a total of 89 measurements.

In our current VA system, users can upload the MTI ground displacement datasets, such as the Hoseynabad-e Kalpush data set, and explore it using various visualization and exploration tools (Figure 1(a)). The interface provides options to customize the data and cluster overview visualization, such as color scale options, data filtering, and specific time interval selectors (Figure 1(b)). Users can also specify the classification parameters (Figure 1(c)) and adjust the visualization parameters according to their preferences (Figure 1(b)). The exploration results are immediately presented on the map, allowing for easy and efficient analysis. Users can explore the MTI data (Figure 2), and Figure 3 presents the detection results for two different classification parameter settings. Additionally, Figure 4 presents the time series of the four clusters: stable, linear, quadratic, and bi-linear.

Figure 3(a) shows a predominant active landslide region north of the so-called dam lake. The semi-automated classification and clustering step detected several small-scale active areas, including active areas on adjacent slopes. The cluster overview visualization shows that the predominant clusters have a bi-linear displacement trend, as depicted in Figure 4(d). We inspected the displacement time-series plots of this cluster and noticed a relatively stable behavior in the first eight months. However, we also observed a slope destabilization trend that became more prominent in the bi-linear clusters. An increase in the displacement trend can be an indicator of a potential landslide collapse, which is what precisely occurred with the Hoseynabad-e Kalpush landslide at the end of March 2019. Unfortunately, this event significantly damaged over 300 houses, of which 163 had to be evacuated due to the severity of the destruction.

Furthermore, we discovered that the adjacent active landslide areas also show a predominant bi-linear behavior, which raises questions about their susceptibility to collapse. This initial and representative scenario highlights the capabilities of our current VA system for landslide analysis using MTI data. The outcomes of studying the landslide area using the VA system are as follows: (1) the area of the landslide collapse in March 2019 was unstable since early 2015, (2) the kinematic behavior was predominantly bi-linear, indicating an acceleration trend, and (3) by tuning the classification parameters based on the user's knowledge of the location of the landslide collapse area, we were able to detect active landslide areas on adjacent slopes. However, several questions still need to be answered, such as when changes in trends occurred and under which external conditions. These questions will be addressed in future work.

5. Conclusion and Summary

We discussed the current state of our VA system in our ongoing collaboration between computer scientists and EO scientists. Our collaboration aims to design and develop a versatile, application-oriented, field-ready VA system for detecting and assessing potential active landslide regions. Our VA system aims to support the critical analytical tasks of the landslide assessment workflow: to detect slow-moving landslide regions over large geographic areas using MTI ground displacement data, determine the type of slow-moving landslide by estimating their average displacement and velocities, predict areas of potential collapse by detecting changes, identify potential external triggering factors by correlating landslide kinematics to additional external data streams. Our research and development activities will contribute to a VA system that supports users to develop proper landslide mitigation measures and reduce the devastating impacts of landslide events.

We conducted interviews with EO data scientists to design and develop the VA system. Based on their feedback, we derived four crucial design requirements. The VA system should offer (i) semi-automated detection of potential active landslide regions, (ii) visual assessment of detected clusters and displacement trends, (iii) the specification of visual queries and immediate visual feedback, and (iv) steering of the semi-automated analysis step. Our VA system provides (i) a semi-automated classification and clustering step, (ii) classification overview visualization, and (iii) intuitive mechanisms to formulate visual queries and steer the classification step to meet these requirements.

We demonstrated the versatility of the current VA system in a representative test application scenario. We explained how the VA system enabled scientific collaborators to assess detected landslide regions. We received feedback from our scientific collaborators from using the VA system in the application scenario. The feedback suggests that the analytical interaction and the mechanism to formulate visual queries were crucial for users in understanding the temporal displacement characteristics of the detected landslide regions. The feedback also suggests that the VA system (i.e., visual queries and steering) increased users' confidence in the automatically detected landslide regions.

In the future, our research and development activities will focus on several research issues to enhance the analytical capabilities of the VA system. Firstly, we aim to provide users with the option to combine different MTI datasets over the same area, allowing for a more comprehensive analysis of ground displacement processes. Secondly, we plan to integrate additional information, such as geological maps, digital elevation models, and land cover data, into the semi-automated classification and clustering step. Thirdly, we plan to address temporal correlations between MTI ground displacement time series and environmental variables such as precipitation and reservoir water levels. Fourthly, we aim to provide users the capability to decompose MTI ground displacement time series into trends and seasonal behavior, which will help users better understand the patterns and causes of ground displacement. Lastly, we aim to apply our VA system to large MTI data sets to support analysis at the regional scale, ensuring that users can use our VA system in a broad range of landslide scenarios.

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