



Challenges in reconstructing seasonally driven landslide motion from optical satellite data: insights from the Del Medio catchment, NW Argentina

Ariane Muetting¹, Laurane Charrier^{2,3,4}, and Bodo Bookhagen¹

¹Institute of Geosciences, University of Potsdam, Karl-Liebknecht-Str. 24-25, Potsdam-Golm 14476, Germany

²Univ. Grenoble Alpes, CNRS, IRD, INRAE, Grenoble-INP, Institut des Géosciences de l'Environnement (IGE, UMR 5001), 38000 Grenoble, France

³Univ. Grenoble Alpes, CNRS, Inria, Grenoble INP (Institute of Engineering Univ. Grenoble Alpes), LJK, 38000 Grenoble, France

⁴Meteo-France, CNRS, Univ. Grenoble Alpes, Univ. Toulouse, CNRM, Centre d'Etudes de la Neige, 38000 Grenoble, France

Correspondence: Ariane Muetting (muetting@uni-potsdam.de)

Abstract.

Optical satellite images are a valuable resource for studying slow-moving landslides from space. However, monitoring displacement through pairwise image correlation and time-series inversion presents several challenges, including the impact of seasonality on measurement accuracy. Seasonal biases arise from systematic measurement errors related to variable illumination conditions and shadows. These errors manifest in the form of an oscillation pattern in the satellite-derived time series. This complicates the identification of a true seasonal component linked to feedback mechanisms between landslide displacement and a seasonally variable climate.

Here, we provide a comprehensive evaluation of different strategies to reduce the magnitude of seasonal biases. These include modeling the seasonal error component, restricting correlation to pairs with similar illumination, weighting, and upsampling optical images. We find that all methods can reduce the impact of systematic seasonal bias at different trade-offs: longer processing times, creation of sparse or disconnected networks, dependence on topographic data, or potential alteration of the true displacement signal.

We evaluated the removal of seasonal bias from displacement time series derived from optical satellite data (Landsat-8, Sentinel-2, PlanetScope) over a large slow-moving landslide in the Río Del Medio catchment in northwest Argentina. The transition zone between the Altiplano-Puna plateau and the Andean foreland is characterized by a highly seasonal climate, with intense rainfall during the South American summer monsoon and semi-arid conditions throughout the rest of the year. Over the 10-year observation period, the landslide accumulated approximately 35 m of displacement at spatially and temporally variable rates. After the removal of the seasonal bias component, three acceleration phases remain. These date to early 2017, early 2018, and late 2021, and all fall within the rainy season of the respective year. The timing of the acceleration suggests precipitation as a major driver of a landslide that is already preconditioned by infiltration and sliding through inherited fault structures, weakened lithologies, and freeze-thaw processes at high altitudes of up to 4500 m above sea level.



Based on this example, our study provides a basis for selecting the appropriate correction methods to address seasonal biases. Considering all effects of seasonality is essential to improve the accuracy of satellite-derived displacement measurements and better constrain the feedback mechanisms between landslide velocity and a seasonal climate.

25 1 Introduction

Slow-moving landslides are a common phenomenon in mountainous regions, where they pose threats to local infrastructure, alter sediment-transport patterns, may fail catastrophically, and ultimately lead to cascading effects downstream (e.g., Handwerger et al., 2013; Lacroix et al., 2018; Handwerger et al., 2019a; Lacroix et al., 2020; Van Wyk de Vries et al., 2022). Given their hazard potential, there is an interest in detecting and monitoring unstable slopes. For landslides moving at rates of 1-100
30 m per year, cross-correlation of optical satellite imagery is a viable and cost-effective method for measuring surface displacement, especially in steep and inaccessible terrain. Displacement time series from optical data are traditionally obtained through pairwise correlation of images acquired at different points in time, thereby establishing a redundant network of displacement maps. Subsequently, a displacement signal can be reconstructed from the temporally overlapping measurements by solving a matrix system through time-series inversion (e.g., Bontemps et al., 2018; Lacroix et al., 2019; Ding et al., 2021; Dille et al.,
35 2021; Provost et al., 2022) – an approach adapted from the time-series analysis of Interferometric Synthetic Aperture Radar data (Doin et al., 2011). The derived time series is the basis for subsequent interpretations of the landslide’s behavior, making it essential to obtain reliable results from this step. However, displacement measurements obtained from satellite images can be biased due to several reasons, including image distortions, limited co-registration accuracy, orthorectification errors, algorithmic errors, seasonal shadow, or landcover effects (e.g., Leprince et al., 2007; Scherler et al., 2008; Stumpf et al., 2014;
40 Lacroix et al., 2019; Mueting and Bookhagen, 2023; Antoine and Liu, 2025). Erroneous measurements will degrade the quality of inverted displacement time series, depending on their magnitude and distribution.

In this study, we used optical imagery from different satellites to investigate the displacement history of a large, slow-moving landslide located in the Río Del Medio catchment, within the Quebrada del Humahuaca in northwest Argentina. The landslide failed catastrophically in 2009 (Savi et al., 2016; Purinton and Bookhagen, 2018), but the subsequent behavior and driving
45 factors are largely unknown. Meter-scale displacement rates of $\sim 2.5 \text{ m yr}^{-1}$ estimated over the landslide for the years 2020 - 2023 (Mueting and Bookhagen, 2023) are well suited for detection with optical imagery. However, the high seasonal variability that characterizes the study area poses difficulties: during the rainy season, clouds at major orographic barriers obstruct the satellite’s view, and the high-relief terrain generates moving shadows throughout the year. When images from different seasons are correlated, variable illumination and shadows lead to systematic measurement errors because they are falsely interpreted
50 as movement. This seasonal bias in pairwise displacement measurements results in an oscillation pattern in the time series obtained from inversion (Lacroix et al., 2019). At the same time, heavy rains during the South American summer monsoon are a major driver of slope movements in northwest Argentina, including landslides and debris flows (e.g., Savi et al., 2016; Angillieri et al., 2020; Olen and Bookhagen, 2020). Slow-moving landslides are known to respond to changes in porewater pressure induced by rainfall or snow melt (e.g., Hilley et al., 2004; Handwerger et al., 2013). A relationship between landslide



55 motion and seasonally changing environmental conditions may, however, not be identifiable when overprinted by seasonal
biases related to variable illumination. Because in-situ instrumentation is often not available, a reduction of seasonal errors
can only be achieved by improving the satellite-derived measurements and thus reconstructing the true landslide displacement
as reliably as possible. Previous studies have taken different approaches to mitigate the effect of variable illumination and
shadows, including modeling seasonal oscillations on static terrain with exposition similar to the landslide through harmonic
60 functions (Lacroix et al., 2019), masking shadows before correlation (Provost et al., 2022), or restricting correlation to image
pairs acquired under similar illumination conditions (Dehecq et al., 2015; Hollingsworth et al., 2017; Ding et al., 2020, 2021).
However, there is no consensus yet on which approach is best suited to address seasonal biases in time series retrieved from
optical image matching.

In this study, we compare different mitigation strategies and assess their advantages and limitations. In this way, we aim to
65 (1) achieve the best possible reconstruction of the displacement history of the last 10 years in the Río Del Medio catchment
area, and (2) provide a basis for selecting a suitable correction approach considering local conditions, data availability, and
processing capabilities. We used imagery from PlanetScope, Sentinel-2, and Landsat-8 to obtain a displacement time series
over the landslide surface through inversion. We assess seasonal measurement biases in displacement estimates from different
sensors at different spatial resolutions; determine if and how a potential real seasonal displacement signal can be decoupled
70 from measurement errors; and uncover the external forcing factors of slope movement at the Del Medio landslide, including
changes in landslide motion in response to a seasonally variable climate.

2 Study area

Our analysis focuses on a slow-moving landslide located in the catchment of the Río (or Arroyo) Del Medio, which we sub-
sequently refer to as the Del Medio landslide. The Río Del Medio is a tributary of the Río Grande, draining the intermontane
75 Humahuaca Basin in the Eastern Cordillera of northwest Argentina. The landslide is situated on the steep slopes of the eastern
drainage divide of the Del Medio catchment with peaks that reach 4500 m above sea level (Figure 1 a). Due to the eastward
dip of the landslide slope, we primarily consider the east-west component of displacement in this study. The Del Medio basin
is bounded by two north-south striking faults, both of which are inherited normal faults that have been inverted under a com-
pressional regime (Rodríguez Fernández et al., 1999). The exposed lithologies include the pervasively sheared phyllites of the
80 Puncoviscana Formation and the quartzitic rocks of the Mesón group in the upper part of the catchment (Savi et al., 2016;
Rodríguez Fernández et al., 1999). Notable is the scar and deposits of a catastrophic rockfall event that occurred during the
rainy season of 2009 (Figure 1 b-c), which caused several tens of meters of elevation changes (Purinton and Bookhagen, 2018).
Recent research showed that the landslide is still active: downhill movement with rates between 2-5 m yr⁻¹ was detected for
the years 2020-2023 in the area of the 2009 failure (Mueting and Bookhagen, 2023). Using satellite imagery from multiple
85 sources, this study extends displacement monitoring to the time period between 2014 and 2024.

Landslides and rockfalls in the Del Medio catchment provide large amounts of material that is transported by debris flows and
deposited in an actively aggrading fan (Savi et al., 2016). Debris flows sourced from the Del Medio and adjacent catchments



typically occur during the austral summer monsoon when heavy rainfall can mobilize loose material and transport it downstream (Savi et al., 2016; Angillieri et al., 2020). This high seasonality observed in the sediment transport processes raises the question of whether landslide displacement rates in the Del Medio catchment are also driven by high precipitation rates during the rainy season – a question this study tries to answer based on displacement time series inferred from optical satellite data.

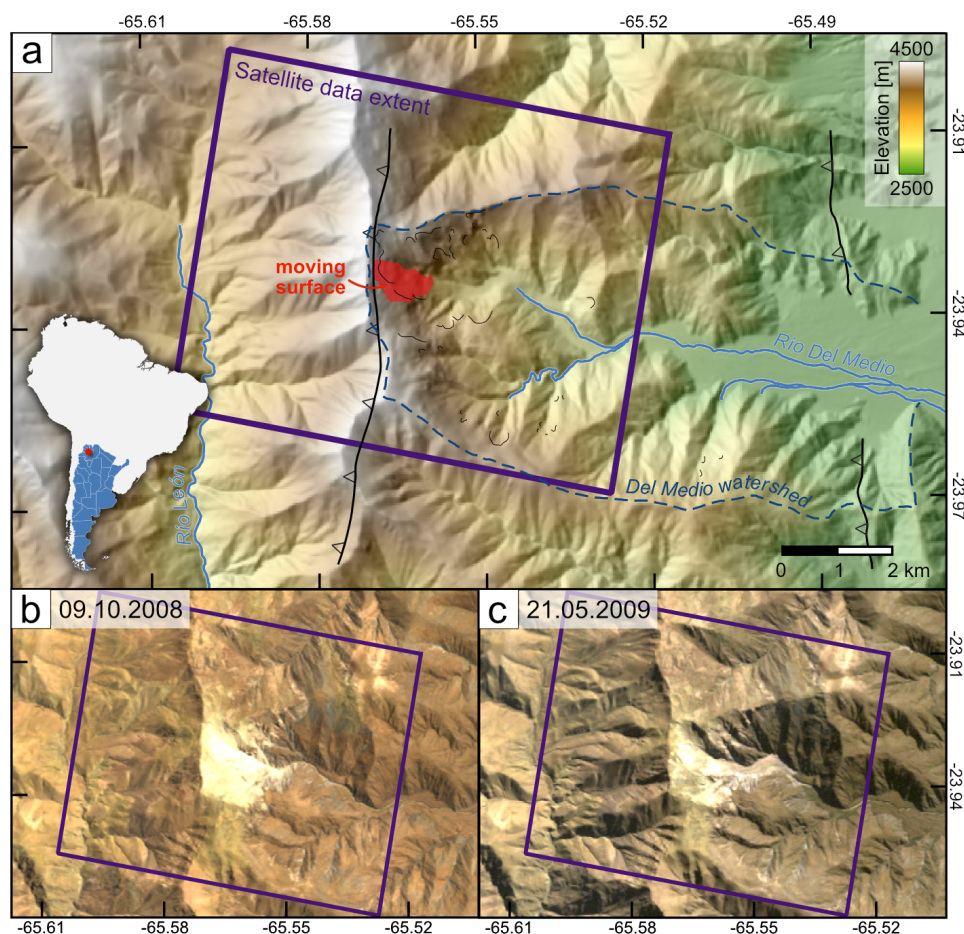


Figure 1. (a) Topographic map of the Del Medio catchment in the Quebrada del Humahuaca. Scarps of historical landslide events and geologic structures (inverted normal faults) (Rodríguez Fernández et al., 1999) are indicated in black. The surface of the actively moving block is highlighted in red. The area of interest to which all satellite data was cropped is shown in purple. Figures (b) and (c) depict two cloud-free Landsat-5 images before and after the major rockfall event that occurred at the Del Medio landslide during the rainy season in 2009. Additional Landsat-5 acquisitions with partial cloud cover constrain the timing of the rockfall between January 13 and March 2, 2009. Landsat-5 imagery is courtesy of the U.S. Geological Survey.



3 Materials and Methods

3.1 Satellite data

Offset tracking was performed using cloud-free optical satellite imagery from Landsat-8 (43 images), Sentinel-2 (41 images), and PlanetScope (87 images). The archive of the PlanetScope constellation consists of data captured by different instrument generations. We made use of imagery acquired by the PSB.SD instrument (SuperDove) in orbit since March 2020, and the older PS2 (Dove-C) generation with the earliest available imagery over the Del Medio landslide from mid-2016. Taken together, all satellites provide insights into the displacement history of the Del Medio landslide since 2014 and allow a comparison for a common timespan from 2017 to 2024. Imagery was chosen based on cloud- and snow-free conditions and full area of interest (AOI) coverage, except for the PlanetScope PS2 instrument, where the comparably small scene sizes of 24 x 8 km did not always fully align with the study area. During the dry season, when many suitable scenes are available, only a representative subset was selected to reduce computational load. For Landsat-8, we worked with the panchromatic band because of its highest spatial resolution (15 m). For Sentinel-2 and PlanetScope, we isolated the green band. The use of other bands (blue, red, infrared) from Sentinel-2 was shown to provide similar results (Lacroix et al., 2018). All Landsat-8 scenes used in this study belong to the Collection 2, Tier 1, Level-1 dataset provided by the USGS. Sentinel-2 data were downloaded as Level 1C (geo- and radiometrically corrected) from the Copernicus Data Space Ecosystem. We selected Sentinel-2B to have data from a single satellite only, and also ensured that the images were processed with a baseline that used the Copernicus DEM for orthorectification. Geo- and radiometrically corrected PlanetScope data (Level-3B) were obtained through Planet's Education and Research program (Planet Team, 2022). Acquisition dates for the newer PSB.SD images align with the imagery used by Mueting and Bookhagen (2023), but all scenes were downloaded again to ensure a common processing baseline, because we observed that the reference DEM used during orthorectification has likely changed since the last data access (see Supplementary Figure S1). We also added PS2 scenes, as well as additional PSB.SD acquisitions to extend and densify the correlation network. A list of all scenes used in this work can be found in the Supplementary Material, Tables S1 to S4. Sun elevation and azimuth angle of the scenes are plotted in Figure S2.

3.2 Image correlation

Image correlation was carried out using Ames Stereo Pipeline (Beyer et al., 2018). To ensure true comparability between the satellite imagery at different resolutions, we upsampled both Landsat-8 and Sentinel-2 to the 3-m spatial resolution of PlanetScope using cubic interpolation. Parameters were set to conform with Mueting and Bookhagen (2023): block matching with a correlation kernel of 35x35 pixels and subpixel refinement using an affine adaptive window with Bayes expectation-maximization weighting. We initially experimented with keeping the original resolution of the input imagery and adjusting the correlation kernel to be constant in size (meter), but found a link between spatial resolution and magnitude of seasonal errors (see Section 4.3). A first estimation of the landslide displacement signal was obtained by correlating all possible Landsat-8 image pairs with a minimum baseline of half a year. Based on the interannual trend of this time series, we filtered image pairs for all satellites that can be expected to show displacement beyond the detection threshold (assuming 1/10 of the native reso-



125 lution). With respect to the half-year threshold, this added connections in phases of rapid movement and reduced the number
of correlation pairs in years with no or very little displacement. For PlanetScope data, we added a constraint for the satellite
viewing angle and only formed pairs among images with a common perspective to reduce the effect of orthorectification er-
rors (Mueiting and Bookhagen, 2023). Also, PSB.SD and PS2 data were correlated separately due to the different instruments.
Overall, the pairing strategy resulted in 785 (Landsat-8), 752 (Sentinel-2), 271 (PlanetScope PSB.SD), and 220 (PlanetScope
130 PS2) correlation pairs. See Supplementary Figures S3 – S5 for a representation of all networks.

3.3 Post-processing

For Landsat-8 and Sentinel-2, we applied a median shift following image correlation to account for global shifts between
reference and secondary image pairs. Median values were calculated with the landslide pixels masked out, assuming that the
135 surrounding terrain remained stable. For PlanetScope, which is often affected by more complex co-registration error patterns,
we modeled and removed global shifts, ramp, and orthorectification errors through a second-order polynomial taking into ac-
count local elevation (Mueiting and Bookhagen, 2023).

3.4 Time-series inversion

140 Coherent time series were retrieved through an inversion based on the temporal closure of displacement measurement networks.
The following system of linear equations is solved:

$$AX = B \quad (1)$$

where B is the vector storing all available displacement measurements obtained by the correlation of image pairs, A is the
design matrix, and X denotes the vector containing the displacement estimates at each date. The design matrix A contains
145 the values 0 and 1. 1 is assigned to each time step contained within the interval defined by the reference and secondary dates
of acquisition of the image pair, and 0 elsewhere. This framework, known as the Leap Frog approach (Hadhri et al., 2019;
Charrier et al., 2022b, c), solves for displacement at each time step, which is then added cumulatively to produce the final
time series. For a connected network, the design matrix A is of full rank ($rank(A) = \min(m, n)$ with m being the number
of correlation pairs (rows in A) and n the acquisition dates (columns in A)). The system can be solved using an ordinary
150 least-squares approach, which minimizes the sum of squared residuals:

$$\arg \min(\|AX - B\|^2) \quad (2)$$

Optionally, weights can be added to the matrix system to favor displacement measurements that are less affected by errors.
To add weights, both the design matrix A and the displacement measured through pairwise image correlation (vector B) are
multiplied by a vector W containing the weights assigned to each displacement measurement:

$$155 \quad WAX = WB \quad (3)$$



We experimented with weighting to reduce seasonal biases. Weights were based on the absolute difference of solar incidence angle of the reference and secondary image taking into account the local topography of each pixel. This difference ($\Delta\theta$) was calculated as:

$$\Delta\theta = \text{atan2}(\sin(\theta_2 - \theta_1), \cos(\theta_2 - \theta_1)) \quad (4)$$

160 where θ_1 is the solar incidence angle of the reference image and θ_2 the incidence angle of the secondary scene. To give higher weights to image pairs with a low angle difference, weights (w) were set as follows:

$$w = \frac{1}{(1 + \Delta\theta^2)^2} \quad (5)$$

The inversion was carried out separately for each satellite, to allow for a comparison between the three data sources. Only for
165 PlanetScope, we jointly inverted PSB.SD and PS2 correlation pairs. Due to the different instrument generations and grouping strategy based on common view angle, the PlanetScope network is disconnected, but with temporal overlap between groups. If not all dates within a network are connected through correlation, the matrix system (Equation 1) becomes rank deficient ($\text{rank}(A) < \min(m, n)$) and, in consequence, the inversion problem becomes ill-posed. In this case, we include a first-order Tikhonov regularization term, as proposed by Bontemps et al. (2018); Charrier et al. (2022b, c, a), which adds a penalty or
170 regularization term as an additional minimization constraint to the least squares problem:

$$\arg \min(\|AX - B\|^2 + \|\Gamma X\|^2) \quad (6)$$

Here, Γ represents the regularization matrix, which is of size $n - 1 \times n$. The matrix is filled with zeros, except for the diagonal, which is assigned the values $-\frac{1}{\Delta\tau_i}$ and the above element, which is set to $\frac{1}{\Delta\tau_i}$ (Charrier et al., 2022b):

$$\Gamma = \begin{bmatrix} -\frac{1}{\Delta\tau_{i d_{0,1}}} & \frac{1}{\Delta\tau_{i d_{1,2}}} & 0 & \dots & 0 \\ 0 & -\frac{1}{\Delta\tau_{i d_{1,2}}} & \frac{1}{\Delta\tau_{i d_{2,3}}} & & 0 \\ \vdots & & & \ddots & \\ 0 & 0 & 0 & -\frac{1}{\Delta\tau_{i d_{n-2,n-1}}} & \frac{1}{\Delta\tau_{i d_{n-1,n}}} \end{bmatrix} \quad (7)$$

175 $\Delta\tau_i$ corresponds to the temporal difference between each subsequent acquisition date. Including weights, the analytical solution of the matrix system, with the regularization term, can be formulated as:

$$\hat{X} = (A^T W A + \lambda \Gamma^T \Gamma)^{-1} A^T W B \quad (8)$$

The regularization parameter λ is a scaling constant with a default value of 1. The system, including the regularization term, is solved using a least squares solver for each pixel and for each component separately. This results in a multi-band raster
180 that stores the cumulated displacement for each time step. The time series of the Del Medio landslide was generated by extracting all pixels on the actively moving surface and calculating the mean and standard deviation. The landslide surface was outlined through thresholding the maximum displacement field in combination with some manual adjustments based on photo interpretation.



3.5 Estimation of seasonal biases

185 Seasonal biases in pairwise displacement measurements typically manifest in the form of a regular seasonal oscillation pattern in the inverted time series. To estimate the magnitude of this signal per pixel, we first remove any nonlinear inter-annual displacement trend. The trend is estimated using a rolling mean with a kernel of 13 months, as suggested by Lacroix et al. (2019). Then, we fit a sine wave with a fixed frequency of one year to the detrended signal:

$$y(t) = A \sin(2\pi ft) + C \quad (9)$$

190 where y is the cumulative displacement signal, A the amplitude, f the frequency, which is set to a fixed value of $\frac{1}{365.25}$, t the time in days, and C a constant that allows for vertical shift, in case the trend removal did not fully center the time series at zero. The amplitude of this sine wave is used in the following to quantify the effect of illumination changes on time-series inversion. We also employ a sine fit to explore the mitigation of seasonal biases as described in Section 4.4.1.

4 Results

195 4.1 Landslide displacement

Figure 2 illustrates the initial results of the correlation and subsequent time-series inversion of the east-west component separated by satellite system. We find distinct changes in the kinematic behavior of the Del Medio landslide through time. For the years 2014 to 2017, no or very little displacement was detected according to available Landsat-8 images. At the beginning of 2017, all satellites recorded a rapid acceleration in their respective time series, where the Del Medio landslide acquired
 200 approximately 20 m of displacement until March/April 2018, reaching an average velocity of $\sim 13 \text{ m yr}^{-1}$. Subsequently, the displacement rates decreased to about 2.5 m yr^{-1} , which remained constant until the end of the observation period in October 2024.

4.2 Impact of variable illumination

205 In addition to the described trends, all displacement time series (Figure 2 d-f) are characterized by seasonal oscillations with an average amplitude of approximately 1 m over the landslide surface (see Supplementary Material, Figure S7 for precise amplitudes). This pattern is not restricted to the Del Medio landslide, but occurs throughout the scene over stable terrain with variable magnitudes up to 5 m and more in areas largely affected by shadows (Figure 3). Therefore, it can be assumed that the oscillation signal does not reflect the actual landslide motion but is instead caused by changing illumination conditions
 210 throughout the year. Another indication of this hypothesis is the strong relationship between the amplitude (and phase, see Supplementary Figure S8, S10) of the oscillation and the topography, as previously observed by Lacroix et al. (2019). The root cause of the seasonal oscillation affecting the time series is a systematic error in pairwise displacement measurements that are used for the inversion. Figure 4 shows the average displacement estimated over stable terrain in the PlanetScope

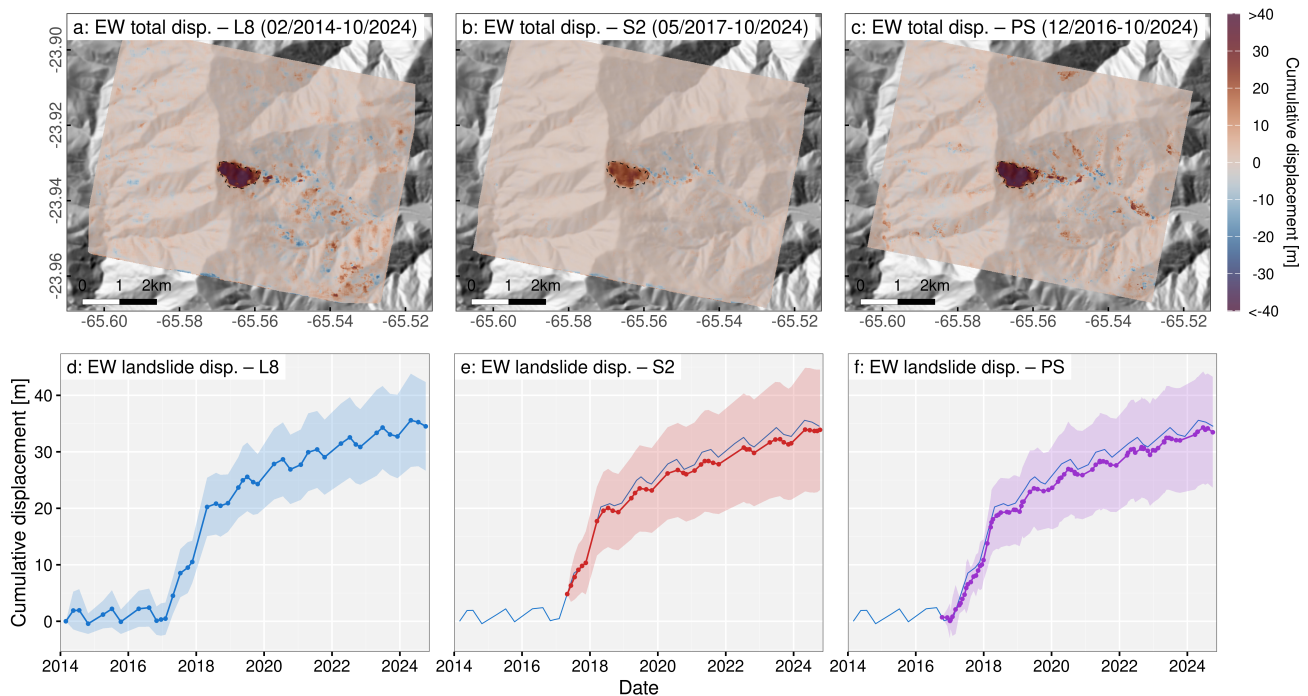


Figure 2. Map view of the total cumulative displacement estimated at each pixel after inversion for Landsat-8 (a), Sentinel-2 (b), and PlanetScope (c) networks over the respective time span covered by the available satellite data. The plots show the east-west (EW) component, which is most significantly affected. A figure for the north-south component can be found in the Supplementary Material, Figure S6. Plots (d) to (f) show the mean and standard deviation (ribbon) of the cumulative displacement estimated over the landslide surface (see dashed polygon in a-c) for all three data sets. For better comparison, the shorter time series of Sentinel-2 and PlanetScope were offset by the Landsat-8 displacement (blue line), approximated at their respective start date. A clear seasonal oscillation bias pattern is visible.

displacement maps retrieved from image correlation. Through binning pixels by the aspect, slope, and the difference in sun
 215 elevation between the reference and secondary image, we note a distinct distribution of measurement errors. As measurement
 errors, we interpret any non-zero displacement assuming that the terrain surrounding the landslide has remained stable. The
 first observation is that the higher the difference in sun azimuth (and elevation, see Supplementary Material, Figure S11),
 the stronger the deviation from zero. Whether this discrepancy is positive or negative depends on the sign of the sun-angle
 difference. In addition, we note a particularly strong relation with terrain aspect: for the east-west component, there is a
 220 positive (eastern) and negative (western) measurement bias that peaks at slopes with a south-west facing aspect ($180 - 270^\circ$).
 This is consistent with the direction of shadow extension, which is opposite to the sun's azimuth angle. For the PlanetScope
 scenes, the sunlight is coming from the north-east (60°) on average (Supplementary Material, Figure S2). For the north-south
 displacement component, we see a similar trend, but the relation is less pronounced. Regarding slope, steeper terrain generally
 corresponds to larger measurement errors, which is expected since shadowing effects are more pronounced in such areas.
 225 The general decadal displacement history of the Del Medio landslide, as described at the beginning of this section, clearly



exceeds the seasonal bias in magnitude (~ 35 m). Nevertheless, the presence of the seasonal oscillation pattern impedes our ability to assess smaller-scale magnitude variations that could point to velocity changes in response to a seasonal climate. We therefore evaluate mitigation strategies to reduce seasonal biases while preserving the true displacement signal as much as possible.

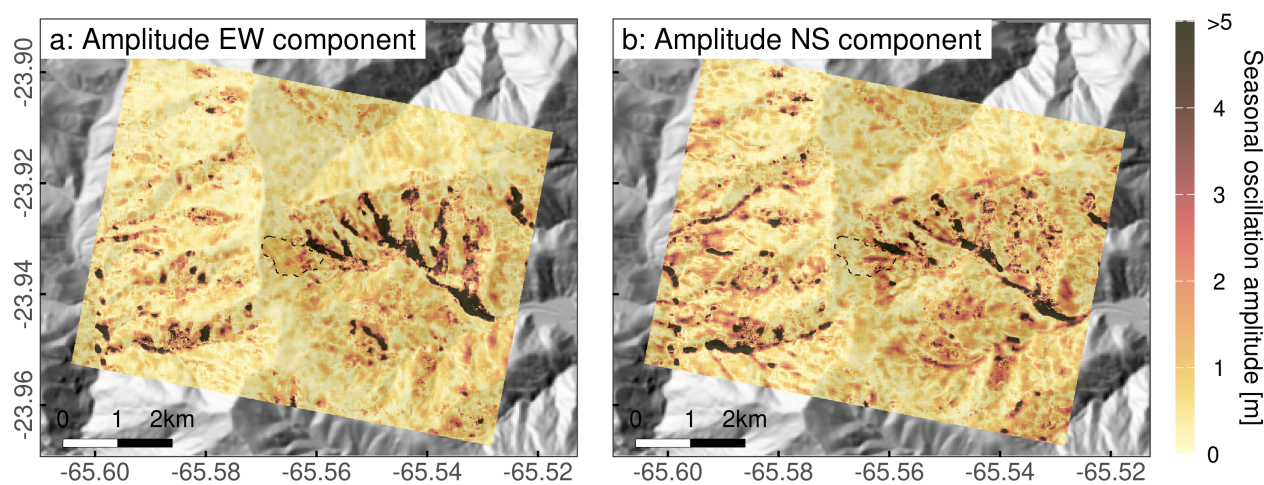


Figure 3. Amplitude of the seasonal oscillation in the PlanetScope inversion results for the east-west (EW) (a) and north-south (NS) (b) component. The amplitude was estimated by removing the long-term trend from the displacement signal and fitting a sine with a one-year wavelength. The distribution of the phase component is illustrated in the Supplementary Material, Figure S8. Plots for Sentinel-2 and Landsat-8 can be found in the Supplementary Material, Figure S9 and S10. The dashed black line outlines the landslide surface.

230 4.3 Impact of spatial resolution

We initially correlated imagery from all three satellite missions at their native resolution, only adjusting the correlation and subpixel refinement kernel size to be as comparable in meters as possible, taking into account the odd-integer constraint. However, we noticed that the lower-resolution Landsat-8 and Sentinel-2 correlation results were more strongly affected by seasonal biases than the 3-m PlanetScope displacement maps. A test with two PlanetScope scenes with very different illumination
 235 conditions (May and September 2020) resampled to 3, 6, and 9 m confirmed this observation (Figure 5): Over stable terrain (estimated zero displacement), the seasonal bias increased significantly as the spatial resolution of the input imagery decreased. A similar observation was made by Antoine and Liu (2025), who found that correlation noise decreases when the images are upsampled. We attribute this effect to the subpixel refinement step of the correlation process, which refines the integer pixel match obtained from previous block matching. We use the mode that applies the Bayes expectation-maximization weighted
 240 affine adaptive window correlator, which is slow in runtime but recommended for high-quality results (Beyer et al., 2018). The effect of spatial resolution is, however, observed also for other subpixel refinement methods and matching algorithms (Supple-

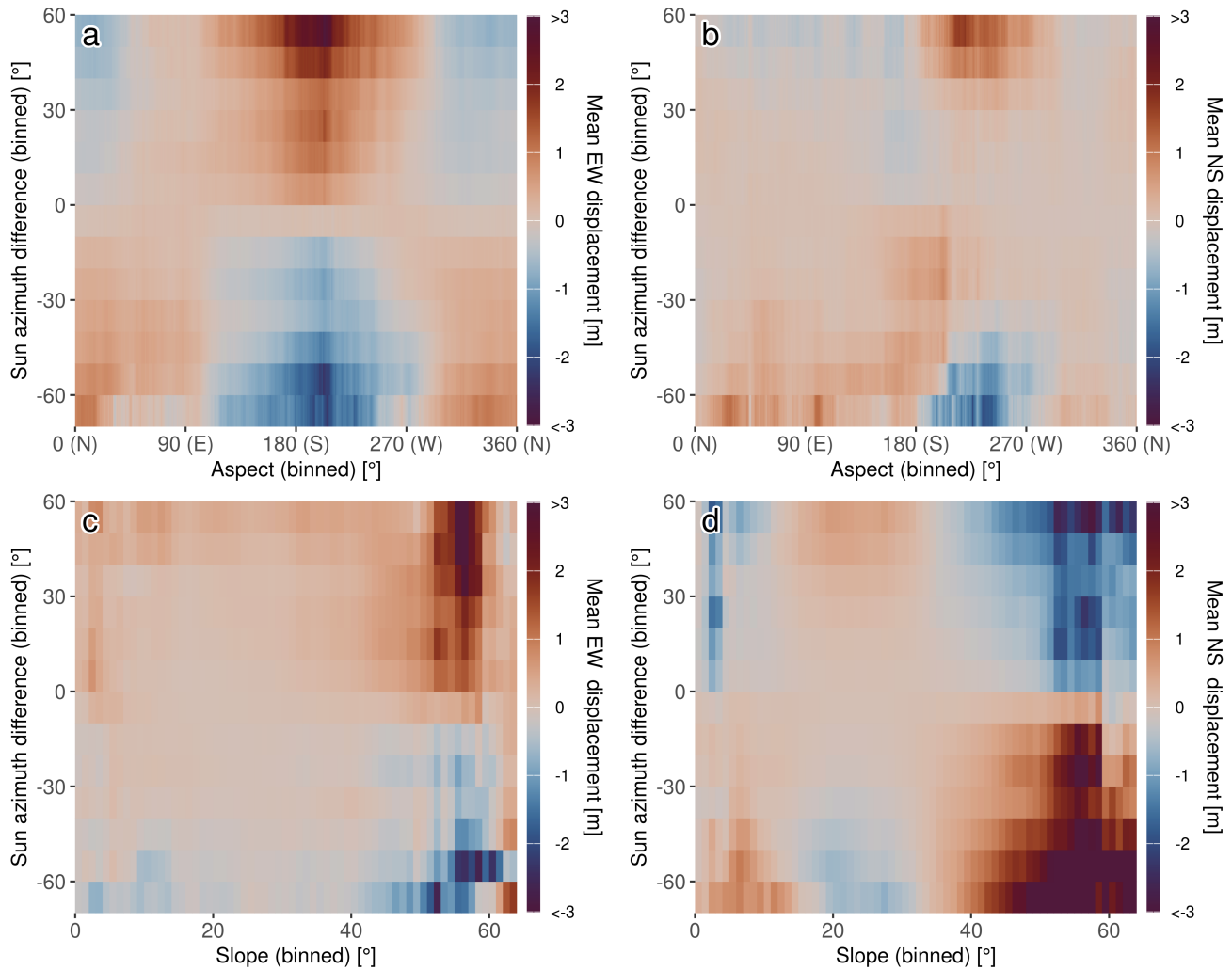


Figure 4. Mean displacement estimated over stable terrain in all 491 displacement maps retrieved from PlanetScope imagery. We binned pixels according to the sun azimuth difference between the correlated image pair (5-degree bins) and the terrain aspect (a, b) and slope (c, d), both in 1-degree bins. Sun azimuth differences were calculated by subtracting the solar position of the reference image from that of the secondary image. While over stable terrain the displacement is expected to be zero, we can observe a systematic error related to the terrain aspect at high sun azimuth differences. This relation also has a dependence on terrain slope. These measurement errors are the basis for the subsequent oscillation pattern when the network is inverted. Results for the sun elevation difference are similar and shown in the Supplementary Material Figure S11 and the pixel counts per bin in Figure S12.

mentary Material, Figures S13 – S16). At lower image resolution, the pinpointing of the match within a larger pixel may be less precise. Furthermore, the variable number of pixels in the subpixel refinement window may have resulted in slightly different

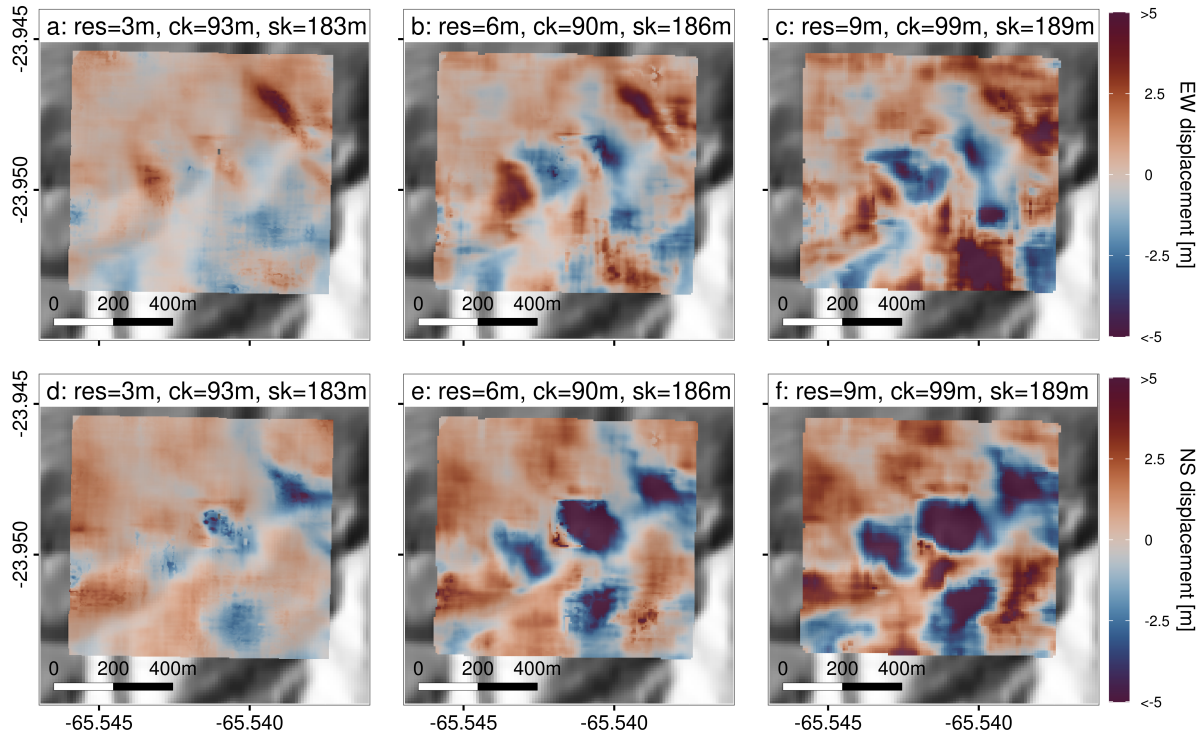


Figure 5. Displacement estimated from a PlanetScope image pair (16.05.2020 and 05.09.2020) in east-west (EW) (a–c) and north-south (NS) (d–f) direction over a small sample area of stable terrain. The plot illustrates the seasonal bias at different resolutions. Panels (a) and (d) showcase the displacement fields retrieved at the native 3-m PlanetScope resolution, while for (b) and (e) the input imagery was downsampled to 6 m and to 9 m for (c) and (f). Correlation and subpixel refinement kernel were kept approximately constant in terms of area (i.e., fewer pixels at lower spatial resolution). We find that as the resolution of the input imagery becomes coarser, the magnitude of seasonal measurement errors increases.

weights for different resolutions. For better comparability between satellite imagery, we therefore correlated all imagery only
 245 after resampling to a common 3-m resolution.

4.4 Mitigation of seasonal biases

The relationship between spatial resolution and measurement biases opens the door to mitigate seasonal oscillations by upsam-
 pling input imagery. However, while seasonal bias is reduced, it is not eliminated (see Figure 3). In addition, longer processing
 times naturally limit the extent to which this strategy remains practical and call for alternative mitigation approaches. Therefore,
 250 further strategies are needed to reduce seasonal bias in time-series inversion results. We have compared several strategies.

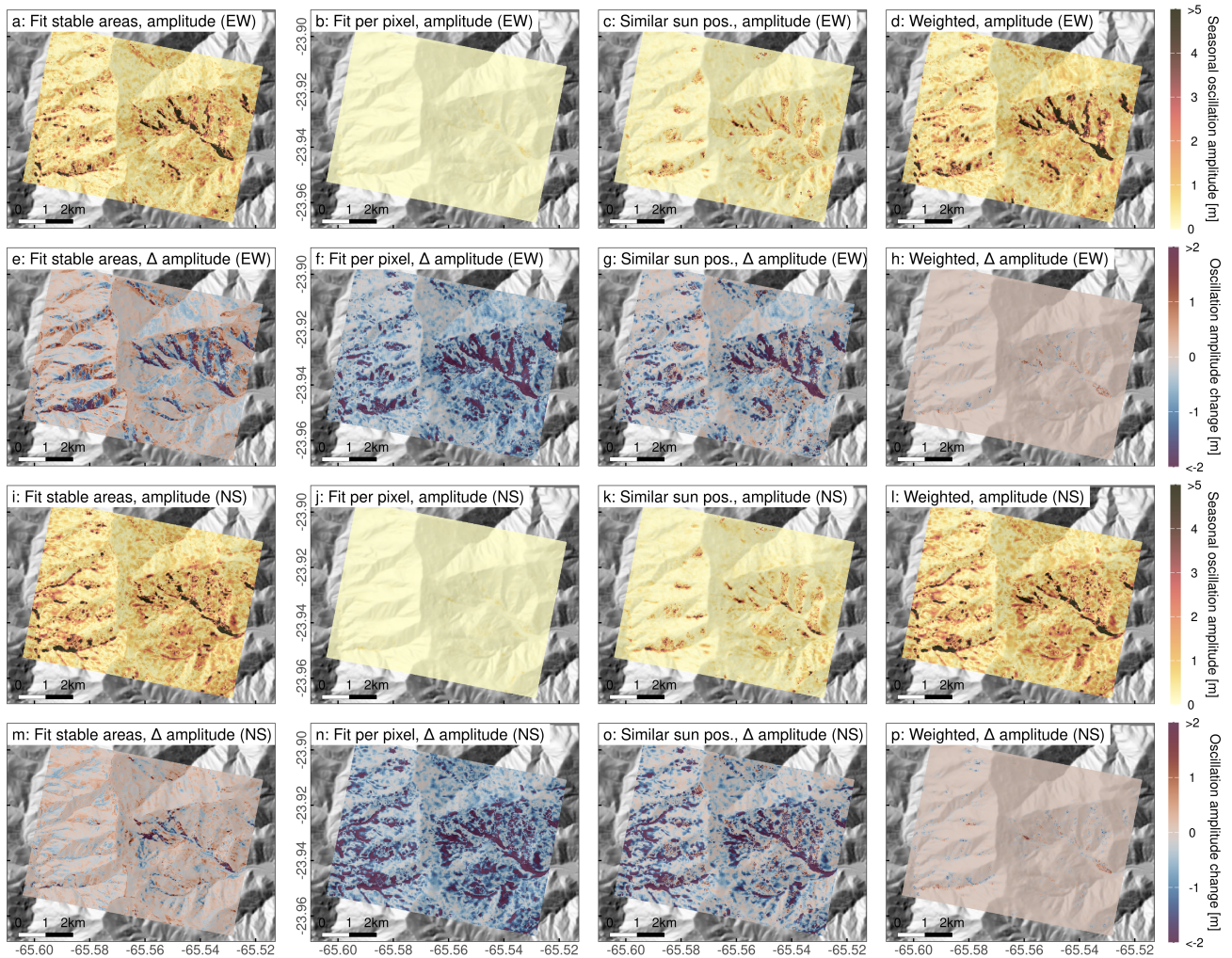


Figure 6. Amplitude of the seasonal oscillation pattern in the PlanetScope inversion results after the application of four different mitigation approaches. We plot the estimated amplitude of the seasonal oscillation bias after correction for the east-west (a–d) and north-south (i–l) component, as well as the change of amplitude in comparison with the uncorrected inverted timeseries (see Figure 3) for the east-west (e–h) and north-south (m–p) component. The following approaches are compared: removal of the best-fit sine over stable terrain with common slope and aspect (first column); removal of the best-fit sine estimated per pixel (second column); inversion of a network with similarly illuminated image pairs only (third column); and weighting based on the difference in solar incidence angle (fourth column).

4.4.1 Modeling seasonal oscillations

Seasonal oscillations related to changing illumination represent systematic biases with a common wavelength and fixed recurrence interval. Therefore, the bias can be approximated through a harmonic function when multi-annual data are present. In a



previous study by Lacroix et al. (2019), seasonal oscillations were modeled through a sine function and subsequently removed from the displacement time series. For the correction Lacroix et al. (2019) considered the average fit over stable pixels with similar slope and aspect as the landslide. We tried to replicate this approach for our study area by creating 831 unique groups with common slope and aspect (5° bins). For each group, we calculated the average displacement time series excluding the landslide pixels and modeled the oscillations through a fixed-frequency sine function as described in Section 3.5. The resulting fit was subtracted from all pixels with a common slope and aspect. The amplitude of the seasonal oscillations and the change with respect to the initially estimated amplitudes (Figure 3) are shown in the first column of Figure 6. We find that the estimated amplitude is reduced particularly in areas heavily affected by shadows. For other pixels where the fit per group exceeds the initial oscillation bias, the amplitude after correction increases. Over the landslide surface, amplitude changes are minor. The effectiveness of this correction method is based on the alignment between the reference DEM and the observed seasonal bias. Lacroix et al. (2019) used a 2-m stereo DEM, while we rely on the Copernicus DEM with 30 m spatial resolution that will not depict features whose shadows are well visible in the 3-m optical data. In addition, landslide topography changes over time, and the use of an outdated DEM may introduce unexpected artifacts (Mueting and Bookhagen, 2023). This limited resolution and temporal alignment, combined with the complex topography of our study area, could be the reason why the correction approach has limited success in reducing the oscillation bias over the Del Medio landslide.

An alternative strategy that relies on no external reference layer is the removal of the best-fit sine per pixel, irrespective of whether it is located over the landslide or stable ground. Naturally, this method is very effective at removing any seasonal oscillation from the displacement time series (Figure 6, second column). However, unlike the previous approach based on stable terrain, a per-pixel fit does risk the partial removal of true seasonal responses with uniform magnitudes at or below the wave height of the seasonal oscillation pattern (Supplementary Material, Figure S17). For the Del Medio landslide, however, we argue that it is safe to subtract a best-fit sine from the detrended displacement time series of each pixel because (1) the landslide surface does not show significantly higher oscillation amplitudes compared to its surroundings (Figure 3), which would be the case when seasonal biases and true response are additive, and (2) responses to displacement to the rainy season are assumed to be variable.

4.4.2 Pairing based on similar illumination

Instead of correcting time series affected by seasonal biases, another strategy targets the reduction of measurement errors that result from the correlation directly. Measurement noise has been shown to increase for correlation pairs acquired during different seasons (Bontemps et al., 2018; Mueting and Bookhagen, 2023) (Figure 4). Consequently, image pairs with similar illumination conditions will be least affected by seasonal biases and should therefore be the most reliable basis for reconstructing a displacement signal. Restricting the correlation to similarly illuminated scenes has previously been used to reduce the effects of seasonality (Dehecq et al., 2015; Hollingsworth et al., 2017; Ding et al., 2020, 2021). This strategy avoids the need for post-processing during which the true components of the displacement signal could also be altered. However, a major



difficulty is selecting a suitable tolerance threshold for the difference in illumination. Ding et al. (2020) determined suitable thresholds for the sun elevation and azimuth difference, as well as spatial and temporal baselines, through an iterative pairing process. Thresholds were defined to reduce differences in sun position while retaining enough image pairs to ensure a stable time-series inversion. Because narrow thresholds can split a network into several disconnected groups, a regularization term needs to be introduced to the inversion (see Equation 6). When the network structure is already constrained, e.g. to the same viewing geometry for PlanetScope data, or simply by the number of available scenes, the threshold must be further loosened or even disregarded (Ding et al., 2021). To find an appropriate threshold for the data used in this work, we iteratively carried out the inversion over the Del Medio landslide using different sun azimuth and elevation thresholds for the pairwise measurements. We refined the sun positions provided in the scenes' metadata by calculating the sun elevation and azimuth angle for the latitude and longitude of the Del Medio landslide at the given acquisition time (Anderson et al., 2023). For every threshold, we estimated the seasonal oscillation amplitude and selected the threshold that minimized amplitudes but maximized the number of image pairs going into the inversion (Supplementary Material, Figure S18). This was five degrees of sun elevation and azimuth difference for Landsat-8 and Sentinel-2, and six degrees for PlanetScope. The effects of applying this over the entire study area are shown in Figure 6, third column. The method proved to be effective in largely reducing seasonal oscillations. Only areas heavily affected by shadows showed a remaining bias component.

The lower number of displacement fields in a network constrained by similar illumination reduces the computational load, but it also allows errors related to other sources to propagate more easily. When connections are sparse, the relative importance of each measurement in a network is higher, increasing the impact of potential errors. This is certainly a drawback of this mitigation approach, as suitable correlation partners may be sparse, particularly during the rainy period, and when other constraints (e.g., same view angle) are applied. In a densely connected network, on the other hand, the impact of a few erroneous displacements can be mitigated by redundancy of numerous pairwise measurements, leading to a reduction of uncertainties through time-series inversion (Charrier et al., 2022c). In fact, in a fully connected network with regular temporal sampling, positive and negative seasonal biases would cancel each other out, requiring no further correction at all (Supplementary Material, Figure S19).

4.4.3 Weighting

In addition to the mitigation approaches described, the addition of weights to the time-series inversion has been used to reduce the impact on less reliable measurements. Various quality indicators have been proposed, including the temporal baseline between an acquisition pair (Lacroix et al., 2019; Provost et al., 2022), standard deviation of displacement (Bontemps et al., 2018), temporal closure of the network (Bontemps et al., 2018; Provost et al., 2022; Charrier et al., 2022b), or the correlation coefficient for the inverted pixel (Provost et al., 2022). Bontemps et al. (2018) also suggest that weighting correlation pairs as a function of their sun elevation differences could be used to reduce the uncertainties caused by illumination changes. Illumination changes may not affect all parts of a scene equally. We therefore experimented with integrating spatially variable weights based on the solar incidence angle, i.e., the angle between the sun's rays and the normal on a surface. In this way we take into account both the sun position and the local topography impact, but again rely on an external reference DEM to



derive terrain attributes. We computed the difference between the solar incidence angle of the reference and secondary image using the cosine and sine of the solar incidence angle as explained in equations 4. Seasonal oscillation amplitudes and changes compared to the unweighted inversion are plotted in Figure 6, last column. Compared with the other mitigation approaches, weighting showed the least improvement in reducing the amplitude of seasonal biases. Effects are mostly constrained on the heavily shadowed areas, where both positive and negative amplitude changes are observed. Further experiments with a higher resolution DEM, or improved weight scaling could yield better results.

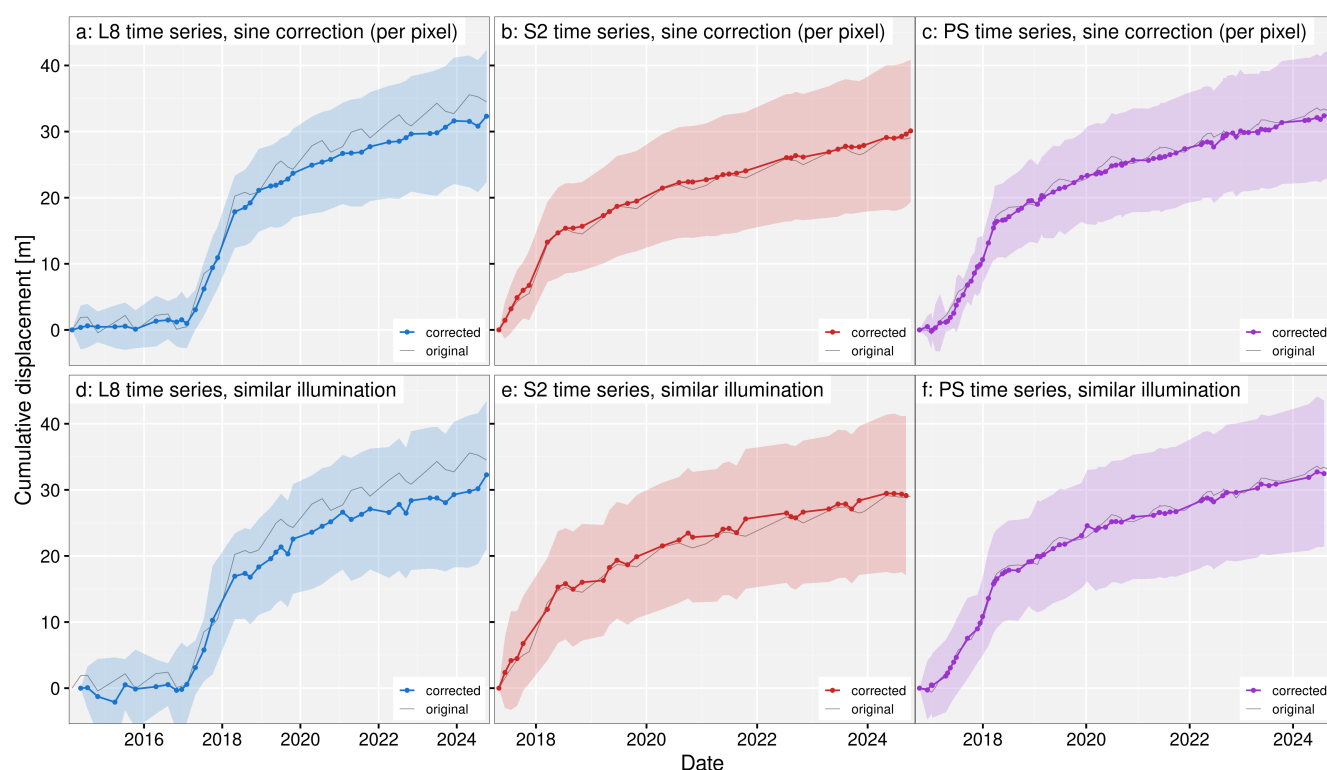


Figure 7. Average displacement time series over the Del Medio landslide after mitigation of the seasonal bias component for Landsat-8 (a, d), Sentinel-2 (b, e), and PlanetScope (c, f). Figures a–c show the time series after the removal of the best-fit sine per pixel, and Figures d–f the inversion results of a network based on similar illumination image pairs. For comparison, the uncorrected time series are plotted in gray. Ribbons indicate the standard deviation.

Overall, subtracting the best-fit sine per pixel and the selection of similar illuminated image pairs for the inversion reduced seasonal oscillations most reliably in our study area. A few problematic regions remain along steep and heavily shadowed slopes throughout the Del Medio catchment, where the correlation often fails or produces mismatches. Here, the residuals to the estimated sine function are high. If supported by the correlator, shadows could be masked prior to the image matching to reduce their impact (Provost et al., 2022). The average displacement time series over the Del Medio landslide, corrected for



seasonal effects based on a per-pixel sine fit and a same-season network, is depicted in Figure 7. The good correspondence
 335 between both approaches gives us confidence that considering also unstable terrain for the sine fit has not largely altered
 any parts of the true displacement signal of the landslide. The cumulative displacement time series retrieved from the similar
 illumination pairs shows a slightly higher variability, which is a result of the lower number of correlation pairs. For subsequent
 analyses we therefore rely on the sine fitting approach per pixel.

4.5 Spatially variable landslide motion

340 The high standard deviations following the relative uniform acceleration in early 2017 (see Figure 7) suggest that different parts
 of the landslide have moved at different speeds following this event. Therefore, in addition to the averaged landslide motion,
 we investigate cumulative displacement after seasonal bias correction along a horizontal profile across the landslide. Figure
 8 a, d, and g show a close-up of the total displacement accumulated during the observation period, as well as the location
 of the selected profile line. Here, we find that the highest displacement magnitudes are concentrated along the upper scarp
 345 and a central block at about 4000 m elevation. Taking into account the temporal evolution of the cumulative displacement
 along a horizontal profile across the landslide (Figure 8 b, e, h), we observe that these parts moved faster after the 2017/2018
 monsoon season. Subsequent continuous displacement was interrupted by a surge at the upper scarp at the end of 2021 (near
 point A'). These observations are consistent across all three satellite data sources, but most clearly visible in the Landsat-8
 and PlanetScope time series. To better highlight these points of acceleration, we have calculated the east-west velocity from
 350 the smoothed displacement time series (Figure 8 c,f,i). Velocities may become negative when the estimated movement has a
 westward (uphill) direction, which is the result of measurement errors affecting the lower, heavily shadowed part of the profile
 ($\sim 0 - 150$ m along profile). The reactivation of the landslide in early 2017, as well as the acceleration during the monsoon
 season of 2017/2018, are clearly visible. The small acceleration at the end of 2021 is less noticeable and is best captured by
 the densely sampled PlanetScope time series. In addition, we observe slightly higher velocities until the end of 2020, as well
 355 as recurring phases of marginally higher velocities along the entire profile. The pure downhill (positive, eastward) motion
 suggests the reliability of these measurements and could point to a low-magnitude seasonal response in the landslide motion.
 However, the signal is too low to be reliably identified as a true seasonal signal without ground control data.

5 Discussion

5.1 Drivers and preconditioning factors of landslide activity

360 While our analysis does not support a systematic annual feedback mechanism between seasonal climate and landslide motion,
 the mitigation of seasonal biases allowed to clearly identify three acceleration phases in the displacement history of the Del
 Medio landslide: the initial reactivation in early 2017, a steep acceleration at the beginning of 2018, and a smaller surge in late
 2021 that was constrained along the upper scarp of the landslide. In the following section, we evaluate potential triggers and
 preconditioning factors for these three acceleration phases.

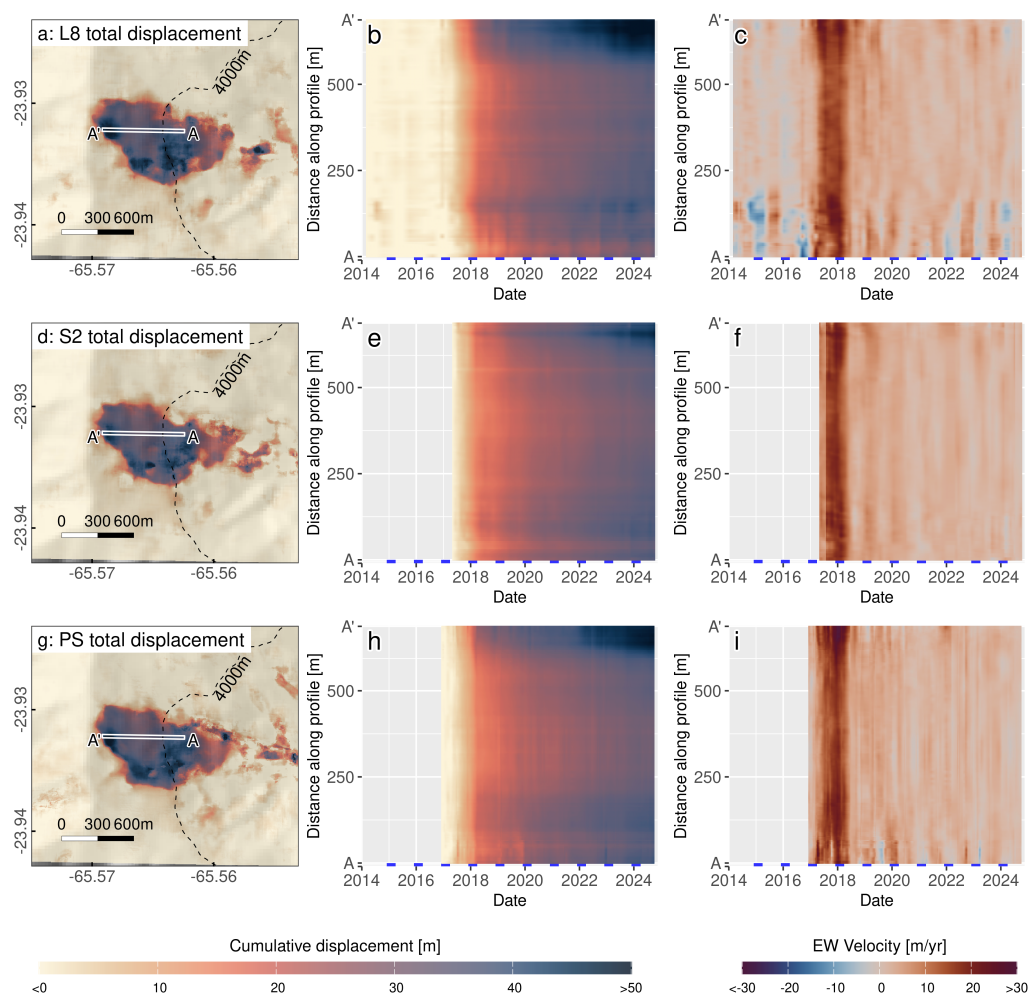


Figure 8. Spatially variable displacement rates along a profile over the Del Medio landslide. The maps in the first column show the total displacement estimated over the landslide throughout the observation period, the location of the profile, and the 4000 m contour line for Landsat-8 (a), Sentinel-2 (d), and PlanetScope (g). The cumulative displacement through time along this profile is plotted in the second column for the respective satellites. To better identify periods of acceleration, we derived the velocity from the smoothed (rolling mean with a half-year window) cumulative displacement, as shown in Figures c, f, and i. For both the second and third columns, we indicate the monsoon season (December - March) with blue bars along the x-axis. Seasonal biases were compensated for by subtracting the best-fit sine estimated per pixel. Results from the inversion of similarly illuminated scenes can be found in the Supplementary Material, Figure S20.

365 In the Andes of Argentina, rainstorm events and seismic shaking in conjunction with geological preconditioning in the form of structures and weathered lithology were identified as the primary triggers of landslides (Moreiras and Coronato, 2009). After assessing all seismic events recorded in the USGS earthquake catalog (U.S. Geological Survey, 2025) in a 100 km radius of the study area, we concluded that there was no major seismic activity in close range and shallow depth coinciding with the de-



scribed events. This leaves precipitation as a likely candidate for triggering reactivation in 2017, as well as subsequent surges.

Several studies have linked landslide reactivation to prolonged and intense rainfall (e.g., Uhlemann et al., 2017; Handwerger et al., 2019a). At the Del Medio landslide, the onset of all accelerations can be timed to approximately January 2017, January 2018, and December 2021 according to the densely sampled PlanetScope time series. All of these dates fall into the summer monsoon season from December to March, supporting the hypothesis of precipitation as the primary forcing. Due to a lack of ground measurements, we approximate precipitation affecting the Del Medio landslide using the ERA5 climate reanalysis dataset (~ 31 x 31 km grid size) (Hersbach et al., 2020) and data from the Global Precipitation Measurement Mission (GPM) (~ 10 x 10 km grid size) (Huffman et al., 2023). The daily sum of precipitation together with the cumulative displacement time series at the upper scarp of the Del Medio landslide, including all three acceleration phases, is shown in Figure 9 a–b. Next to precipitation, we also consult ERA5 land surface temperatures (Hersbach et al., 2020) (Figure 9 c) because the landslide is located at elevations above 4000 m, where freeze-thaw processes play a role. Similar permafrost-related patterns were described in the geographic vicinity in the Valles Calchaquies (e.g. Blöthe et al., 2025; Falaschi et al., 2014). Since there is no clearly visible annual pattern of elevated displacement in response to the rainy season, we focus on meteorological extremes. Extended droughts and periods with exceptional rainfall were documented in landslide motion (e.g. Handwerger et al., 2019a; Hopquin et al., 2025), and particularly the shift between wet and dry extremes can lead to catastrophic failures (Handwerger et al., 2019b).

In the Del Medio catchment, the assessment of precipitation and temperature over the entire 10-year study period reveals that none of the rainfall seasons of 2017, 2018, and 2021 have been particularly wet or warm. Still, the large differences between dry and rainy periods are evident, and although there is no sign of prolonged episodes of extreme rainfall or drought, the precipitation time series does record individual days with heavy rainfall exceeding 50 mm. These rainstorm events are shown mainly by the GPM precipitation time series. Its improved resolution may better capture high spatial resolution rainfall variability with localized convective events on orographic barriers, leading to high rainfall amounts (e.g. Bookhagen and Strecker, 2008). Two instances of very high rainfall recorded within 24 hours occurred close to the estimated onset of higher displacement rates in January 2017 and 2018. The 2017 event is also described in the literature, because it triggered a major debris flow in the neighboring Los Filtros basin to the north on January 10, 2017, which was considered the most catastrophic event in the last 40 years (Angillieri et al., 2020). The debris flow occurred as a result of heavy rainfall reported as ~ 170 mm between 8 and 10 am local time in the area (Angillieri et al., 2020) (much higher than the rates suggested by the GPM time series). In pre- and post-event images, Angillieri et al. (2020) found signs of reactivation of a previously inactive landslide, as well as several small slope failures in the Los Filtros basin, which supplied loose material to the debris flow. For the Del Medio catchment, only small changes in the catchment and a minor flow in the south of the basin were observed. For the subsequent rainy season, we found no reports, but the GPM timeseries records a maximum rainfall of 157 mm on January 5, 2018 (Figure 9 b). In the Del Medio catchment, precipitation affects slopes that are already weakened due to their geological preconditioning. Inherited fault structures that bound the basin (Figure 1) and an exposed lithology of heavily fractured phyllites create preferential flow paths that allow fast infiltration. In addition, freeze-thaw cycles that act at high elevations further



degrade rock strength. In such an environment, a single heavy rainstorm may suffice to alter stability conditions beyond a critical threshold to set a slope in motion. Therefore, we suggest that the heavy rainfall on January 10, 2017, was the final trigger to set a landslide in motion, which was already in a fragile state.

For the small acceleration in December 2021, we find no direct link to extreme rainfall recorded in the precipitation time series. While this does not rule out precipitation as a driving force, we also noted that the moving surface identified in this study does not fully align with the scarp of the rockfall event of 2009, but extends further uphill (Figure 1). The large mass removal in the year 2009, which concentrated towards the center and toe of the currently active landslide (Supplementary Figure S1 b), potentially reduced support for the upslope areas. This destabilization may explain the elevated displacement rates observed in this part of the landslide.

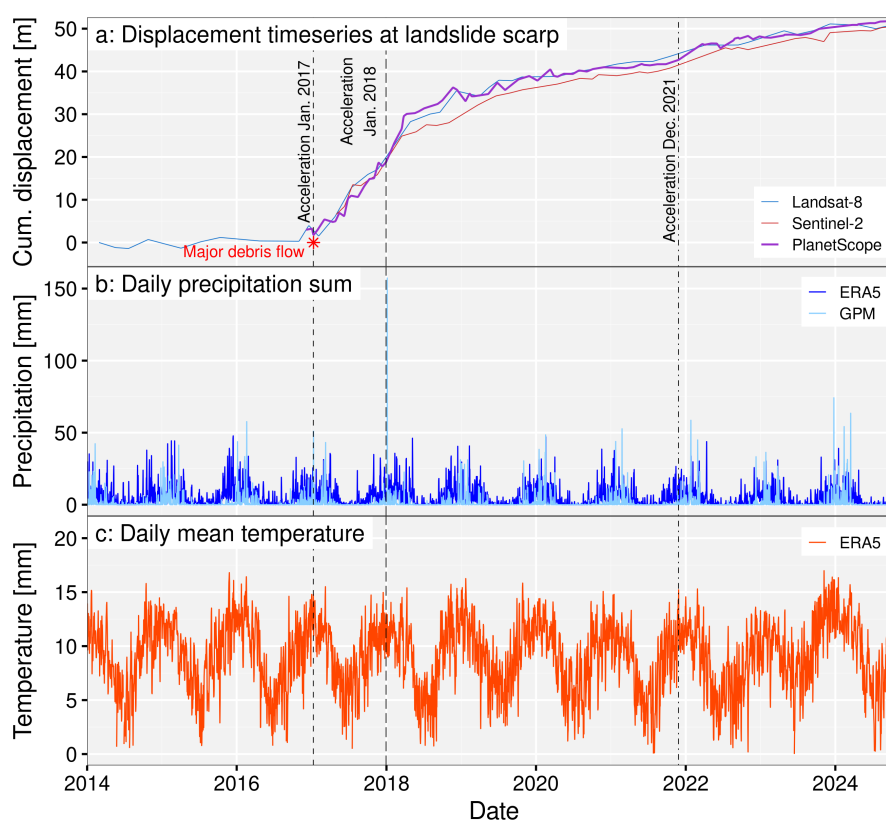


Figure 9. (a) Cumulative displacement time series at the scarp of the Del Medio landslide (upper 30 m of the profile shown in Figure 8) estimated from PlanetScope data in comparison with Sentinel-2 and Landsat-8. We have marked the heavy rainfall and debris flow event on January 10, 2017 (Angillieri et al., 2020), as well as the onset of the accelerations in January 2018 and November 2021. Panel (b) shows the daily precipitation estimated by ERA5 (Hersbach et al., 2020) and GPM (Huffman et al., 2023) with a slightly higher resolution over the landslide area. ERA5-derived mean daily land surface temperatures (Hersbach et al., 2020) are plotted in (c).

5.2 Comparison between the different satellite missions

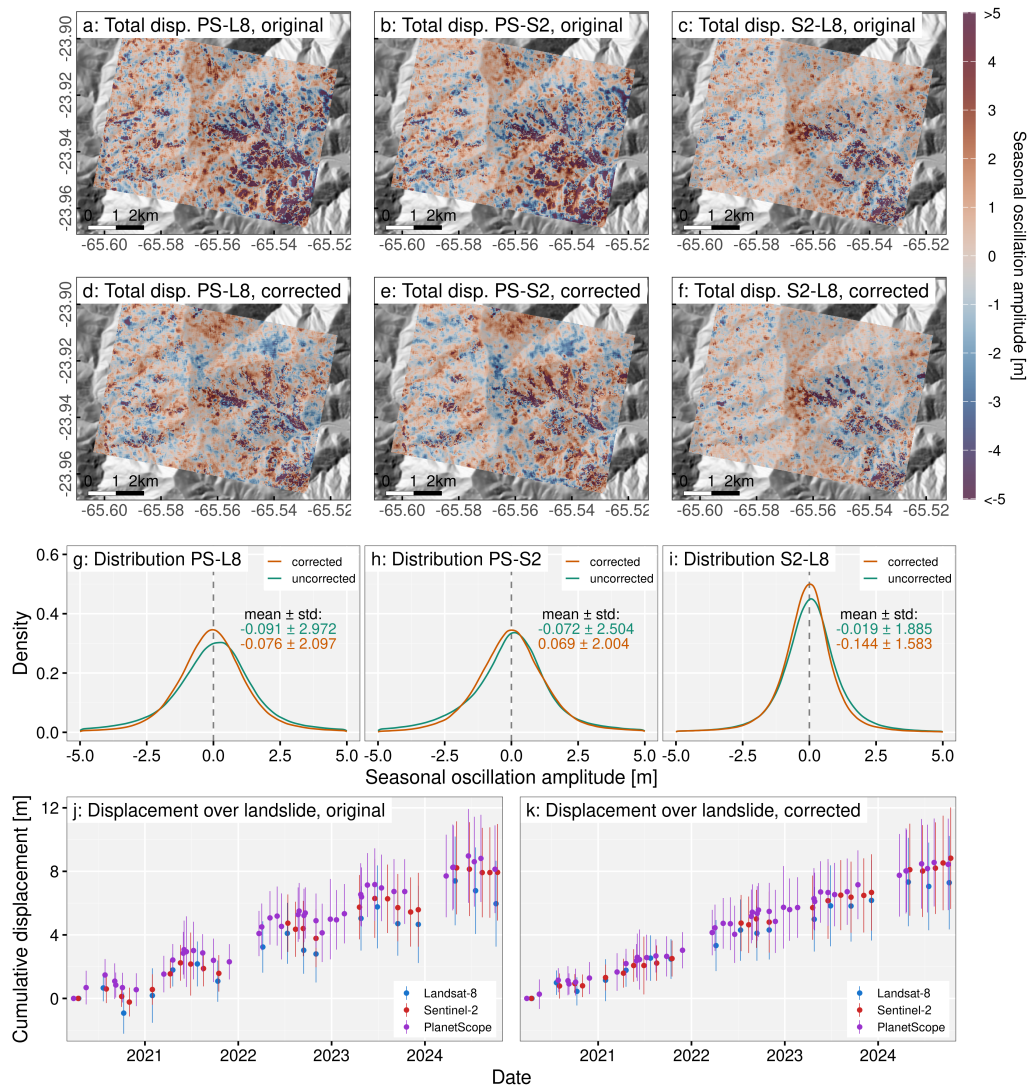


Figure 10. For a common time span between March 2020 and October 2024 over the Del Medio landslide, we have estimated the difference between displacement derived from Landsat-8, Sentinel-2, and PlanetScope (PSB.SD instrument only). Panels a–c show the difference in the total estimated east-west displacement after inversion, panels d–f show the difference with the seasonal oscillation bias corrected through a best-fit sine per pixel. The distribution of differences throughout the study area for both original (uncorrected) and corrected raster differences is depicted in panels g–i. Finally, the mean and standard deviation of displacement over the landslide surface are plotted in panels j and k based on the original (j) and sine-corrected (k) time series.



We have used data from three different satellite missions to analyze the landslide displacement history and also to cross-
415 compare the derived measurements. For better comparability between all missions, we not only resampled data to a common
resolution but also reran the inversion exclusively using correlation pairs falling into a common time span between March
2020 and October 2024. In this way, we compare Landsat-8 and Sentinel-2 data to only the newest generation of PlanetScope
(PSB.SD instrument), and also cover a time span with moderate displacement rates where a few days of difference between
start and end date have a lower impact. From the inversion results, we have calculated the difference in the total estimated dis-
420 placement before and after seasonal bias correction through a sine fit, as well as the average displacement across the landslide
surface (Figure 10). The strategy of selecting image pairs with similar illumination conditions was omitted as it largely reduced
the number of connections remaining in the networks. We find that on the surface of the landslide, the estimated average and
standard deviation of displacement are largely consistent between all satellite missions, despite the difference in spatial resolu-
tion of the native images. In particular, Sentinel-2 measurements align well with the PlanetScope-derived displacements, while
425 Landsat-8 shows a slightly lower estimate. Throughout the study area, the displacement difference between all satellites is centered
around zero. The standard deviations are highest between Landsat-8 and PlanetScope with ± 2.97 m before correction
and slightly lower for Sentinel-2 and PlanetScope with ± 2.5 m. Both values improve to ± 2 m after reducing seasonal biases.
Nevertheless, the highest differences remain concentrated along high-relief areas affected by shadows. The closest correspon-
dence is achieved between Sentinel-2 and Landsat-8 with a standard deviation in the total estimated displacement of ± 1.89 m
430 before and ± 1.58 m after seasonal correction.

With no ground control data available for the Del Medio landslide, the large correspondence between three independent data
sources gives confidence in the validity of the observed trends and measurements. The strong alignment between the measure-
ments may partially relate to the upsampling strategy to a common 3 m resolution. In addition to the reduction of seasonal
biases (Section 4.3), correlation noise was shown to increase linearly with decreasing resolution of input imagery that can
435 be achieved by upsampling (Antoine and Liu, 2025). Our results indicate that at a common grid resolution, Sentinel-2 and
Landsat-8 can be used to derive displacements with similar precision as PlanetScope data, despite their lower native sampling
distance. Their extensive archives make both missions a valuable resource for assessing long-term displacement histories,
and scenes are commonly less affected by complex co-registration errors compared to PlanetScope (Mueting and Bookhagen,
2023). However, only acquisitions with an initially higher resolution will allow capturing small landslides (Lacroix et al.,
440 2018), small-scale variations, or the precise outline of moving objects. Even more important is the high revisit time, which
increases the chances of cloud-free acquisitions during the rainy season, which is a prerequisite for studying slope movements
in seasonal climates using optical data.

6 Conclusions

We successfully derived a decade-long displacement time series based on the temporal closure of pairwise displacement mea-
445 surements using Landsat-8, Sentinel-2, and PlanetScope data for the large, slow-moving landslide in the Río Del Medio catch-
ment. Its location in the transition zone between the Altiplano-Puna plateau and the Andean foreland exposes the landslide



to a highly seasonal climate with intense rainfall during the summer monsoon season. Our analysis focused on the mitigation of seasonal measurement biases to identify potential feedback mechanisms between rainfall and landslide movement. A key challenge in using optical imagery for displacement measurements, particularly in high-relief areas, is the seasonal bias introduced by variable illumination and shadows, which results in artificial seasonal oscillation patterns. This bias was observed to be systematic and strongly related to topography and illumination differences. We evaluated different mitigation strategies.

First, we observed that lower-resolution Landsat-8 and Sentinel-2 correlation results were more strongly affected by seasonal biases than the 3-m PlanetScope correlations. By resampling Landsat-8 and Sentinel-2 imagery to the 3-m resolution of PlanetScope, a first reduction in seasonal bias was achieved, enhancing comparability across platforms, but increasing processing time and data volume.

Second, we modeled and removed seasonal oscillations by fitting a sine wave with a fixed frequency of one year to the detrended signal. This approach can be applied to stable areas with common slope and aspect, which creates a dependency on an external reference DEM, or per pixel, which may partially remove true seasonality in the displacement time series. Both approaches are straightforward to implement, but require multi-annual data to provide a robust fit. For the Del Medio landslide, the per-pixel approach proved to be most effective at removing periodic oscillations. The good correspondence with other correction methods suggests that the sine fit did not significantly alter the true displacement signal.

Third, we restricted correlation pairs to similar illumination conditions. The seasonal bias was also successfully reduced by defining maximum sun azimuth and elevation difference thresholds. However, the effectiveness of this method depends on the selection of a suitable threshold for the illumination difference. Thresholding also largely reduces the number of correlation pairs, making it applicable only in cases when abundant satellite data is available. In addition, sparse networks may allow other errors to propagate more easily into the derived displacement time series.

Lastly, we experimented with spatially variable weights, taking into account local topography and sun-position difference between the correlated image pairs. This method, however, was least effective, indicating that other weighting factors may be more suitable. For subsequent analyses we proceeded with a correction through a per-pixel sine fit.

The mitigation of seasonal biases decreased systematic errors, which helped to clearly identify changes in the kinematic behavior of the Del Medio landslide, specifically noting three distinct accelerations: the initial reactivation in early 2017, a steep acceleration at the beginning of 2018, and a smaller surge in late 2021. The reactivation of the landslide occurred during the 2016/2017 rainy season after a relative quiescence period of at least three years. The landslide accumulated approximately 20 m of displacement between January 2017 and March/April 2018. Subsequently, average displacement rates decreased to about 2.5 m yr^{-1} until the end of the observation period in October 2024. Displacement rates varied spatially, with higher values concentrated along the landslide scarp.

While our findings do not support a clear systematic annual feedback between seasonal climate and landslide motion, the three acceleration phases strongly suggest that precipitation is a primary forcing factor. The onset of all observed accelerations coincided with the South American summer monsoon season (December to March) and could be linked to individual heavy



rainstorms recorded in the precipitation time series, such as the one in January 2017 that also triggered a major debris flow in the neighboring watershed. The susceptibility of the slopes of the Del Medio catchment to sliding is attributed to preconditioning factors, including inherited fault structures, weakened lithologies (phyllites), and freeze-thaw processes occurring at high altitudes (up to 4500 m above sea level).

Our observations highlight the challenges of interpreting displacement time series derived from optical satellite data when both velocities and measurement bias are correlated with seasonality. By evaluating different mitigation strategies, we outline strategies towards improved management of seasonal measurement bias. This can help to reduce systematic errors in the displacement time series and contribute to a better understanding of the true feedback mechanisms between seasonal precipitation and slope movements.

Code availability. The code for landslide tracking used in this work is publicly available on GitHub: https://github.com/UP-RS-ESP/timeseries_inversion.

Data availability. Landsat-8 data are available from the USGS Earth Explorer <https://earthexplorer.usgs.gov/>, Sentinel-2 data from the Copernicus Dataspace Ecosystem <https://dataspace.copernicus.eu/>, and for non-commercial and academic purposes, PlanetScope data can be accessed through Planet's Education and Research Program (Planet Team, 2022).

Author contributions. **Ariane Mueting:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization. **Laurane Charrier:** Methodology, Software, Writing - Review & Editing. **Bodo Bookhagen:** Conceptualization, Methodology, Software, Writing - Review & Editing, Visualization, Supervision, Funding acquisition.

Competing interests. The authors declare that no competing interests are present.

Acknowledgements. We acknowledge the Universität Potsdam Remote Sensing Computational Cluster for image-correlation processing. We acknowledge Planet Labs PBC for granting access to the PlanetScope data used in this study through the Research and Education Program (Planet Team, 2022). Laurane Charrier acknowledges support from the CNES for her postdoctoral fellowship. Scientific colormaps used throughout this work are from Crameri et al. (2020).



505 References

- Anderson, K. S., Hansen, C. W., Holmgren, W. F., Jensen, A. R., Mikofski, M. A., and Driesse, A.: pvlib python: 2023 project update, *Journal of Open Source Software*, 8, 5994, <https://doi.org/10.21105/joss.05994>, 2023.
- Angillieri, M. Y. E., Perucca, L., and Vargas, N.: Spatial and temporal analysis of debris flow occurrence in three adjacent basins of the western margin of Grande River: Quebrada de Humahuaca, Jujuy, Argentina, *Geografiska Annaler: Series A, Physical Geography*, 102, 83–103, <https://doi.org/10.1080/04353676.2020.1744075>, 2020.
- Antoine, S. L. and Liu, Z.: Impact of Optical Imagery and Topography Data Resolution on the Measurement of Surface Fault Displacement Using Sub-Pixel Image Correlation, *Earth and Space Science*, 12, e2024EA003660, <https://doi.org/https://doi.org/10.1029/2024EA003660>, e2024EA003660 2024EA003660, 2025.
- Beyer, R. A., Alexandrov, O., and McMichael, S.: The Ames Stereo Pipeline: NASA's open source software for deriving and processing terrain data., *Earth and Space Science*, 5, <https://doi.org/10.1029/2018EA000409>, 2018.
- Blöthe, J., Falaschi, D., Vivero, S., and Tadono, T.: Rock Glacier Kinematics in the Valles Calchaquies Region, Northwestern Argentina, From Multi-Temporal Aerial and Satellite Imagery (1968–2023), *Permafrost and Periglacial Processes*, 36, 123–136, <https://doi.org/https://doi.org/10.1002/ppp.2260>, 2025.
- Bontemps, N., Lacroix, P., and Doin, M.-P.: Inversion of deformation fields time-series from optical images, and application to the long term kinematics of slow-moving landslides in Peru, *Remote Sensing of Environment*, 210, 144–158, <https://doi.org/https://doi.org/10.1016/j.rse.2018.02.023>, 2018.
- Bookhagen, B. and Strecker, M. R.: Orographic barriers, high-resolution TRMM rainfall, and relief variations along the eastern Andes, *Geophysical Research Letters*, 35, <https://doi.org/https://doi.org/10.1029/2007GL032011>, 2008.
- Charrier, L., Yan, Y., Colin, E., Mouginot, J., Millan, R., and Trouvé, E.: Fusion of Multi-Temporal and Multi-Sensor Ice Velocity Observations, <https://doi.org/10.5194/isprs-annals-V-3-2022-311-2022>, 2022a.
- Charrier, L., Yan, Y., Koeniguer, E. C., Leinss, S., and Trouvé, E.: Extraction of Velocity Time Series With an Optimal Temporal Sampling From Displacement Observation Networks, *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1–10, <https://doi.org/10.1109/TGRS.2021.3128289>, 2022b.
- Charrier, L., Yan, Y., Trouvé, E., Koeniguer, E. C., Mouginot, J., and Millan, R.: Fusion of Multitemporal Multisensor Velocities Using Temporal Closure of Fractions of Displacements, *IEEE Geoscience and Remote Sensing Letters*, 19, 1–5, <https://doi.org/10.1109/LGRS.2022.3227413>, 2022c.
- Crameri, F., Shephard, G., and Heron, P.: The misuse of colour in science communication, *Nature Communications*, 11, <https://doi.org/10.1038/s41467-020-19160-7>, 2020.
- Dehecq, A., Gourmelen, N., and Trouve, E.: Deriving large-scale glacier velocities from a complete satellite archive: Application to the Pamir–Karakoram–Himalaya, *Remote Sensing of Environment*, 162, 55–66, <https://doi.org/https://doi.org/10.1016/j.rse.2015.01.031>, 2015.
- Dille, A., Kervyn, F., Handwerger, A. L., d'Oreye, N., Derauw, D., Mugaruka Bibentyo, T., Samsonov, S., Malet, J.-P., Kervyn, M., and Dewitte, O.: When image correlation is needed: Unravelling the complex dynamics of a slow-moving landslide in the tropics with dense radar and optical time series, *Remote Sensing of Environment*, 258, 112 402, <https://doi.org/https://doi.org/10.1016/j.rse.2021.112402>, 2021.



- Ding, C., Zhang, L., Liao, M., Feng, G., Dong, J., Ao, M., and Yu, Y.: Quantifying the spatio-temporal patterns of dune migration near Minqin Oasis in northwestern China with time series of Landsat-8 and Sentinel-2 observations, *Remote Sensing of Environment*, 236, 111 498, <https://doi.org/https://doi.org/10.1016/j.rse.2019.111498>, 2020.
- Ding, C., Feng, G., Liao, M., Tao, P., Zhang, L., and Xu, Q.: Displacement history and potential triggering factors of Baige landslides, China revealed by optical imagery time series, *Remote Sensing of Environment*, 254, 112 253, <https://doi.org/https://doi.org/10.1016/j.rse.2020.112253>, 2021.
- Doin, M.-P., Lodge, F., Guillaso, S., Jolivet, R., Lasserre, C., Ducret, G., Grandin, R., Pathier, E., and Pinel, V.: Presentation of the Small Baselin NSBAS Processing Chain on a Case Example: The Etan Deformation Monitoring from 2003 to 2010 Using Envisat Data, in: *Fringe Symposium*, 2011.
- 550 Falaschi, D., Castro, M., Masiokas, M., Tadono, T., and Ahumada, A. L.: Rock Glacier Inventory of the Valles Calchaquies Region ($\sim 25^{\circ}\text{S}$), Salta, Argentina, Derived from ALOS Data, Permafrost and Periglacial Processes, 25, 69–75, <https://doi.org/https://doi.org/10.1002/ppp.1801>, 2014.
- Hadhri, H., Vernier, F., Atto, A. M., and Trouvé, E.: Time-lapse optical flow regularization for geophysical complex phenomena monitoring, *ISPRS Journal of Photogrammetry and Remote Sensing*, 150, 135–156, <https://doi.org/https://doi.org/10.1016/j.isprsjprs.2019.02.007>,
555 2019.
- Handwerger, A. L., Roering, J. J., and Schmidt, D. A.: Controls on the seasonal deformation of slow-moving landslides, *Earth and Planetary Science Letters*, 377–378, 239–247, <https://doi.org/https://doi.org/10.1016/j.epsl.2013.06.047>, 2013.
- Handwerger, A. L., Fielding, E. J., Huang, M.-H., Bennett, G. L., Liang, C., and Schulz, W. H.: Widespread Initiation, Reactivation, and Acceleration of Landslides in the Northern California Coast Ranges due to Extreme Rainfall, *Journal of Geophysical Research: Earth*
560 *Surface*, 124, 1782–1797, <https://doi.org/https://doi.org/10.1029/2019JF005035>, 2019a.
- Handwerger, A. L., Huang, M.-H., Fielding, E. J., Booth, A. M., and Bürgmann, R.: A shift from drought to extreme rainfall drives a stable landslide to catastrophic failure, *Scientific Reports*, 9, 1569, <https://doi.org/10.1038/s41598-018-38300-0>, 2019b.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J.,
565 Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049, <https://doi.org/https://doi.org/10.1002/qj.3803>, 2020.
- Hilley, G. E., Bürgmann, R., Ferretti, A., Novali, F., and Rocca, F.: Dynamics of Slow-Moving Landslides from Permanent Scatterer Analysis, *Science*, 304, 1952–1955, <https://doi.org/10.1126/science.1098821>, 2004.
- Hollingsworth, J., Ye, L., and Avouac, J.-P.: Dynamically triggered slip on a splay fault in the Mw 7.8, 2016 Kaikoura (New Zealand) earthquake, *Geophysical Research Letters*, 44, 3517–3525, <https://doi.org/https://doi.org/10.1002/2016GL072228>, 2017.
- Hopquin, C., Gayer, E., Michon, L., Lucas, A., Smittarello, D., d’Oreye, N., and Villeneuve, N.: Unveiling tropical slow-moving landslide response to seasonality and extreme meteorological events using a combination of InSAR and optical imagery: The case study of Grand
575 Eboulis (Réunion island), *Geomorphology*, 489, 109 965, <https://doi.org/https://doi.org/10.1016/j.geomorph.2025.109965>, 2025.
- Huffman, G. J., Stocker, E. F., Bolvin, D. T., Nelkin, E. J., and Tan, J.: GPM IMERG Final Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V07, <https://doi.org/10.5067/GPM/IMERG/3B-HH/07>, accessed: 31.08.2025, 2023.



- Lacroix, P., Bièvre, G., Pathier, E., Kniess, U., and Jongmans, D.: Use of Sentinel-2 images for the detection of precursory motions before landslide failures, *Remote Sensing of Environment*, 215, 507–516, <https://doi.org/https://doi.org/10.1016/j.rse.2018.03.042>, 2018.
- 580 Lacroix, P., Araujo, G., Hollingsworth, J., and Taipei, E.: Self-Entrainment Motion of a Slow-Moving Landslide Inferred From Landsat-8 Time Series, *Journal of Geophysical Research: Earth Surface*, 124, 1201–1216, <https://doi.org/https://doi.org/10.1029/2018JF004920>, 2019.
- Lacroix, P., Handwerger, A., and Bièvre, G.: Life and death of slow-moving landslides, *Nature Reviews Earth Environment*, 1, <https://doi.org/10.1038/s43017-020-0072-8>, 2020.
- 585 Leprince, S., Ayoub, F., Klinger, Y., and Avouac, J.-P.: Co-Registration of Optically Sensed Images and Correlation (COSI-Corr): an operational methodology for ground deformation measurements, in: 2007 IEEE International Geoscience and Remote Sensing Symposium, pp. 1943–1946, <https://doi.org/10.1109/IGARSS.2007.4423207>, 2007.
- Moreiras, S. M. and Coronato, A.: Landslide Processes in Argentina, in: Natural Hazards and Human-Exacerbated Disasters in Latin America, edited by Latrubesse, E. M., vol. 13 of *Developments in Earth Surface Processes*, pp. 301–332, Elsevier, [https://doi.org/https://doi.org/10.1016/S0928-2025\(08\)10015-3](https://doi.org/https://doi.org/10.1016/S0928-2025(08)10015-3), 2009.
- 590 Mueting, A. and Bookhagen, B.: Tracking slow-moving landslides with PlanetScope data: new perspectives on the satellite’s perspective, *EGUsphere*, 2023, 1–36, <https://doi.org/10.5194/egusphere-2023-1698>, 2023.
- Olen, S. and Bookhagen, B.: Applications of SAR Interferometric Coherence Time Series: Spatiotemporal Dynamics of Geomorphic Transitions in the South-Central Andes, *Journal of Geophysical Research: Earth Surface*, 125, e2019JF005141, <https://doi.org/https://doi.org/10.1029/2019JF005141>, 2020.
- 595 Planet Team: Planet Application Program Interface: In Space for Life on Earth. San Francisco, CA., <https://api.planet.com>, 2022.
- Provost, F., Michéa, D., Malet, J.-P., Boissier, E., Pointal, E., Stumpf, A., Pacini, F., Doin, M.-P., Lacroix, P., Proy, C., and Bally, P.: Terrain deformation measurements from optical satellite imagery: The MPIC-OPT processing services for geohazards monitoring, *Remote Sensing of Environment*, 274, 112 949, <https://doi.org/https://doi.org/10.1016/j.rse.2022.112949>, 2022.
- 600 Purinton, B. and Bookhagen, B.: Measuring decadal vertical land-level changes from SRTM-C (2000) and TanDEM-X (~ 2015) in the south-central Andes, *Earth Surface Dynamics*, 6, 971–987, <https://doi.org/10.5194/esurf-6-971-2018>, 2018.
- Rodríguez Fernández, R., Heredia, N., Seggiaro, R. E., and González, M. A.: Estructura andina de la Cordillera Oriental en el área de la Quebrada de Humahuaca, Provincia de Jujuy, NO de Argentina, *TRABAJOS DE GEOLOGÍA*, 21, 321–333, <https://doi.org/10.17811/tdg.21.1999.321-333>, 1999.
- 605 Savi, S., Schildgen, T. F., Tofelde, S., Wittmann, H., Scherler, D., Mey, J., Alonso, R. N., and Strecker, M. R.: Climatic controls on debris-flow activity and sediment aggradation: The Del Medio fan, NW Argentina, *Journal of Geophysical Research: Earth Surface*, 121, 2424–2445, <https://doi.org/https://doi.org/10.1002/2016JF003912>, 2016.
- Scherler, D., Leprince, S., and Strecker, M. R.: Glacier-surface velocities in alpine terrain from optical satellite imagery—Accuracy improvement and quality assessment, *Remote Sensing of Environment*, 112, 3806–3819, <https://doi.org/https://doi.org/10.1016/j.rse.2008.05.018>, 2008.
- 610 Stumpf, A., Malet, J.-P., Allemand, P., and Ulrich, P.: Surface reconstruction and landslide displacement measurements with Pléiades satellite images, *ISPRS Journal of Photogrammetry and Remote Sensing*, 95, 1–12, <https://doi.org/10.1016/j.isprsjprs.2014.05.008>, 2014.
- Uhlemann, S., Chambers, J., Wilkinson, P., Maurer, H., Merritt, A., Meldrum, P., Kuras, O., Gunn, D., Smith, A., and Dijkstra, T.: Four-dimensional imaging of moisture dynamics during landslide reactivation, *Journal of Geophysical Research: Earth Surface*, 122, 398–418, <https://doi.org/https://doi.org/10.1002/2016JF003983>, 2017.
- 615

<https://doi.org/10.5194/egusphere-2025-6445>

Preprint. Discussion started: 14 January 2026

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U.S. Geological Survey: Search Earthquake Catalog, <https://earthquake.usgs.gov/earthquakes/search/>, accessed October 4, 2025, 2025.

Van Wyk de Vries, M., Bhushan, S., Jacquemart, M., Deschamps-Berger, C., Berthier, E., Gascoin, S., Shean, D. E., Shugar, D. H., and Kääh, A.: Pre-collapse motion of the February 2021 Chamoli rock–ice avalanche, Indian Himalaya, Natural Hazards and Earth System Sciences, 22, 3309–3327, <https://doi.org/10.5194/nhess-22-3309-2022>, 2022.