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Permanent terrestrial LiDAR monitoring in mining, natural hazard prevention and infrastructure protection – Chances, risks, and challenges: A case study of a rockfall in Tyrol, Austria

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ABSTRACT

The objective of this work is the development of an integrated monitoring service for the identification and evaluation of ground surface and slope movements in the context of coal mining, the prevention of natural hazards and protection of infrastructure. The focus is set on the integration of a long-range terrestrial laser scanner into a continuous monitoring system from an engineering geodetic point of view. In the Vals valley in Tyrol, a permanently installed laser scanner was successfully operated via a web portal to monitor surface processes in the area of rockfall debris on a high-mountain slope in the summers of 2020 and 2021. This paper describes the practical benefits of this permanent laser scanning installation. In addition to the potentials of automatic data acquisition, possibilities for multitemporal analysis with respect to spatio-temporally variable changes are presented, using advanced 3D change detection with Kalman filtering. The level of detection for deformation analyses therein depends on the quality of the georeferencing of the sensor and the noise within the measured point cloud. We identify and discuss temporally variable artifacts within the data based on different methods of georeferencing. Finally, we apply our change detection method on these multitemporal data to extract specific information regarding the observed geomorphologic processes.

I. INTRODUCTION

Analysis of mass movements and of geomorphic processes in general are a key subject in the prevention of natural hazards and protection of infrastructure (Bremer *et al.,* 2019). Such events are induced by various environmental processes as drivers while their occurrence is causally linked to climate change, therefore posing an increasing risk in terms of magnitude and frequency (Huggel *et al*., 2012). In the context of climate change and the expansion of areas of urban settlement, *e.g.* in Alpine regions, the demand for high-quality, *i.e.* spatially and temporally detailed, datasets as well as the integration in risk management as an early warning system is increasing.

Monitoring high-mountain areas is often difficult and dangerous. Remote sensing techniques are hence preferable for observation and to achieve high spatial and temporal coverage (Hermle *et al*., 2022). The technical advancement of terrestrial laser scanning (TLS) instruments towards communication-capable, programmable multi-sensor systems, compact and robust design as well as economically attractive systems allow the installation of permanent laser scanning (PLS) systems in areas of interest, and their integration into near real time early warning systems. A major advantage of PLS compared to measurements at selected points in time is that time series contain morphometric measures at high temporal resolution, which allow gaining a deeper insight into Earth surface processes (Eitel *et al*., 2016). With regard to the application of PLS within an early warning system, false alarms and misinterpretations of the results due to low levels of detection (LOD) or systematic deviations must be avoided. The risk of a poorly designed system provokes a lack of acceptance by stakeholders or derivation of incorrect conclusions on observed surface changes due to the influence of systematic errors.

Past research on point cloud registration and atmospheric influences often only used data limited to a few points in time over limited periods, from few hours to several days. The results, conclusions and recommendations derived from them are only generalizable to a limited extent. In this contribution, we present data integration of a permanent TLS installation which took place in 2020 and 2021 in Vals (Tyrol, Austria), emphasizing on quality-checked point cloud data and extraction of change information. We expect to provide a better understanding of the parameters influencing the observations and subsequent change analysis, which are variable on different temporal scales over long periods. From an engineering geodetic point of view, initial results demonstrate the need for improving the compensation of daily variations, which commonly occur in permanent TLS installations. We further present results of a change analysis using a new approach considering the full temporal domain of the 3D time series. Our results contribute to improved geoscientific monitoring using PLS by reducing uncertainty in the interpretation of processes that shape the Earth's surface.

II. Related Work

Deformation measurement in a geodetic sense (Lang, 1929) is conducted by surveying an area of interest at different epochs and identifying geometric changes based on the captured data. Despite its long existence and the development of novel sensors and algorithms, the processing chain of deformation measurement is still valid. Hence, it is recommended to carry out all steps of the following processing chain:

- Viewpoint planning (*e.g.*, Bechtold and Höfle, 2016; not elaborated in this paper),
- Data acquisition at different points in time (*cf.* Section A),
- Transformation of individual epochs into a stable reference frame (*cf.* Section B), and
- Quantification of deformation (*cf.* Section C).

A. *Permanent Laser Scanning (PLS)*

PLS is being used in numerous applications for the observation of natural surface dynamics (*e.g.*, Kromer *et al*., 2017; Vos *et al*., 2017; Williams *et al*., 2018; Voordendag *et al*., 2021). The automatic acquisition from a fixed position at regular intervals, *e.g.* hourly to daily, enables capturing surface changes at a large range of spatial and temporal scales (Eitel *et al.*, 2016).

As one of the first applications of PLS, Kromer *et al*. (2017) implemented a landslide monitoring system with half-hourly data acquisition over six weeks. The resulting 3D time series contained information on slope deformation preceding the occurrence of a rockfall event. Hourly PLS of a coastal cliff was conducted by Williams *et al*., (2019) to investigate the magnitude-frequency distribution of rockfalls, which provides information about their hazard potential.

In PLS, monitoring systems are assumed to be stable in terms of position and orientation to acquire 4D point clouds from the exact same instrument origin throughout the entire observation period. Theoretically, no further alignment of data would be required. In practice, applications of PLS have shown various effects that arise specifically in setups with high temporal acquisition frequency. In a coastal monitoring setting, Kuschnerus *et al*. (2021a) identified movement of the survey instrument, which needs to be corrected between epochs before applying point cloud comparisons for change analysis to reduce systematic errors.

Another important challenge that arises from high-frequency TLS acquisition is that variable atmospheric conditions influence the measurements at a scale which affects the detectability of changes. Variation in surface measurements linked to changing atmospheric conditions were found to strongly exceed the expected measurement accuracy in use cases of hourly coastal (Anders *et al*., 2020; Kuschnerus *et al*., 2021a) and glacier monitoring (Voordendag *et al*., 2021). The influence of (changing) atmospheric refraction on long-range TLS was determined to reach decimeter scales at kilometer acquisition ranges by Friedli *et al*. (2019). How these temporally variable uncertainties and measurement error can be fully accounted for in PLS-based monitoring is subject to current research.

B. *Registration*

Methods to analyze geometric changes in multitemporal point clouds are based on the assumption that individual scans are available in a common reference frame. Thus, bi- or multitemporal scans require transformation into such a frame (*cf.* Friedli and Wieser, 2016). Erroneous effects that occur in this step have an immediate and systematic impact on the quantification of deformation. Thus, all conclusions that are drawn based on the generated results are affected. Typically, parameters of a 6- or 7-parameter Helmert transformation are estimated using stable parts of the scene, and the derived transformation is subsequently applied to the whole scene (Vosselman and Maas, 2010). By using redundant computation of the parameters residuals can be quantified, and variances and covariances are available as a result for further processing.

In general, two strategies can be deployed to transform point clouds into common coordinate systems, either by georeferencing or co-registration approaches. Since deformed areas that occurred in between epochs would influence the outcome of registration, it is vital to exclude these from this process. Solutions to automatically reject deformed areas from the registration process are presented by Friedli and Wieser (2016), as well Wujanz *et al*. (2016).

C. *Quantification of surface changes*

A crucial factor for the practicability of PLS-based monitoring is the ability to fully automatically derive information from the large amount of 4D topographic data and to present interpretable layers to stakeholders. For use cases of topographic monitoring, the result of these analyses can be, *e.g.* maps of change magnitude and direction, the points in time when change occurs, a time series of change for each spatial location, or other information derived from the time series (*e.g.*, Winiwarter *et al*., 2022). In applications of natural hazards, near real time analysis may provide a warning when surface change surpass a defined threshold (*e.g.*, Kromer *et al*., 2017).

Currently, one of the main challenges for analyzing data acquired with PLS is that, while the information content is very high, the types of changes to be extracted from the data are not known *a priori*. Recently, new methods have therefore been presented, focusing on such change analysis tasks and information extraction from 4D topographic point cloud data. Due to the fixed setup and repeated scanning from the same position some error sources can be disregarded, whereas others appear more pronounced (Kuschnerus *et al*., 2021a). The requirement for an appropriate consideration of measurement uncertainties to separate small-scale displacements from noise is pointed out by Lague *et al.* (2013), and demonstrated by Fey and Wichmann (2017) for a rockfall area. The LOD, representing this separation threshold, is typically derived using a statistical test at a certain level of confidence.

Different methods to minimize the influence of noise in the quantification of change and to identify important change events have been developed. Among them is the multiscale model-to-model cloud comparison (M3C2, Lague *et al*., 2013). Though the M3C2 is a strictly bitemporal point cloud distance measure, differencing of successive epochs can be employed, for example, with respect to a fixed reference epoch. The M3C2 includes a statistical significance test, where the uncertainty of the measurements is derived from the data, combined with a globally constant value representing the alignment quality (Lague *et al*., 2013). To improve the quantification of measurement uncertainty, Winiwarter *et al*. (2021) have developed a method to integrate error propagation, which uses knowledge on the sensor's accuracy to predict the uncertainty in bitemporal point cloud distances.

To leverage the temporal domain of PLS data, the results of bitemporal surface change quantification can subsequently be processed as a time series for each location. Kromer *et al*. (2017) have used temporal averaging using a moving window to decrease uncertainty for a dense 3D time series. A similar approach has been employed by Anders *et al*. (2021), who further use the time series for the detection and spatial delineation of temporary surface changes on a sandy beach. Another approach which uses the full temporal information of hourly PLS is time series clustering, presented by Kuschnerus *et al*. (2021b) to identify characteristic change patterns on a beach.

In Winiwarter *et al*. (2022), the use of a Kalman filter is presented to reduce uncertainty through informed temporal smoothing. The smoothed time series enable to additionally output a set of physically descriptive features, such as the maximum change velocity or the acceleration. Different feature groups can then be used to create clusters, which can give additional insights when interpreting results. 4D point cloud data can hence be visualized as 2D clusters and magnitude maps, with additional time series at selected locations, to provide the temporal information.

III. Data Description

Our test site is the Vals valley in Tyrol (Austria). A rockfall occurred in this area on 24 December 2017, leaving a large debris cone at the lower part of the Alpine slope. Though causing neither human casualties nor significant damage to buildings, a road located directly below the rockfall slope was covered with 8 m of debris and a total volume of 116,000 m^3 of rock was relocated (Hartl, 2019). The local authorities set up a geodetic monitoring system, consisting of a total station with 21 corresponding prisms (Model: LEICA GPR1) and geotechnical sensors (*e.g.* extensometers) distributed over the source area of the rockfall on the upper mountain slope. As no significant rock movements were detected in the acquired data, the infrastructure of the existing monitoring system was made available for research. Point cloud data of the rockfall and debris area below was recorded during three campaigns using two different RIEGL VZ-2000i laser scanners (referred to as Model A and B), which were permanently installed on a survey pillar in a shelter on the opposite slope about 800 m from the rockfall area:

- Measuring setup 1 (M1): 13 August 2020 to 08 September 2020 – bi-hourly.
- Measuring setup 2 (M2): 10 May 2021 to 17 June 2021 – tri-hourly.
- Measuring setup 3 (M3): 28 July 2021 to 17 December 2021 – tri-hourly.

The acquisition was designed for various research and development activities regarding the deployment of long-range terrestrial laser scanners within a remotely controlled, web-based monitoring system from an engineering geodetic perspective. In addition to the laser scanner, a total station (LEICA TM30), inclination sensors on the survey pillar where the scanner was mounted on (aligned to the scanner-own coordinate system; PC-IN 1-1° by POSITION CONTROL). Various meteorological sensors were installed in the shelter and around the monitored slope area.

The additional measurements can be used to verify diurnal and seasonal systematic effects on the results of surface change quantification. Furthermore, the prisms of the total station monitoring installed in the stable rock part and support different methodical approaches to verify such effects, as the RIEGL TLS instruments are able to detect these prisms as corresponding measuring points in the multitemporal scan data. During PLS acquisition, a high-resolution scan of the area was carried out with a resolution of 15 mdeg in azimuth and elevation at a pulse repetition rate of 50 kHz every 2 hours (M1) and every 3 hours (M2 and M3), respectively. As outlined in Table 1, fine-resolution scans of the prisms were acquired in-between regular scanning intervals.

Table 1. Applied sensors and their measuring frequency

Data	Sensor	Acquisition interval	Campaign
3D point cloud of rockfall area 3D point cloud of each prism	RIEGL VZ-2000i (Model A)	Meas. prog. interval of 120 min: ▪ 1 areal scan (15 min) ▪ 5 prism scans (Every 21 min)	M1
3D point cloud of rockfall area 3D point cloud of each prism	RIEGL VZ-2000i (Model B)	Meas. prog. interval of 180 min: ▪ 1 areal scan (15 min) ▪ 2 prism scans (Every hour)	M2, M3
3D meas. to each prism	LEICA TM30	Every hour	M1, M2
Inclination of the pillar	POSITION CONTROL, PC-IN1-1°	Every 15 sec	M1, M2, M3
Air temperature Air pressure Relative Humidity	WIESEMANN & THEIS (WUT), WEB THERMO-HYGROBAROMETER 57713	Every 15 sec	M1, M2, M3
Air temperature Relative Humidity	ELITECH TEMPERATURE-LOGGER, RC-51H	Every 15 min	M1, M2
Global radiation	ZAMG. AC. AT METEOSTATION: SCHMIRN, BRENNER, STEINACH	Every 10 min	M1, M2
Air temperature Air pressure Rel. Humidity Wind speed Wind direction Global radiation Dew point	LAMBRECHT U[SONIC]WS7	Every 15 sec	M2, M3

Due to logistical constraints, the more accurate web thermo-hygrobarometers by WuT were only installed in the shelter, at the valley basin and in the lower part of the observed slope area. Elitech temperature loggers that require no additional power supply, were installed at the top of the rockslide so that no additional power supply is needed in these areas. A different scanning instrument, but of the same type and model, was deployed for the M2 and M3 acquisition periods. The remainder of this paper, *i.e.* all analyses, focus on the data acquired from 28-07-2021 to 15-11-2021 (M3).

IV. Methods and Initial Results

A. *Registration of 4D point clouds*

The investigation of systematic long-term effects in the measurement data, a study of local effects in terms of spatial and temporal scale is initially omitted. Data from 19 prisms within the study area are analyzed for a period from 28-07-2021 to 31-10-2021. The time series of each prism is (1) reduced to a daily mean, then (2) relative changes to a global reference scan on 29-07-2021 at 13:00 are evaluated, and finally (3), in order to investigate global effects on the point cloud data, an average value for each coordinate axis in the scanner's own coordinate system (SOCS) is calculated. Figure 1 shows these time series in black color.

The assumption that the surveying pillar is stable and exempt from any movement does not apply. It is evident that the raw data varies over time and leads to non-negligible deviations. A linear drift is evident on the Y-axis and significant time-varying deviations on the Z-axis. This supports the requirement of data referencing before multitemporal change analysis.

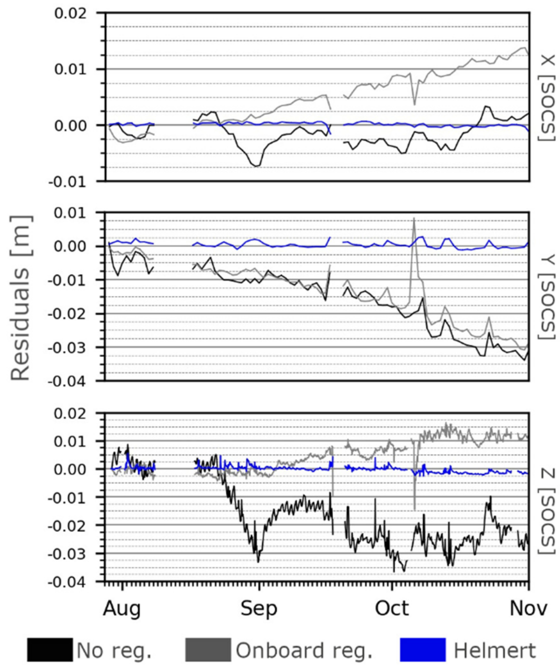

Figure 1. The comparison of different registration approaches as impact mapping: [1] No registration, [2] Onboard registration and [3] Helmert transformation.

As an initial registration procedure, onboard algorithms of the scanning device are applied. They use a simple ICP approach with the entire point cloud as input for the determination of the transformation parameters. The distances between two corresponding point clouds are minimized for this purpose. No classification and segmentation of the point cloud is performed within this process, so that non-stable areas are included in the analysis. It is noticeable that there is almost no correction on the Y-axis since this axis runs parallel to the valley, which lacks measurement data. On the X- and Z-axes, we see a change in their signs. A visual comparison of the parameters with records of the inclination sensors (*cf.* Figure 2) allows a first conclusion that the values cannot be explained exclusively by movements of the survey pillar. Rather, when assessing the measurement data, it can be seen that the predominant part of the scene is characterized by vegetation, which increases or decreases linearly in the course of a measurement series depending on the season. The non-consideration leads to misinterpretations. An alternative approach demonstrates that the classification of stable areas in the geodetic sense remains important. The current lack of an automatable algorithm for the application of the whole point cloud can be compensated by the possibility of detection the prisms in the respective scans. Thus, a 7-parameter Helmert transformation can be applied. The procedure also offers the possibility to estimate a scale parameter as another quality criterion. A visual inspection of the transformation parameters does not indicate any systematic effects, so that this mathematical model demonstrates an adequate consideration of stable areas.

A set of impact maps (Figure 3), showcasing the effects of different transformation parameter sets on resulting point cloud distances, is derived by applying the M3C2-EP (Winiwarter *et al.*, 2021) on two point clouds, which were acquired on 28-07-2021 and 03-10-2021. For the parameterization of this numerical example, we introduce transformation parameters exclusively. The influence of registration is considered and realistic accuracy measures are disregarded. The map is generated by comparing the two scans with respect to their differences in the transformation parameters. Without using transformation parameters, a tendency to higher values is visible, corresponding to a shift of the normally distributed deviations by 0.015 m in the mean (*cf.* Figure 3 – [1]). The application of the simplified registration algorithm of the scanner shows a normal distribution with the mean tending towards zero, but with a slight bias of -0.008 m (*cf.* Figure 3 – [2]). The transformation using 7 parameters shows a Gaussian distribution at almost zero (-0.002 m), which is the expected magnitude of differences (*cf.* Figure 3 – [3]).

B. *Change detection using Kalman filtering for full 4D point cloud analysis*

The dense time series of the 4D point clouds contains spatially and temporally detailed information on surface processes. We use data acquired every three hours over 110 days (from 28-07-2021 to 15-11-2021), yielding a total of 766 epochs. To extract and visualize information on surface changes, which occur at variable a-priori unknown locations and timespans, we apply a recent method using a Kalman filter to combine the spatial and temporal properties of 4D point clouds for change analysis, following Winiwarter *et al*. (2022). We explain this method in the following.

First, M3C2-EP (Winiwarter *et al.*, 2021) is used to calculate bitemporal surface change for each epoch, using the first epoch as reference. No filtering of changes by statistical significance is applied at this point, but uncertainty information is recorded (as suggested by Anderson, 2019). We use the following parameter settings for M3C2-EP: normal radius 5 m, projection radius 0.5 m, maximum cylinder length 3 m, core point density 0.45 pts/m², ranging uncertainty: 0.005 m, angular uncertainty 0.0675 mrad.

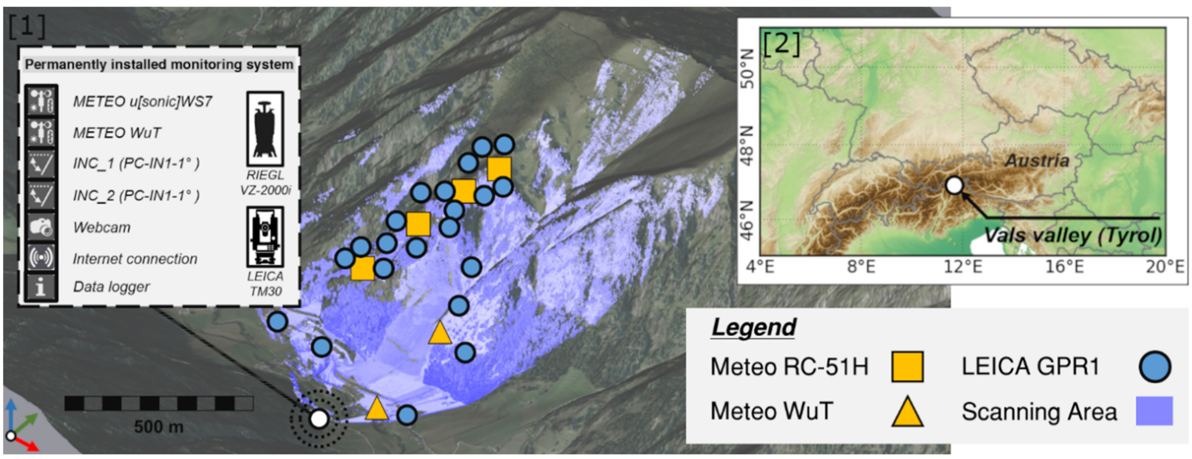

Figure 2. Figure Three-dimensional overview of the test site in the Vals Valley including applied sensor technology and overview of the geographical situation of the Vals Valley. (Data Source: Land Tirol - data.tirol.gv.at [1] and http://ows.mundialis.de/services/service?;layers=SRTM30-Colored-Hillshade [2]).

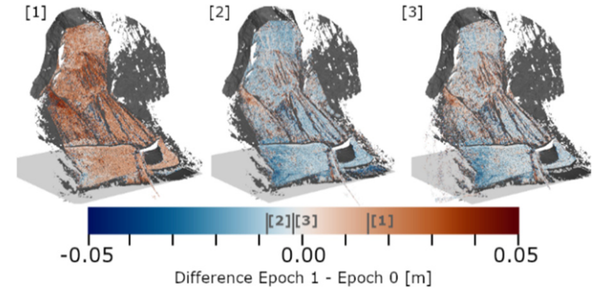

Figure 3. The comparison of different registration approaches as impact map: [1] No registration, [2] Onboard registration and [3] Helmert transformation.

We use a Kalman filter on each spatial location (*i.e.*, core point) individually to model the displacement at this location over time. A Kalman filter represents a dynamical system by a state vector, a measurement function, and a state transfer function, and requires errors in the obtained bitemporal surface change to be normally distributed. As we modelled these changes with M3C2-EP, we assume that this condition is met. In the Kalman filter, the state vector contains the parameters (in our case, the estimated displacement value, the change rate, and the acceleration at a single location) for a single point in time. From this state, a future state can then be predicted using the state transfer function, linearized to be representable by a matrix. This is referred to as the prediction step. If observations, *i.e.*, measurements are available, they can be introduced to the state in the update step. Again, a linearized model is used to represent the relation of observations and parameters. In both the predict and update steps, uncertainty is employed. The state vector itself is accompanied by a covariance matrix. In the prediction step, the uncertainty generally increases, as the last observations become less recent.

The increase of uncertainty over time due to a lack of measurements is modelled by the Kalman filter. As the behavior of the observed surface is not known prior to analysis, a piecewise (discrete) white noise model is employed, following Labbe (2021). We assume that for each time step, an uncorrelated (to the previous change) and random change in the acceleration value may happen, where the expected value of this change is normally distributed with mean zero and a standard deviation of $\sigma = 0.05$ m/day². Hence, the more time has passed since the last measurement, the more uncertain the model will be about its state. Our choice of σ was made to allow the filter to closely follow the observations, yet smoothing daily or diurnal patterns (Figure 4; *cf.* Winiwarter *et al.*, 2022).

The Kalman filter is combined with a Rauch-Tung-Striebel smoother to create a smoothed time series considering both future and previous measurements for any point in time. This also allows interpolation over data gaps. Figure 4 shows a time series for a single spatial location with the measurements, the smoother value and the respective uncertainties, together with the derived velocity and the acceleration. At the end of the measurement period (starting on 01-11-2021), snowfall occurred in Vals. The deposition and melt of this large-scale surface change show in all time series of this dataset, and induce uncertainty that is not well represented by the Kalman filter.

In Figure 5, the resulting change magnitudes (a) at the end of the 110-day period and (b) at their maximum value for each spatial location are shown. The red areas in (a) correspond to deposited material, the blue ones to eroded material. The overall orange color in (b) corresponds to snowfall in the beginning of November.

Similar values, such as the time when significant change was first recorded at each location (Figure 6) can be extracted from the time series at each location.

The erosion channels following a thunderstorm can be seen in pink, as well as anthropogenic works in the lower area of the slope. Snowfall in the first days of November is the cause for the major peak that can be seen in cyan, covering large areas. We subsequently use 20 such attributes derived for each location as feature vectors for unsupervised classification, i.e., clustering, using a Gaussian Mixed Model (following Winiwarter *et al.*, 2022). The result of the clustering is shown in Figure 7, where individual change processes can be identified through visual interpretation.

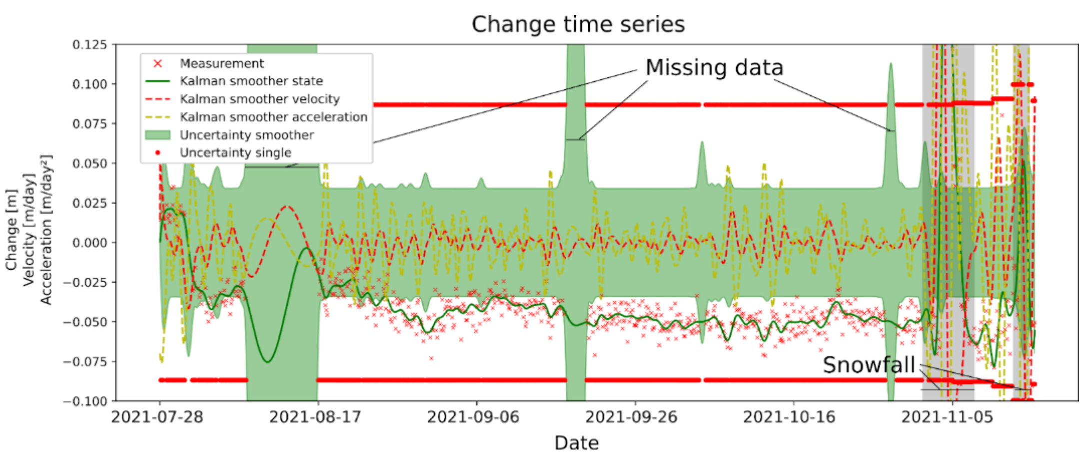

Figure 4. Exemplary time series at a location with subtle, but continuous erosion. Note how data gaps are interpolated, but if they are too long, a ringing effect occurs (as seen in the days before 17-08-2021). A daily pattern can be observed, especially in the velocity and acceleration estimations. Snowfall at the end of the observation period causes large displacement values.

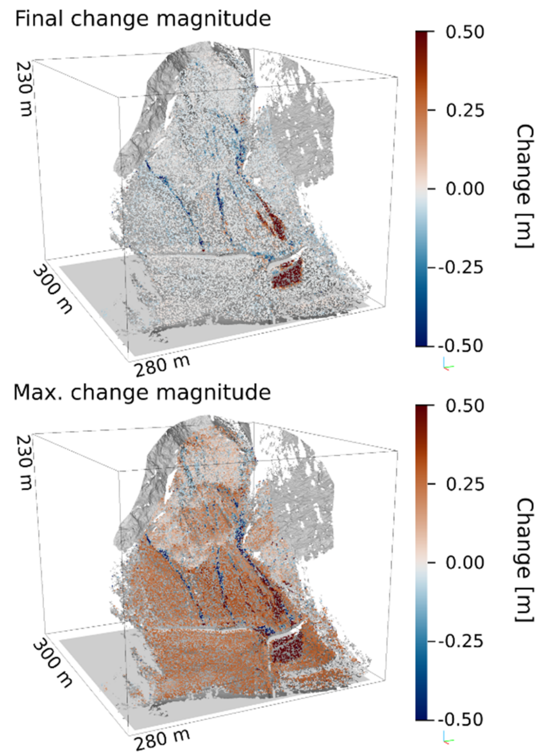

Figure 5. Resulting change magnitudes: a) Change magnitude between the first epoch and the last epoch; b) Maximum change magnitude.

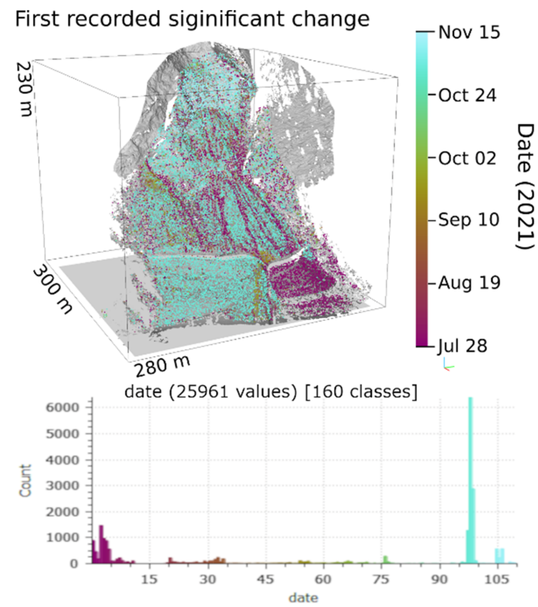

Figure 6. Date when change is larger than LOD.

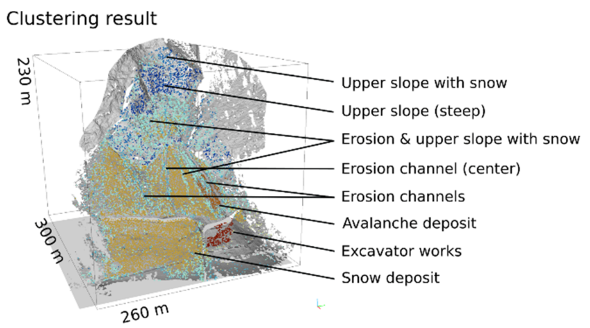

Figure 7. Result of clustering on features derived from the Kalman-filtered time series.

V. Conclusion and Outlook

The use of bitemporal data from a TLS to verify surface changes is widely used and discussed. We discuss the transition to permanent installations and the acquisition of multitemporal data sets. The quality of the extracted information is directly dependent on the underlying data quality. With regard to data qualification, the focus in this paper is on different registration procedures. It becomes obvious that registration is absolutely necessary when integrating the system into an automated monitoring system with a corresponding alarm function. The level of detection (LOD) varies with the application of the different registration procedures. The simplified ICP algorithm, as used by the employed scanner instrument, is valid if the area undergoing change is small in extent compared to the whole scene. Under certain conditions (large areas covered by vegetation or other moving objects in the scene) it comes to its limits.

For example, an alarm value set at the beginning is triggered by the drift effects in the co-registration alone after a specific point in time and leads to false alarms. The use of a rigorous approach shows the necessity of segmenting and classifying the point cloud into stable and non-stable areas as described by Friedli and Wieser (2016) and Wujanz (2016). We show that data alignment is of vital importance for subsequent change quantification and analysis, even in the widely stable survey setup of permanent TLS.

We reduce the uncertainty of change analysis by employing a Kalman filter operating on M3C2 distances in the point cloud, which makes use of the full spatiotemporal information in the dataset. The consideration of uncertainty in this analysis is not purely data-based, but also uses information from the previous alignment step by means of the derived covariance in the transformation parameters. Periodically appearing deviations are evident both in the time series of measurements and of the transformation parameters.

Whereas no methods are currently available to remove periodic measurement effects, reducing uncertainty in change analysis from high-frequency TLS time series is subject to ongoing research efforts. In the course of these research activities, causal descriptions of the above-mentioned error influences will be verified and modelled. The first objective is to more efficiently design the permanent installation of terrestrial laser scanners within an integrative monitoring system in order to avoid misinterpretations and false alarms. The second objective is to achieve a higher degree of automation of the entire system. Automatic processing chains are only available in parts of the full workflow and there is no holistic software solution yet. In addition, a high level human expertise is typically necessary. Now that point cloud acquisition is highly automated, there is strong need for research and development in the individual fields of 4D point cloud analysis within a monitoring system, with a focus on extracting change information and final quality assessment from an engineering geodetic point of view.

VI. Acknowledgements

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