List of relevant changes	
Title	Changed title to reflect new focus of manuscript on assesing landslide activity
Abstract	Rewrote abstrat to reflect new focus of manuscript
Introduction	Added additional background on SAR processing and challenges
Methods and data	Provided additional background and references on SAR processing, coherence loss and NDVI; removed backscatter analysis and added evaluation of NDVI pattern changes
Results	Removed radar backscatter analysis; included NDVI spatial patterns
Discussion & conclusion	Rewrote discussion and conclusions to reflect new focus of manuscript, highlighted advantages and challenges of presented methods and included list of future research opportunities.

Reviewer 1	Answer
General Comments:	
The manuscript you have submitted for publication provides a good insight on the information that is provided by SAR coherence and NDVI for the detection of areas affected by a landslide. In general, your work is well structured but is missing significant information in some sections of your article. The methodology section does not fully present the proposed methodology, and also the conclusions section does not summarise your findings and no future work/steps are provided to fill the gaps of your current work. Calibration/validation of your results and/or methodology is also not provided in the article. This is critical to confirm your findings. Moreover, references need to be added in many parts of your work. Some examples are provided in the attached pdf. Additionally, the tense that your article is written should be passive, i.e. "it was tested" rather than "we tested". Some minor spelling mistakes are also noted in your article. Your figures needs some changes and also make sure that they are cross-referenced in the text (e.g. Figure 1) Please see in the attachment a comprehensive list of changes comments within the text of your manuscript.	Thank you for your comments. We have expanded several sections significantly, with a particular focus on the discussion, including adding the suggested, and other, references. A particular focus was put on describing future research questions and challenges. We are not sure exactly what is expected in terms of calibration or validation, since we make no attempt at mapping the landslide in our work. We have elaborated on this in more detail below. With regards to the tense of the the writing, we consider the passive voice in academic writing appropriate only in select cases, and chose to keep the majority of this paper written in an active voice. This is in accordance with, for example, recommendations made by Nature (https://www.nature.com/nature-research/for-authors/write). We hope to have addressed all spelling mistakes and have updated several of the figures.
Specific comments	
Term early warning in title is not justified. Maybe detection or monitoring is more appropriate. Additionally, you should add "case study" to the title. Suggestion: Radar coherence and NDVI ratios as landslide detection indicators. The case study of Mud Creek landslide in California	We have changed the focus of the study to focus more on the time-series analysis of these indicators, and have therefore adjusted the title to: *Leveraging time series analysis of radar coherence and NDVI ratios to characterize pre-failure activity of the Mud Creek landslide, California*
Add references	We have added significantly more information and references to this part of the introduction (lines 34ff).

Add more references (Tzouvaras et al., 2020 https://doi.org/10.3390/rs12101560 ; Ohki et al., 2020 https://doi.org/10.1186/s40623-020-01191-5; Jung and Yun, 2020 https://doi.org/10.3390/rs12020265)	Thank you for pointing us to these very timely publications. The Ohki et al., (2020) and the Jung and Jun (2020) references in particular are relevant to our work and we have included these references.
Add more references (Rocca et al., 2000 https://doi.org/10.1023/A:1006710731155)	We have added this and other references.
Add more references (same as above)	See comment above. We have also included information from Ohki et al., (2020) and the Jung and Jun (2020) in the text to better reflect the current state of reseach.
Add proper map with coordinate frame, north arrow, scale, loacation in world	Thank you for noticing that we did not reference the first figure in the text. We believe that it shows all the necessary content (we've added a few additional notes to outline the size of the landslide and added a scale bar and north arrow).
us --> used	Thanks for catching that, we corrected this typo accordingly.
change to radar coherence	Thanks for noticing the editing mishap. The sentence now reads: *In this study we used SAR data from ESA's Sentinel-1A and 1B satellites to perform a traditional InSAR displacement analysis and to compute the radar coherence.*
Add references	We have added more references
Add cross reference in text	Good catch, thank you. We have now referenced the figure in the description of the study site.
Add a rectangle showing extents of area affected by landslide	We have zoomed in on the area, replaced the Sentinel-1 images with higher resolution images from Planet and outlined the edges of the landslide.
Add references	We have added more references.
More recent research is available on this topic. These references can also be used to explain the displacements results that are lower than expected. Wasowski and Bovenga, 2014 https://doi.org/10.1016/j.enggeo.2014.03.003 Manconi et al., 2018 https://doi.org/10.3390/rs10050672 Tzouvaras et al. 2020 https://doi.org/10.3390/geosciences10060236	We have added more references and background on this topic throughout the manuscript.
Explain why you haven't used Sentinel-1A and Sentinel-1B to reduce revisit time to 6 days	We did indeed use both Sentinel-1A and 1B, but this does not lead to a repeat time of 6 days in this part of the world. We have clarified the use of both in the text: In this study we used SAR data from ESA's Sentinel-1A and 1B satellites to perform a traditional InSAR displacement analysis and to compute the radar coherence.
Please specify the type of DEM you used	We used the 1/3 arc second DEM provided by the USGS. This is the hightest resolution, seamless DEM available for the coterminous United States. Various data sources can go into this product: https://www.sciencebase.gov/catalog/item/4f70aa9fe4b058caae3f8de5. We have specified this in a bit more detail in the text as: ...the highest resolution seamless DEM available for the conterminous United States

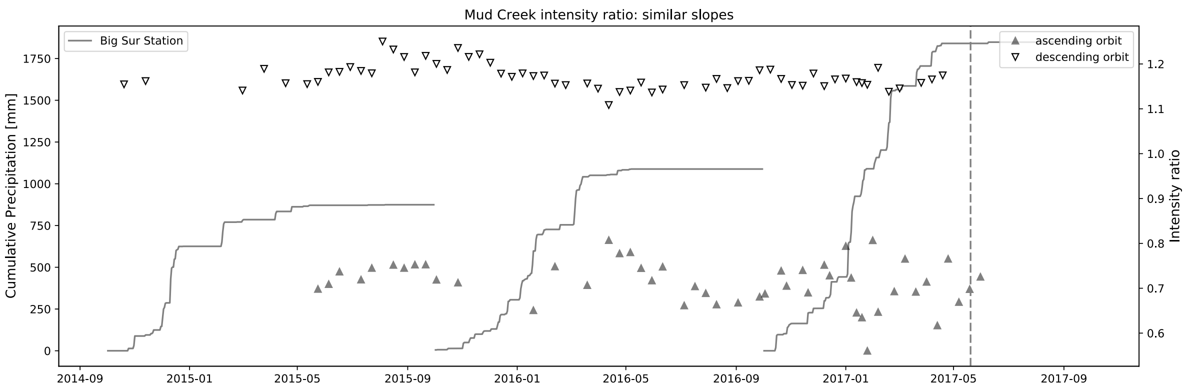
	(downloaded from: [https://viewer.nationalmap.gov/basic/)](https://viewer.nationalmap.gov/basic/)
What is that threshold. You define it later on, specify here too and explain why this threshold is appropriate supporting it by references	We have described this in more detail and justified why the different thresholds are necessary. There are no references for the threshold we use in the ratio analysis because, to our knowledge, there are no prior applications of this technique. We had added additional references to support the statement about the coherence threshold of 0.2 to 0.3 that is typically used in InSAR processing. See lines 160 ff.
You need to explain the displacement calculation methodology further to justify your results	We are not entirely sure what this comment refers to, but hope that in addressing the following points, we manage to address this request.
Why is that. Explain and add appropriate references	A coherence threshold of 0.2 - 0.3 is typically used for InSAR analysis. If a large area is analyzed, pixels below that threshold can sometimes be masked. But coherence also provides important information the reliability of the information in an individual interferogram. The decision of whether or not to include any given interferogram in a time-series analysis is frequently based on visual inspection by the user, and poor quality interferograms are removed manually. In the spirit of reproducibility, we decided to define a threshold, rather than make a manual selection. We have clarified this approach in the methods section as follows (lines 163 ff): *Decisions about the quality of an interferogram and the reliability of the data for time series analyses are usually based onradar coherence. For individual interferograms, pixels with a coherence of less than 0.2 are typically masked (e.g., Rosen et al.,2000). Images with low overall coherence are usually omitted from InSAR time series analyses. This selection is often basedon visual inspection and performed manually (e.g., Handwerger et al., 2019). To increase the reproducibility of our work, we experimented with a set coherence threshold that we used to filter out poor quality interferograms. Because our area of interestis small relative to the size of the interferogram, mean image coherence over the entire interferogram is a poor indicator for the data quality in the landslide area. Instead, we calculated the mean coherence for each interferogram within just our area of interest and only retained images with a mean coherence above a defined threshold (0.35 for the displacement analysis and 0.5 for the coherence ratio analysis; see details in sections 3.2.2 and 3.2.1). Fig. 2 illustrates why relatively aggressive filtering is necessary for the ratio calculations. If the entire area of interest is affected by low coherence, the ratio becomes meaningless. After filtering, we computed the time series of displacement and radar coherence ratio from all the retained images.*
Why do you chose this specific point? What are it's characteristics? You need to explain in detail in your methodology as the selection of a moving point can affect your results significantly.	We chose a point that is well outside the landslide and in an area that experienced no apparent deformation. To clarify this, we have also plotted the mean displacement of a 9x9 cell area around the reference point (~30x30m) and explain in the

	text: *We selected a point west of the landslide as our stable reference region. This area is the same geologic unit, its vegetation cover is representative of the larger area, and it did not fail in the landslide. A preliminary displacement analysis also suggested it had not experienced any significant deformation.*
Add more specific NDVI threshold values for various types of soil.	We are not entirely sure what this comment referes to, since NDVI reflects vegetation growth, not soil types. However, we have added additional details about typical NDVI values; *Typical values for dense, healthy vegetation are around 0.6, values for bare ground or minimalvegetation are typically below 0.2 (Jensen, 2009).*
No calibration/validation of your results is presented. This is critical as your findings are not confirmed by any means. See work from Burrows et al, 2019; Tzouvaras et al., 2020 https://doi.org/10.3390/rs12101560	Thank you for this input. We are not sure what type of calibration or validation you are hoping to see. Both Burrows et al. (2019) and Tzouvaras (2020) use ROC analysis to assess how well co-event coherence loss can be used - in various ways - to map landslides (on in the Tzouvaras case, just one landslide). In our work we make no attempt at mapping the landslide. We realize that our original title was somewhat confusing in this regard, and hope that our refocusing on the time series analysis alleviates this concern. Instead, we try to understand how **pre-event** coherence changes can be interpreted to understand landslide activity. Unlike all other authors, we do not use co-event image pairs. An additional analysis to use the pre-event time series of coherence ratio to map the landslide is beyond the scope of this work, but we have adressed this issue in the conclusions section.
Discuss your results further. Why did InSAR failed to detect the deformation to its full extent? Did soil moisture due to rainfall affect the results? Is it due to the acceleration of displacement? See the references I provided in row 95	We have added some extra information describing the unwrapping errors in the results section and now discuss these in detail in the discussion.
Add scale and north arrow. Change the color of the white line.	Excellent points. We have added a north arrow and length scale and made the white line black.
Why is that? Explain further. How do you remove the effect of rainfall/soil moisture to isolate the surface change due to the landslide? Additionally, from bibliography there is coherence drop with increasing temporal baseline between SAR acquisitions. Check and analyzse your findings better.	Thank you for pointing out that we had not made it clear that the temporal baseline does not matter int his approach, because both the reference hillslope and the landslide experience the same drop in coherence, therefore the effects cancel out. We have highlighted this in several places in the manuscript. For instance, we have added the following statement to the methods section: *The advantage of the ratio calculation is that it cancels out the effects of regional-scale environmental factors and processing artefacts that affect the hillslope and the landslide equally.Therefore, when using the landslide/hillslope ratio, values less than 1 indicate decreasing landslide NDVI or coherence values, while values greater than 1 indicate decreasing hillslope values.* (Line 112 ff)
Some text from the discussion should move to conclusions section which is rather poor. Future	We have added additional information to the conclusion and discussion sections. See comment below.

steps, ways to overcome problems you encountered etc.	
You should add more references: Wasowski and Bovenga, 2014 https://doi.org/10.1016/j.enggeo.2014.03.003 Manconi et al., 2018 https://doi.org/10.3390/rs10050672 Tzouvaras et al. 2020 https://doi.org/10.3390/geosciences10060236	We have added additional references, including Handwerger et al., 2019; Manconi et al., 2018; Dai et al., 2020
This can also be justified on seasonal change of vegetation	The change in NDVI actually cannot be explained by the seasonal vegetation cycle, since it is the *ratio* that is steadily declining, not the NDVI itself. This means that relative to its surroundings, the vegetation on the slide is declining. This is also shown in Fig. 8, where the NDVI in the slide area clearly deviates from that of the surrounding hillslope, indicating that it is no longer following the typical seasonal vegetation cycle. We have now also included an additional figure that shows the spatial evolution of the NDVI on the landslide and shows the ever growing area of low NDVI values. (Fig. 7)
You should try to eliminate any interference of vegetation, soil moisture (reflectivity) from your final results. You should also add some future research in your conclusion section.	We are not aware of any method that allows us, at this point, to definitively exclude any given factors. The goal of this work is to examine the information that can be gained from these different measures. If we eliminate the effects of soil moisture and vegetation dynamics, we exclude factors that are important for landsliding. However, we make an attempt at bringing our results and conclusions together in a more concise manner.
This section needs significant improvement as it doesn't summarize your work nor refers to any future work/research to improve findings further.	Thank you for highlighting this. We have added the following information to the conclusions section: *In particular, if a few criteria are met, the ratio calculation between the surrounding slope and the landslide eliminates interference due to temporal coherence loss, atmospheric disturbances, or vegetation cycles. Our analysis also indicates that this type of analysis can fill data gaps in places where data from only one orbit are suitable for deformation measurements. Nevertheless, questions around whether it is possible to fully disentangle the different factors leading to the pre-failure coherence loss and how common this kind of signal is for different kinds of landslides remain to be resolved. Similarly, it is worth investigating how the presence of more or less vegetation and use of different radar wavelengths influence the results. We also believe that it could be possibleto automatically identify drastic drops in radar coherence ratios and NDVI ratio decreases, suggesting that this tool could be used to identify impending failures. All things considered, we strongly believe that the encouraging initial results presentedhere motivate further investigations of these parameters.* In addition, we have elaborated further on these points in the discussion.
Reviewer 2	**Answer**
General comments	
If one wants to use the relative indicies for early warning purposes, the landslide needs to be known	Thank you for this comment. Indeed, this is true. We have refocused the manuscript on characterizing

before the failure occurs. While large slow moving landslides often known (especially in the vicinity of urban environments), it is not always known which part actually moves. However, this is required (at least approximately) if relative indices are used, otherwise the landslide specific signal mixes with the non-landslide reference signal and thus the ratio gets less pronounced.	landslide activity and not early warning. However, we do touch on the topic of how these indicies could be used for detection in the discussion and conclusion.
To analyze the relative ratio and its changes over time requires same or at least very similar conditions (e.g. land cover/use) for both regions. Otherwise the changes in the ratio can occur e.g. due to different use of the land. In many cases (at least that I have experienced) the land cover is actually different, e.g. agriculture, pasture in the surrounding and natural vegetation on the slow moving landslide, especially when the knowledge that a slow moving landslide exists at this place (wich is a requirement to apply the proposed approach) prevents people to use this site as agricultural area, because of the potential risk.	Thank you for this interesting point that we had not considered previously. We have elaborated on the topic in the discussion.
Alternatively if the conditions are not the same the temporal behavior of the indices between these two areas need to be known (e.g. from a long-term reference period), and then a relative change to the typical behavior can be analyzed in regard to potential landslide acceleration. However, this can also only be applied if the reference behavior is similar throughout the years.	This is an interesting and promising approach that we have also included in our discussion. Thank you for suggesting it.
The discussion and analysis for relation between coherence and NDVI needs to be elaborated in more detail. Assuming a decrease in NDVI is related to vegetation decrease, as done in this paper, we expect more coherence in the period related to NDVI decrease (please see Bai et al. (2020), Scientific Reports volume 10, Article number: 6749 (2020); https://www.nature.com/articles/s41598-020-63560-0). But this is not the case here and the coherence is decreasing in the period when we see a declining trend in NDVI. This is not surprising as several studies (e.g. Van doninck et al. (2012), Hydrol. Earth Syst. Sci., 16, 773–786, 2012, www.hydrol-earth-syst-sci.net/16/773/2012/ doi:10.5194/hess-16-773-2012) have shown that changes in NDVI can also be related to changes in soil moisture depending on the elevation (See Fig. 5 and other figures in Van doninck et al. (2012)). It seems that the NDVI changes that the authors observe here is more related to soil moisture change rather than vegetation change. Please elaborate more on this in the paper.	Indeed, we have significantly expanded and restructured the discussion, in the hopes to better address the various aspects. We do not agree, however, that a reduction of vegetation should necessarily lead to increased coherence. While this is certainly true for seasonal cycles, it would not hold true if there is a continuous removal of vegetation. Indeed the Bai paper shows two distinct clusters of vegetation vs. coherence, and though they suggest a linear relationship between the two, there is no data to back this up. While it is possible that there is an influence of soil moisture on NDVI (and coherence!), it hardly explains the whole trend. VanDoninck et al. link soil moisture to radar backscatter and NDVI, but find little, or only temporally offset, correlation between NDVI and soil moisture. This is not surpising since vegetation would need some time to respond to the increased soil moisture. In our case, vegetation is decreasing when there is a suspected increase in soil moisture. We have added an extra figure in the results section adressing the spatial patterns of NDVI changes (Fig. 7) prior to the failure and will interpret those results with regard to both the vegetation and soil moisture changes, as well as discussing potential impacts on NDVI.
This is not surprising as the ascending geometry suffers from foreshortening. Due to this geometrical distortion in the ascending data, I would not focus on ascending data. Rather, please use amplitude time-series from both polarimetry channel. If soil	We believe that expanding our analysis to include polarimetric data is beyond the scope of this paper. We investigated the amplitude time-series in more detail and have decided that little information about the processes going on on the landslide can be gained from

moisture is the main contributor to the coherence decrease, we would probably be able to see it by comparing the backscattering between different polarization that we have for S1. The authors have mentioned this in the paper, but have not investigated this in detail.	this data. We have therefore decided to no longer include it in the manuscript, and focus fully on the coherence and NDVI instead. For what its worth, we have included a refined plot of the backscatter data in this response. We did not fully correct for terrain, but just compared the landslide to a neighboring slope with very similar terrain statistics. We do want to point out that despite some foreshortening, the ascending data holds more information than the descending data (which, due to its oblique angle, gets very little backscatter). However, we cannot link the increased variability of the backscatter amplitude starting in January 2017 to any definitive process, and therefore do not include this data in the mansucript.



The results of this pilot study show high potential to get early indicators of landslide failure. However, since it is not quite clear (as authors state by themselves) what the underlying processes are that allow to distinguish between normal accelerations and accelerations towards the failure it is absolutely not clear if this methodology is transferable to other landslides. Do you have any other examples to test your findings? If so, this would definitely strengthen your findings and raise the need to publish this manuscript. In your conclusion at L246f you also mention this need ": : : a more in-depth analysis of NDVI ratio and coherence ratio at multiple landslide sites is necessary to assess their full value."	We currently do not have other sites where we have performed a similar analysis. However, we have adressed the question of what types of landslides might show this kind of signal in the discussion section.
Specific comments	
delete "the"	Thanks for catching this, we have corrected as suggested.
This statement is quite general. Do you have any references for that statement? Since this is a major motivation why you propose a different approach than InSAR, please elaborate this part a bit more. What are the challenges? Are these challenges, which are challenging but can be solved or do these challenges really impede the use of InSAR in analyzing slow moving landslide accelerations.	We have added a paragraph describing the challenges of InSAR in the introduction (lines 34 ff).
This whole paragraph describes landslide inventory mapping (in terms of mapping post failure landslides), which is not related to the scope of this manuscript. Moreover, the selection of your references seems a bit arbitrary (for (semi-	Thank you for this input. We do believe that the various uses of coherence metrics to identify landslides - while aimed at mapping and not at characterizing the dynamics prior to the failure - are still an important framework for - and part inspiration - for our work. We

)automated landslide mapping you cite a single study out of many available studies evolved in the last two decades). Please cite review articles or maybe better skip this part, because as mentioned is not related to the scope of the manuscript.	will re-formulate this paragraph to reflect this more clearly and include additional references.
Why do you indicate "the area the area from which the May 2017 failure originated" by a rectangle. Wouldn't the outline of the landslide as given in Figure 3 be more meaningful if you refer to the landslide area?	Thank you for highlighting this. We have changed the plot to show the reference slope and the slide in the first plot and then left all outlines off the image. We decided not to plot the outline in each panel becasue it obscures the data to some extent.
It might be good to include the reference point also in the right plot. This would give a better insight on how the stable slope behaves in comparison to the other points.	We have plotted the mean of the 9x9 cells around the chosen reference point in the displacement plot.
"The premise is that general environmental and atmospheric changes (e.g., vegetation cycles, meteorologic storms, ionospheric disturbances) affecting InSAR coherence should not vary between a landslide and its surrounding slopes." This is true for the latter two, but as mentioned above vegetation cycles may vary between landslide body and surrounding.	Thank you again for pointing this out, we have included this point in the discussion.
Please elaborate more on the steps that you have done for calculating amplitude time-series. It is not clear if sigma in Formula 5 is just the simple mean of amplitude data or the mean value after corrections (calibration, speckle filter, terrain correction etc...)	As presented in the paper, these are just simple means of amplitude. See the comment and figure above about why we have decided to omit this part of the analysis from the manuscript.

Reviewer 3	**Answer**
General comments	
(1) In addition to the historical studies cited to evident the prediction of sliding time, it is suggested to supply the derivation of displacement (Fig.5) and adding graphic comparison with former observed acceleration data.	Thank you for this suggestion. Indeed, it would be nice to have velocities. However, the unwrapping erros lead to very noisy velocities that do not contribute much to the paper since we are trying to focus on the coherence and NDVI ratios and the velocities have been shown elsewhere (Handwerger et al., 2019).
(2) Based on the data in Figures 6 and 7, it is suggested to comment on the limitations or advantages of the two aspects of data, Radar coherence and NDVI ratios, in landslide prediction, especially factors may influencing results. And the advantage or necessary of combination of Radar coherence and NDVI ratios in landslide prediction, so as to better respond to the scientific problems mentioned in the Introduction part.	We have restructured and extensively rewrittent the discussion and conclusion section of this paper, and hope that we've adequately adressed these points. We also elaborate on where these techniques may work and what factors might hamper their usefulness.
(3) Clarify whether the indicators of Radar coherence and NDVI ratios are competent for landslide prediction and are there any suggestions for future research?	We have added an extensive amount of information about future work in the discussion and summarize as follows in the conclusions: *[...] In particular, if a few criteria are met, the ratio calculation between the surrounding slope and the landslide eliminates interference due to temporal coherence loss, atmospheric disturbances, or vegetation cycles. Our analysis also indicates that this type of analysis can fill data gaps in places where data from only one orbit are*

	suitable for deformation measurements. Nevertheless, questions around whether it is possible to fully disentangle the different factors leading to the pre-failure coherence loss and how common this kind of signal is for different kinds of landslides remain to be resolved. Similarly, it is worth investigating how the presence of more or less vegetation and use of different radar wavelengths influence the results. We also believe that it could be possibleto automatically identify drastic drops in radar coherence ratios and NDVI ratio decreases, suggesting that this tool could be used to identify impending failures. All things considered, we strongly believe that the encouraging initial results presentedhere motivate further investigations of these parameters.

Reviewer 4	**Answer**
General comments	
The abstract should be rewritten: No physical connections can be found between the optical and SAR method, and you may say "a hybrid method" instead of "a novel approach". You should also mention the method that is used to derive displacement, as this is also an important part of your work. I cannot follow the sentence "In contrast, the landslide accelerated during the rainy seasons of 2015 and 2016, but neither of those accelerations resulted in a drop of the radar coherence ratio". This sentence seems to say that the proposed coherence method is not reliable at all.	We have made significant changes to the manuscript, including re-focusing it on the time-series analysis rather than the early warning aspect. The abstract has been rewritten accordingly.
It seems that you only showed three different results within a plot. There is a lack of quantitative integration of these three results.	Thank you. We are not entirely sure what is expected here, since we are comparing the different metrics to understand how they can be used and/or what they can tell us. We hope that once all the edits that have been made, this concern will be addressed. Please refer to the discussion (lines 270ff) for an extensive discussion of how the different measures relate to each other.
The NDVI part is not described in detail. It seems that you use the mean NDVI on the moving slope and calculated the ratio with the surrounding slopes. If the mean NDVI ratio dropped so dramatically, the spatial pattern of NDVI ratios could be used to indicate the spatial pattern of the landslide, or at least the disturbed vegetation should be clearly discernable. Therefore, it may be more suitable to use the spatial patter of the NDVI ratio to indicate the morphology of this imminent landslide.	We have added addtitional details to both the description of the NDVI methodology section, the results and the discussion. Indeed, some information about the processes on the slope are discernible in the patterns of NDVI changes, and we have added this as a brand new Figure 7.
Coherence between two SAR images may also be influenced by their temporal interval. Longer intervals may lead to image incoherence. How to elimiate the influence of time on the derive SAR coherence?	Thank you for this comment. Because we use the ratio between the surrounding hillslope and the slide, both of which are equally affected by coherence loss due to the variable temporal baselines, this effect is effect is eliminated automatically. We have clarified this in several places, for instance in lines 112ff we state: *The advantage of the ratio calculation is that it cancels out the effects of regional-scale environmental factors and processing artefacts that affect the hillslope and the*

	landslide equally.Therefore, when using the landslide/hillslope ratio, values less than 1 indicate decreasing landslide NDVI or coherence values, while values greater than 1 indicate decreasing hillslope values.
Specific comments	
--> used	Thanks for catching that, we've corrected it accordingly.
eliminate repetition	Thank you, we have eliminated this unnecessary information.
Describe temporal resolution of the data and any processing procedures	We have added the following information to the manuscript: *GHCND data provide daily total cumulative precipitation and minimum and maximum air temperature. The Big Sur Station station is located 53 km north-west of Mud Creek at 61 m asl. Data is available from https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USC00040790/detail and was used without any additional processing.*
Citation format error	Thanks for catching that, we've corrected it accordingly.
Can you indicate the dates of images used to calculate Fig. 3	The images in Fig. 3 are simply meant to illustrate the way the image selection based on a coherence threshold works, and therefore do not represent any specific point in time. We hope to have clarified the caption by stating: *Coherence filtering: Interferograms in the upper row exceed the coherence threshold of 0.5 and were therefore included in the ratio analysis, the images in the lower row were excluded. We calculated the mean coherence for the area in the red polygon. The images represent various times throughout the the two year period for which data was available and were chosen purely to show why low mean coherence images cannot be used for the ratio calculation.*

Reviewer 5	**Answer**
General comments	
This manuscript introduces an interesting method for the early detection of landslides using time series of radar coherence ratio, intensity ratio and NDVI ratio. This manuscript is well arranged and the results from this case are sound However, in my mind, two issues should be highlighted, **the** first is what the basic theory is behind the coherence lost, intensity lost and even NDVI lost with respect to the surface deformation. The Second is whether you can give the thresholds for the coherence ratio intensity ratio and NDVI ratio as the precursory information to early warning the failure of slope? Actually, the coherence lost and intensity lost are mainly due to the large surface deformation. In other words, surface deformation can give us much direct information with respect to the failure of landslide. In a word, to which extent,	Thank you for your suggestions. We have added additional details with regard to what causes the changes to coherence, NDVI and intensity and discuss these more in depth in the discussion. You pose many excellent questions that we have tried to better address in the discussion but will also remain open questions for future research. We have expanded on this both in the discussion and the conclusions.

this strategy can be referred for the similar landslides application?	
1. Besides, once the time series of displacement shows an accelerating trend, we should take more attention and take special measures if applicable to prevent the hazard. Actually, it is very hard to forecast the failure of landslide if only satellite InSAR data are considered.	Agreed, will include this point in the discussion (lines 351ff)
2. Taking NDVI as an idicator may not work when landslide occurs in area with barn vegetation cover. The heavy vegetation is a big problem for SAR processing. So how does NDVI can be applied regarding the landslide detection and monitoring?	We now address the issue of differeing vegetation covers in the discussion (lines 270 ff) and in particular lines 355ff.
Specific comments	
The description of the Mud Creek landslide is not clear, please add a description about the scope of the landslide, such as length, width, thickness etc., which can also be depicted in Fig. 1 to an enlarged map of landslide.	We have added the following information to the study site description: *The failure initiated at to 337 m above sea level, was 490 m long, and involved roughly 3 million m3 of earth and rock (Warrick et al.,, 2019).*
--> used	Thanks for catching this typo, we have corrected accordingly!
the numbers of numbers of ascending and descending SAR images are 35 and 42, respectively. So what do the numbers 51 and 64 in lines 97-98 mean?	An unfortunate error in Table 1 likely led to this confusion. There are 51 raw images from the ascending track (track number 42) and 63 raw images from the descending track (track number 35). We corrected all the numbers in the text and table. Thank you for making us aware of the mix up.
In Fig 5b, in April 2017, the time series of deformation marked by Pentagram appeared rebound, is there any unwrapping error?	Yes, because of the high displacement rates during spring of 2017 (and the low coherence), there are a number of unwrapping errors, which make it hard to retrieve the full displacement. We have discussed this in the text and the figure caption more explicitly.
the deformed area is similar to the low coherence area pattern, and the NDVI ratio lost in the meantime. So how can you conclude the coherence loss was due to slope movement rather than vegetation variation. More analysis on this aspect is necessary.	Indeed, we cannot fully disentagle the different factors driving low coherence. However, we believe that the additional datasets can shed some light on this, including an additional analysis of evolution of the spatial pattern of NDVI (new Figure 7).
The amplitude ratio of the ascending orbit is relatively discrete, and the descending orbit is concentrated. What is the reason?	This is due to the different incidence angles, which lead to the data from the descending orbit not containing very much information. We investigated the amplitude time-series in more detail and have decided that little information about the processes going on on the landslide can be gained from this data. We have therefore decided to no longer include it in the manuscript, and focus fully on the coherence and NDVI instead.
Table 1. this table is in "radar data" section but information about optical imates is alsow shown. I advise authors to move this part to section 3.2	We did not want to split this three-line table into two tables and have therefore moved it to the overarching methods section (section 3).

Reviewer 6	Answer
General comments	
This paper shows interesting results regarding the use of several approaches for the identification of pre-	Thank you for this input, this critique is justified and the points not adequately adressed in the

failure indicators, such as displacement time series, coherence ratio, intensity ratio, and NDVI ratio. I think the authors should change general statement of the paper: within the paper, the authors underline several times the potential of coherence ratio approach and NDVI ratio approach for theis application at large scale to detect landslides. BUT: I don't see a global proposed method to be applied nor at large scale nor in other cases of study, I see case-specific approaches related to separated techniques where the results are explained and compared. There is not a proposaol of a general method to be used in order to use and integrate the thechniques of NDVI and coherence ratios. Here we are still looking at a back-analysis result of a specific case of study. Several aspects of the used approach are strictly related to the specific studay in fact there are not a priori answer to questions like: *how to decide on a threshold? how to decide on the landslide area and the surrounding one?* I see this paper an interesting study on the behaviour of several indeces in a specific case of study. I would focus more the paper on one hand on the explanation of the behavior and of the characteristics of each technique, on the other hand I would answer questions like: how the combination of several approaches can be exploited? When? Why? Which are the advantages of one rather than another and in which cases? Which the limiations? All these aspects should be taken into account with a revision of the WHOLE manuscript (with a main effort in the introduction, discussion and conclusions).	manuscript. For one, we have changed the focus of the study to focus more on the time-series analysis of these indicators, and are omitting the reference to early warning. In addition, we have elaborated on the potential and challenges of using these techniques to detect landslides in the discussion and conclusions. See more detailed responses in the comments below.
1: I would focus on the pros and contras of each technique. Explaining better the basic theory behind each one and the factors that can affect them.	We have expanded on several of the issues in the introduction, the methods section as well as the discussion.
2: In the discussion of the results I would at least make a hypothesis in order to explain globally the results considering the behaviour, and thus information from all the methods.	We have restructured the discussion significantly (lines 270 ff) to bring out this synthesis more clearly
3: Emphasize that, as it is proposed, the approach does not detect landslides, since the spatial distribution is not given by the ratios. On the contrary, in order to calculate the ratios, it is necessary to know the landslide, at least the location and the extentsion.	See comment above, as the focus of the entire manuscript has been shifted to emphasize this.
4: I propose this title: "Radar coherence and NDVI ratios as indicators of landslide activity changes. The case study of Mud Creek landslide in California."	We have changed the focus of the study to focus more on the time-series analysis of these indicators, and have therefore adjusted the title to: *Leveraging time series analysis of radar coherence and NDVI ratios to characterize pre-failure activity of the Mud Creek landslide, California*
5: I would TOTALLY avoid the use of the words "early warning" in the text. I would better say pre-alert useful to focus the attention and make deeper analysis and studies also complementing with other techniques.	We have removed all mentions of early-warning with respect to this study from the manuscript.
6: Propose the future studies that you think will be useful to fill the gaps and the uncertainties. For example, what is necessary to use these rations as a detection method? And what is necessary to use these ratios at large scale?	We have included a whole list of future research questions (lines 355ff)

~~Radar~~ Leveraging time series analysis of radar coherence and NDVI ratios ~~as~~ to characterize pre-failure activity of the Mud Creek landslide~~early warning indicators~~, California

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Abstract. ~~The catastrophic failure of the Mud Creek landslide on California's Big Sur Coast on 20 May 2017 highlighted once again how difficult it is to detect a landslide's transition from slow moving to catastrophically unstable. Automatic detection methods that rely on InSAR displacement measurements to detect precursory acceleration are available but can be plagued by imaging geometry complexities and tedious processing algorithms.~~ Assessing landslide activity at large scales has historically been a challenging problem. Here, we present a ~~novel approach for assessing landslide stability by using relative interferometric coherence from Sentinel-1 and Normalized Difference Vegetation Index~~ different approach on radar coherence and normalized difference vegetation index (NDVI) ~~from Sentinel-2~~analyses - metrics that are typically used to map landslides post-failure - and leverage a time series analysis to characterize the pre-failure activity of the Mud Creek landslide in California. Our method computes the ratio of mean interferometric coherence or NDVI on the unstable slope relative to that of the surrounding hillslope. This approach has the advantage that it eliminates the negative impacts of long temporal baselines that can interfere with the analysis of interferometric synthetic aperture (InSAR) data, as well as interferences from atmospheric and environmental factors. We show that the coherence ratio of the Mud Creek landslide dropped by 50% when the slide began to accelerate five months prior to its catastrophic failure in 2017. Coincidentally, the NDVI ratio began a near-linear decline. ~~In contrast, the landslide accelerated during the rainy seasons of 2015 and 2016, but neither of those accelerations resulted in a drop of the radar coherence ratio.~~ A similar behavior is visible during an earlier acceleration of the landslide in 2016. This suggests that radar coherence and NDVI ratios may be ~~able to aid in both the early detection of landslides and indicate whether an acceleration critically threatens the stability of a slope~~useful for assessing landslide activity. Our study demonstrates that data from the ascending track provides the more reliable coherence ratios, despite being poorly suited to measure the slope's precursory deformation. Combined, these insights suggest that this type of analysis may complement traditional InSAR analysis in useful ways and provide an opportunity to assess landslide activity at regional scales.

1 Introduction

~~Rainfall triggered landslides are some of the most~~ Landslides are among the most destructive and costly natural hazards ~~worldwide, causing economic loss through damage to infrastructure and livelihoods every year (Petley, 2012) . To date, our predictions of *where* rainfall triggered landslides are likely to occur mostly rely on regional-to-global scale landslide susceptibility maps (Stanley and Kirschbaum, 2017) . Predicting *when* a slope is expected to fail is a comparatively harder problem(Intrieri et al., 2019)~~ and their occurrence and impacts remain difficult to predict. The numerous triggering processes and controls on landslide size, runout distance or time of failure make it hard to assess the risks and potential impacts for even just a single hillslope. Carrying out such an assessment at the regional level is a comparatively harder challenge. Yet assessing landslide activity over larger regions can be crucial to effective hazard management (van Westen et al., 2006) . Remote sensing techniques using both optical imagery and satellite radar data have long been recognized as useful tools to carry such regional scale assessments (Mantovani et al., 1996; Rosin and Hervás, 2005) . However, while many of these efforts are focused on mapping landslides after they have occurred, assessing the activity of landslides is a harder problem. The most reliable and common approaches for ~~predicting landslides' time of failure all~~ assessing landslide activity and potential for failure rely on measurements of slope displacements and derivatives thereof ~~(e. g., inverse velocity; Fukuzono (1985)). With the exception of open-pit mining, where state-of-the-art monitoring equipment is common and often operates continuously, dense displacement time series of landslides are still the rare (Intrieri et al., 2019) . Presently, Norway employs the most extensive landslide detection and monitoring system by continually processing radar data from Sentinel 1-A and 1-B data (Lauknes et al., 2010; Dehls et al., 2014) . However, generating robust displacement time series from~~ (**?**) . For individual, known instabilities, this is most commonly achieved through on-site monitoring systems using GPS, crack meters, image analysis, automated theodolite measurements or ground based radar and lidar measurements (e.g., Gili et al., 2000; Chelli et al., 2006; Kos et al., 201 Monitoring landslide activity has also been achieved with aerial images and high resolution satellite images, though the focus thereof lies more on individual instabilities than on entire regions (e.g., Hervás et al., 2003) . Recently, interferometric synthetic aperture radar (InSAR) ~~data is not without challenge due to imaging geometry complexities and tedious processing algorithms.~~ techniques have gained popularity for assessing landslide activity because they provided the opportunity to measure slope displacements over large areas. Despite this advantage, Norway is presently the only county systematically leveraging radar interferometry for a country-wide monitoring effort (**?**Dehls et al., 2014) .

~~More commonly, landslides are mapped after they occur. This practice is particularly important for organizing rescue efforts in response to large numbers of landslides triggered by earthquakes or tropical storms. To this end, landslides are frequently mapped by hand from high-resolution optical images (i. e., Roback et al. (2018)), a process that is tedious and time consuming. To speed up the production of such landslide inventories, automated and semi-automated procedures have also developed (Mondini et al., 2011) . Because landslides frequently damage the vegetation cover, many of the (semi-)automated methods draw on the Normalized Difference Vegetation Index (NDVI; Tucker (1979); Rosenthal et al. (1985)), which can be calculated from red and near-infrared bands of multispectral optical images.~~

~~The obvious drawback of approaches that rely on optical imagery is the need for cloud-free imagery, which may not be available immediately after a landslide triggering event (particularly if it was rainfall induced) . In contrast, synthetic aperture radar (SAR) has the capability to see through clouds. Due to the increased availability of SAR data (e. g., freely available~~

~~Sentinel-1 imagery from the European Space Agency), radar-coherence based techniques have recently been explored for the purpose of mapping landslides and damage to infrastructure (Burrows et al., 2019; Yun et al., 2015) . Radar coherence is a measure of the similarity of a target's scattering properties~~ Generating robust displacement time series from InSAR, despite its all-weather and day-and-night capability, is not without challenges. Due to its oblique viewing geometry, radar can be rendered useless in areas of steep topography due to the effects of shadowing and layover (the compression of a large area into only few image pixels) (Wasowski and Bovenga, 2014; Lillesand et al., 2015) . In areas not affected by these geometric artefacts, the maximum detectable deformation gradient is equal to half the wavelength per image pixel ($\frac{\lambda}{2}$; Massonnet and Feigl (1998) . Because radar instruments only measure the component of motion in line of sight, the the measurable deformation is strongly controlled by the viewing geometry (Massonnet and Feigl, 1998) . Further difficulties include the relative nature of radar measurements, making it necessary to know or assume a stable location where there is no deformation, as well as the fact that radar measurements are 2π wrapped (Wasowski and Bovenga, 2014; Massonnet and Feigl, 1998) . The wrapped nature of the data requires that radar measurements are unwrapped to derive the actual displacement in meters rather than radians (Massonnet and Feigl, 1998; Chen and Zebker, 2002) . This process is computationally expensive and phase unwrapping errors can mask the full displacement (Wasowski and Bovenga, 2014) . Additionally, in order to reliably measure ground displacements, the wave scattering properties of ground targets must remain unchanged between two radar ~~acquisitions (Zebker and Villasenor, 1992) . For InSAR applications, where displacements are calculated based on changes of the radar phase, coherence~~ measurements (Massonnet and Feigl, 1998; Zebker and Villasenor, 1992) .

This similarity between two radar images is expressed in the radar coherence metric, which is the primary indicator of ~~data quality. A~~ radar data quality and can be impacted by several different factors. Generally speaking, a reduction in radar coherence indicates that either the ~~surface~~ scattering properties of the target have changed (temporal decorrelation) or that the imaging geometry has shifted substantially ~~. Because imaging geometries for overlapping Sentinel-1 scenes are generally highly stable,~~ (spatial decorrelation; Zebker and Villasenor (1992); Rosen et al. (2000)). Instrument noise (signal-to-noise ratio) can also be a cause of coherence loss (thermal decorrelation), but is typically small in modern systems (Zebker and Villasenor, 1992) . When radar images are re-acquired from the same position, spatial decorrelation is minimized and coherence changes are predominantly temporal in nature~~, making radar coherence a good measure~~ . This can be exploited for detecting changes ~~at the Earth's surface. Coherence based~~ such as soil moisture variations, ground deformation, and ground cover or land use change such as those caused by vegetation cycles, agricultural practices, or damage from natural hazards (e.g. **?**Fielding et al., 2005; **?**; Musa et al.,

These variations in coherence can also be efficiently exploited for landslide mapping. When large numbers of landslides are triggered by earthquakes or tropical storms, fast and precise landslide mapping is key for organizing effective rescue efforts. The increased availability of SAR data (e.g., freely available Sentinel-1 imagery from the European Space Agency ESA) has led to significant developments in this regard. Coherence-based landslide mapping has been achieved ~~by classifying a coherence map based on either an absolute coherence threshold, the difference between a~~ using absolute coherence thresholds, differences between pre-event and ~~a~~ co-event ~~coherence map, or the difference between a~~ or co-event and ~~a~~ post-event coherence ~~map (Burrows et al., 2019; Yun et al., 2015)~~ maps, as well as coherence time series analyses (**??**Ohki et al., 2020; Jung and Yun, 2020) .

~~InSAR has also been applied to detect precursory acceleration of the 20 May 2017 Mud Creek landslide in California. Handwerger et al. (2019) showed that the seasonal accelerations of the Mud Creek landslide could be tracked throughout the period for which radar data is available, and that a larger speed-up occurred in the months prior to the failure. An acceleration of a landslide body is considered the best indicator for a future failure; however, determining how much acceleration is indicative of impending failure remains unknown. As with the~~ Optical images have also been used to map landslides, but are significantly limited in their utility due to cloud cover, shadows and darkness. If high-resolution optical images are available, landslides are frequently mapped by hand, a process that is tedious and time consuming (e.g. Roback et al., 2018) . To speed up the production of such landslide inventories, automated and semi-automated procedures have been developed (Guzzetti et al., 2012; Fiorucci et al., 2019; Behling et al., 2014b, a; Mondini et al., 2011) . Many of the (semi-)automated methods make use of the damage that landslides cause to plants, which can be detected in multispectral optical images using vegetation indices like the Normalized Difference Vegetation Index (NDVI; Tucker (1979); Rosenthal et al. (1985)). Either of these techniques can be severely limited if good ground visibility is not provided, a situation that is particularly common after rainfall-induced landslide events.

Both radar coherence and NDVI based approaches described above offer the possibility to effectively map landslides over large regions, but so far they have been applied purely after landslide events. Here, for the first time, we used time series analysis of radar coherence and NDVI to investigate the behavior of the Mud Creek landslide ~~, unstable slopes frequently accelerate seasonally, or in response to temperature changes or precipitation, without failing catastrophically (Iverson, 2000; Seguí et al., 2020; Handw~~ ~~Here, we introduce two novel measures for assessing landslide stability : Radar coherence and NDVI ratio. We evaluate the value of these measures to provide information about the impending failure~~ in California *before* its catastrophic failure in May 2017. We generated the time series by calculating the ratios between the mean coherence (or mean NDVI) on the slide and that of the surrounding hillslope and then compared these time series to precursory deformation computed by ourselves and **?** . Finally, we assessed the usefulness of these indicators to assess landslide stability and discuss the possibility of using them at regional scales with and without prior knowledge of a landslide location.

In the following, we describe the general setting of the Mud Creek landslide ~~.~~ (Section 2) and the methodology, data selection and methodological assumptions (Section 3.1). In section 4.1 we present our findings, and in section 5 we discuss these in the context of landslide monitoring and lay out the need and opportunities for future research.

2 Study site

The Santa Lucia Mountains rise abruptly from the Pacific Ocean on California's Big Sur Coast, a geologically complex region about 150 miles south of San Francisco ~~.~~ (Fig. 1). Formed in a transpression zone of the San Gregorio-Hosgri Fault System known as the Big Sur Bend, the crest of this rugged, high-relief mountain range rises to over 1700 m asl and is never more than 18 km from the coast (Johnson et al., 2018). Geologically, Miocene marine sediments, Mesozoic to Precambrian granitic and metamorphic rocks, as well as Cretaceous-Jurassic marine sedimentary and metasedimentary rocks make up the Santa Lucia Mountains ~~(Graham and Dickinson, 1978)~~ **(?)** . The Franciscan Mélange that dominates the geology near Mud Creek consists of mesozoic graywacke sandstones, highly sheared argillite shales, metamorphosed greenstones, and conglomerates, and is well known for its highly variable, but generally low, rock strength ~~(Medley and Zekkos, 2011; ?)~~ (?California Geologic Survey) . The Mélange is overlain by unconsolidated, clay rich regolith.

~~The~~

Climatically, the Big Sur region ~~lies in~~ experiences a Mediterranean climate~~, where yearly~~ . Yearly precipitation averages around ~~$1myr^{-1}$~~ 1 m per year and typically falls between November and April. The total yearly precipitation depends strongly on the storm and drought cycles controlled by the El Niño Southern Oscillation (ENSO). Following a multi-year drought, the winter of 2016/2017 brought an extraordinary number of intense atmospheric-river driven storms to California, resulting in the state's wettest year on record (Swain et al., 2018).

The Mud Creek slide occurred on 20 May 2017, after two weeks ~~with minimal rain. It~~ of dry weather. The failure initiated at 337 m above sea level, was 490 m long, and involved roughly 3×10^6 m^3 of earth and rock (Warrick et al., 2019) . Prior to failure, the mean slope was 30° (std = 8.7°), with the steepest areas reaching 58°. Upon failing, the landslide destroyed almost half a mile of Highway 1, a vital transportation corridor for both tourism and local residents and the only direct connection between Carmel Highlands on the north end of Big Sur and San Simeon to the south. The landslide potential of this particular stretch of road became apparent only in the months preceding the slide, as accumulating debris on the road began to require near daily maintenance ~~(?)~~ (Warrick et al., 2019) . Upon recognizing the threat of an imminent landslide, the California Department of Transportation (CalTrans) evacuated all personnel and construction material from the site. Following the catastrophic failure, CalTrans commenced a $54 million project to construct a new road over the landslide deposit. The ~~highway~~ impacted highway segment was reopened on 18 July 2018, more than a year after the slide.

3 Methods and data

3.1 ~~Radar data~~

~~In this study we us SAR~~ For the analyses presented here, we worked with both radar and optical images: We used data from ESA's C-band Sentinel 1A and 1B radar satellites (5.6 cm wavelength) and processed 51 images from the ascending orbit (track 35) and 63 from the descending orbit (track 42). Single Look Complex (SLC) images were obtained from the Alaska Satellite Facility (ASF DAAC: https://search.asf.alaska.edu). Because we focused this study on pre-failure landslide dynamics, we did not include any post-landslide radar images in the analysis. To compute the NDVI, we downloaded 22 cloud-free Sentinel-2 images (10 m resolution) from the U.S. Geological Service's (USGS) Earth Explorer platform (https://earthexplorer.usgs.gov/). We used both datasets to compute time series of ratios that describe the discrepancy between the behavior of the landslide and its surrounding slope. The advantage of the ratio calculation is that it cancels out the effects of regional-scale environmental factors and processing artefacts that affect the hillslope and the landslide equally. Therefore, when using the landslide/hillslope ratio, values less than 1 indicate decreasing landslide NDVI or coherence values, while values greater than 1 indicate decreasing hillslope values. Table 1 shows an overview of the raw data products and associated derivatives (details are given in the sections below).

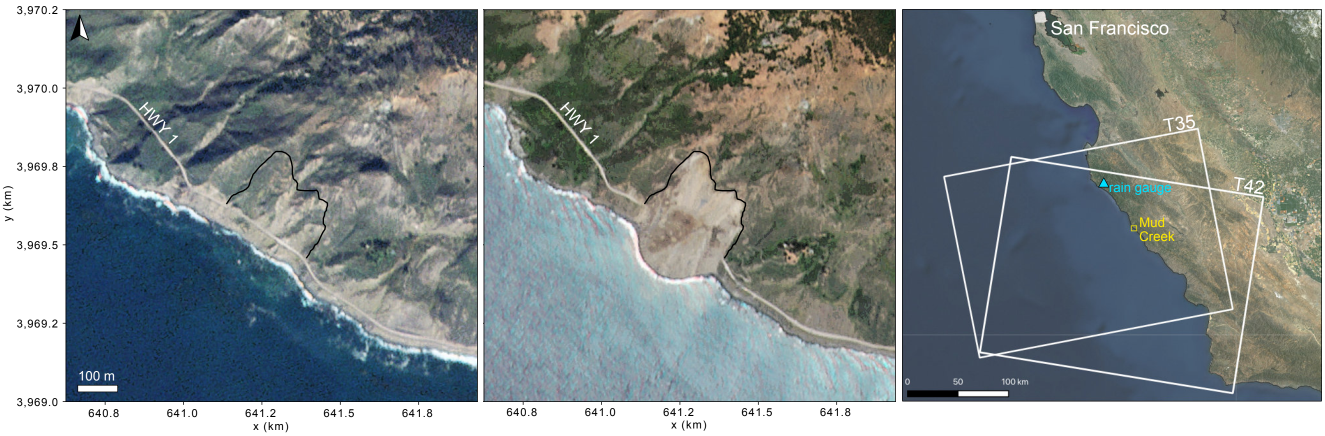

Figure 1. Big Sur coast with Highway 1 before and after the Mud Creek landslide (left and center, ~~images~~ x and y coordinates in UTM Zone 10 N. Images from ~~Copernicus Sentinel-2~~© Planet Team (2017)), and landslide and rain gauge locations and Sentinel-1 ascending (T35) and descending (T42) orbit footprints (right; basemap from ESRI World Imagery - Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community)

Table 1. Overview of data products used in this study and the number of products derived at the different processing steps.

Sentinel-1 ~~satellite to perform a traditional InSAR displacement analysis and to compute the coherence radar . SAR images contain measurements of ba~~

3.1 Radar background

Two SAR images acquired by the same satellite of a given area at different times can be processed into interferograms: images that represent the phase difference [0,2π] between the two acquisitions at each point. ~~With~~ In the initial interferogram, the phase differences contain contributions from the varying orbital geometries, topography, atmospheric path delays and surface displacements. After removing the effects of viewing geometry, topography and atmosphere, and with knowledge of the radar wavelength, these phase changes can be converted to surface displacements (e.g., Massonnet and Feigl, 1998; Rosen et al., 2000; Wasowski
Because InSAR is sensitive to deformation only in the instrument's line of sight (LOS), three independent measurements are required to obtain the true 3-D motion of a target. In the absence of independent ~~measurement~~measurements, LOS deformations can be projected onto the downslope direction by assuming that the primary motion of a landslide follows gravity ~~.~~ (see section 3.2.2 and Fig. 4).

Alongside any computed interferogram is a coherence (γ) image that serves as the primary quality indicator for InSAR data. It is a measure of how similar the ground properties are at the time of the radar acquisitions ~~(Scott et al., 2017)~~ (?Zebker and Villasenor, 199 and is computed from the local phase variance in the interferogram. ~~A loss of coherence can be due to spatial (e.g., a change of satellite viewing geometry) or temporal changes (e. g., change in surface properties like vegetation growth).~~ Given the stable imaging geometries of Sentinel-1 data, coherence changes are expected to be almost exclusively due to temporal variability. On a vegetated~~slope like Mud Creek, coherence is predominantly~~ , active landslide, coherence is likely controlled by three factors: ~~A change in the dielectric properties of the soil due to a change in soil moisture (?) , changes to the geometric characteristics of the surface due to growth or removal of vegetation (e. g., ?) , or displacement of the target that is larger than half a radar wavelength between two SAR acquisitions (Zhou et al., 2009)~~

First, coherence is affected by the surface geometry. The resulting phase of any pixel is the coherent sum of all scatterers within that pixel, and when the geometry of those scatterers changes substantially, the resulting phase changes. Therefore, both changing vegetation and erosion can lead to a loss of coherence (Massonnet and Feigl, 1998; Rosen et al., 2000; Ruescas et al., 2009) . In the non-landslide context, this is effect is visible when fields are plowed, crops are harvested, or snow falls between two image acquisitions, to name just a few examples.

Second, displacements that surpass the temporal and/or spatial aliasing thresholds, even if they do not alter the surface geometry, lead to a loss of coherence (e.g., Massonnet and Feigl, 1998; Rocca et al., 2000; ?; Wasowski and Bovenga, 2014; Manconi et al This effect can be well visible on fast moving glaciers (e.g., Joughin et al., 1996) .

Lastly, soil moisture may be affecting the coherence, because it can alter radar phase and backscatter. This effect has been shown in many studies, but the reasons for this are still debated. Soil moisture variations may change the phase response (and backscatter amplitude) by influencing the penetration depth of radar waves, with drier soils allowing deeper penetration. This influences the number of scatterers controlling the phase and backscatter amplitude in any given pixel. Therefore, interferograms created from images with varying soil moisture contents may decorrelate due to the altered number of scatterers. In addition, if soils expand or contract with changing moisture, changing the distance to the radar instrument, the phase response may also be altered, leading to lower coherence (?Rabus et al., 2010; Nolan et al., 2003; Ulaby et al., 1996) . Recent studies, however, suggest that coherence loss is better explained by the filling of pore space with water, which increases the dielectric constant, which in turn increases the wavenumber in the soil (Eshqi Molan and Lu, 2020; Zwieback et al., 2015) .

~~For our analyses, we used~~

3.2 Radar processing

We processed the InSAR data using JPL's InSAR Scientific Computing Environment (ISCE; Rosen et al. (2012))~~and processed 51 Sentinel-1 images from the ascending orbit (track 35) and 64 from the descending orbit (track 42)~~. SAR images for our study site were available ~~back to~~ beginning in April 2015, with images typically acquired every 12 days ~~. We obtained Single Look Complex (SLC)images for tracks 35 (ascending) and 42 (descending) from the Alaska Satellite Facility (ASF DAAC:)~~(a few pairs with 6 day spacing were available). We allowed for a maximum time difference of 48 days between images and produced 172 interferograms from the ascending orbit and 208 from the descending orbit (see Table 1). ~~Because of a gap~~

~~in data availability from the ascending orbit~~ A gap in the ascending data between late 2015 and early 2016 ~~, we increased~~ led us to increase the permissible time difference between images in that period to ~~6 months. This allowed us to produce a connected network of interferograms for both orbits. We multi-looked the images with~~ one year (maximum resulting temporal baseline = 342 days). Because the study site is relatively small compared to the native spatial resolution of the SAR imagery, we downsampled the images to two looks in range and one look in azimuth, and removed the topographic phase with ~~a 10m DEM obtained from~~ the USGS'~~National Map Server (~~s 1/3 arc second DEM, the highest resolution seamless DEM available for the conterminous United States (downloaded from: https://viewer.nationalmap.gov/basic/). Due to the small size of our area of interest, we did not perform any tropospheric or ionospheric corrections. We unwrapped the interferograms using the statistical-cost, network-flow phase-unwrapping algorithm (SNAPHU; Chen and Zebker (2002)) and applied a standard power spectral filter (value 0.5) to reduce the phase noise (Goldstein and Werner, 1998) . We subsequently used the generated coherence images and unwrapped interferograms for this study.

Decisions about the quality of an interferogram and the reliability of the data for time series analyses are usually based on radar coherence. For individual interferograms, pixels with a coherence of less than 0.2 are typically masked (e.g., Rosen et al., 2000) . Images with low overall coherence are ~~typically~~ usually omitted from InSAR ~~analyses.~~ time series analyses. This selection is often based on visual inspection and performed manually (e.g., **?**) . To increase the reproducibility of our work, we experimented with a set coherence threshold that we used to filter out poor quality interferograms. Because our area of interest is small relative to the size of the ~~full~~ interferogram, mean image coherence over the entire interferogram is a poor indicator for the data quality in ~~our areaof interest. Rather than manually identifying low quality images~~the landslide area. Instead, we calculated the mean coherence ~~within~~ for each interferogram within just our area of interest ~~for each interferogram~~ and only retained images with a mean coherence above a defined threshold ~~. We then computed~~ (0.35 for the displacement analysis and 0.5 for the coherence ratio analysis; see details in sections 3.2.2 and 3.2.1). Fig. 2 illustrates why relatively aggressive filtering is necessary for the ratio calculations. If the entire area of interest is affected by low coherence, the ratio becomes meaningless. After filtering, we computed the time series of displacement ~~,~~ and radar coherence ratio ~~and amplitude ratio~~ from all the retained images.

~~Overview of data products used in this study and the number of products derived at the different processing steps. Product Raw images Cloud-free NDVI images Interferograms Ratio processing Displacement processing Sentinel-2 23 22-22 -Sentinel-1 ascending 35 - 172~~

3.2.1 Coherence ratio

To construct a time series of coherence evolution, we filtered out all interferograms with mean coherence of less than 0.5 in our area of interest (Fig. 2). This higher threshold was necessary to detect any differences between the unstable part of the slope and the surrounding area. In cases where the coherence of the entire area is low, the ratio value becomes meaningless. We retained 132 ~~-Sentinel-1 descending 42 - 208~~ interferograms from the ascending track and 141 ~~193~~ interferograms from the descending track after applying this filter criterion (Tab 1).

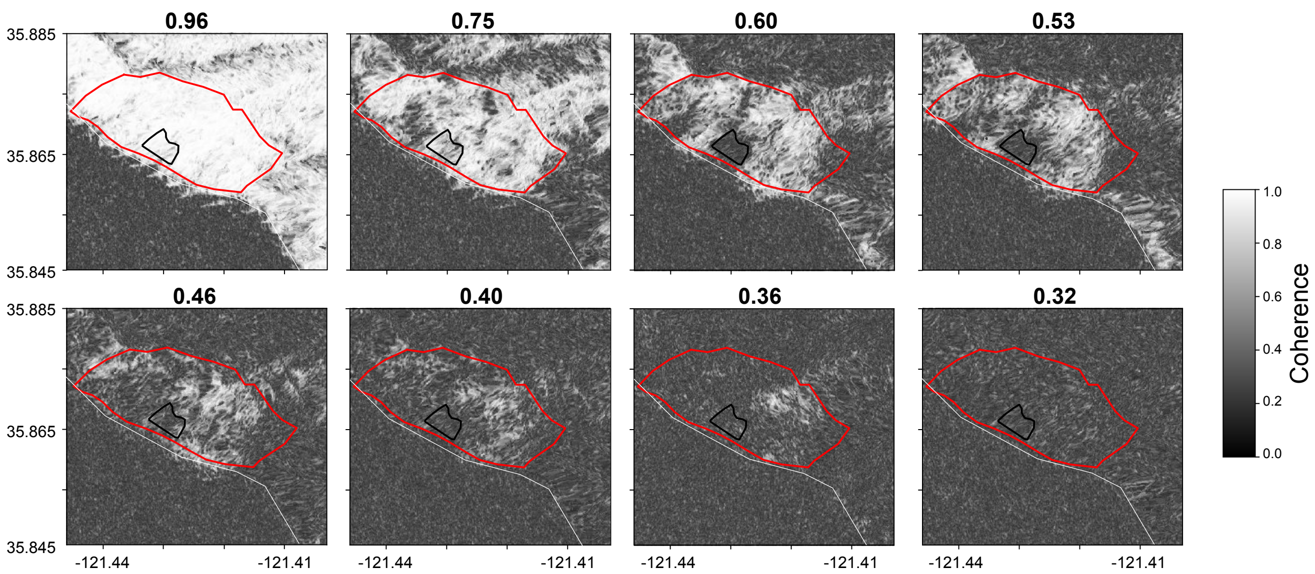

Figure 2. Coherence filtering: Interferograms in the upper row exceed the coherence threshold of 0.5 and were therefore included in the ratio analysis, the images in the lower row were excluded. We calculated the mean coherence for the area in the red polygon. The images represent various times throughout the the two year period for which data was available and were chosen purely to show why low mean coherence images cannot be used for the ratio calculation. The 20 May 2017 landslide occurred inside the black outline (corresponding to dashed gray line in Fig. 8). Coherence derived from Copernicus Sentinel-1 data.

ISCE computes coherence using a 5 x 5 pixel triangular weighted window. For signals s_1 and s_2, coherence is given by

$$\gamma = \frac{|\langle s_1 s_2^* \rangle|}{\sqrt{\langle s_1 s_1^* \rangle \langle s_2 s_2^* \rangle}} \qquad 0 \leq |\gamma| \leq 1, \tag{1}$$

where * indicates the complex conjugate (Jung et al., 2016) .

We created a time series of radar coherence ratio (C_R) by calculating the ratio between the mean coherence over the slide (the area that ultimately failed) and the mean coherence over the surrounding slope (termed Reference Slope, see Figure 3) as:

$$C_R = \frac{\overline{\gamma}_{Slide}}{\overline{\gamma}_{RefSlope}} \tag{2}$$

Figure 3 shows the evolution of the coherence in the area of interest as well as the polygons used to calculate the mean coherence on the slide and the surrounding hillslope for four interferograms acquired in the fall of 2016 and spring 2017. For the slide polygon, we mapped the area that failed in the landslide. The reference hillslope was mapped as the area immediately surrounding the landslide with similar slope, aspect and vegetation cover.

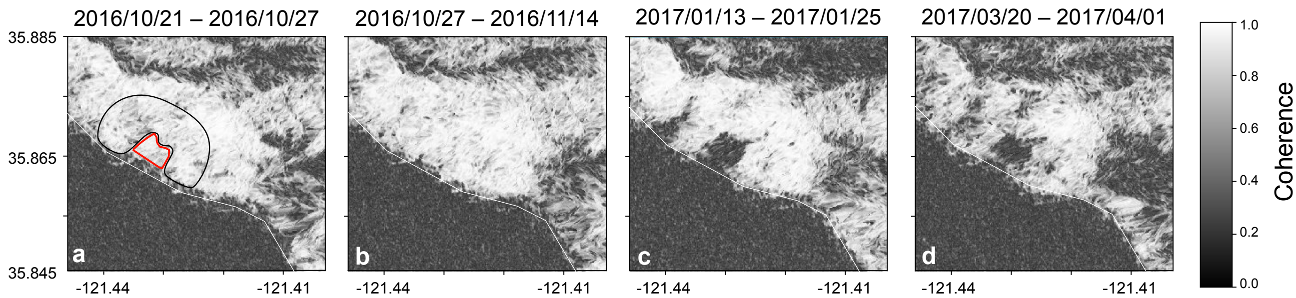

Figure 3. Interferometric coherence of the Mud Creek landslide and surrounding slope in Fall 2016 (a & b) and Spring 2017 (c & d). the landslide outline is marked in red, and the coherence loss in that area is clearly visible in panels c and d. The reference hillslope is outlined in black. Coherence derived from Copernicus Sentinel-1 data.

3.2.2 Displacement

~~To produce~~ To complement the coherence ratio time series we also computed a displacement time series. For this part of the analysis, we used only ~~data~~ the interferograms from the descending track ~~and removed all interferograms with~~ that had a mean coherence of ~~less~~ more than 0.35 in our area of interest. This produced a fully connected time series with 193 interferograms ~~.~~ (Tab. 1). The ascending data does not lend itself to measuring the displacement because the local incidence angle is around 90°, leading to minimal motion in the satellites line of sight. We selected a point ~~just south~~ west of the landslide as our stable reference region~~and computed a~~. This area is the same geologic unit, its vegetation cover is representative of the larger area, and it did not fail in the landslide. A preliminary displacement analysis also suggested it had not experienced any significant deformation. We computed the displacement time series using the ~~NSBAS~~ New Small Baseline Subset (NSBAS; Berardino et al. (2002)) method implemented in JPL's Generic InSAR Analysis Toolbox (GIAnT; Agram et al. (2013)) ~~. We~~ and applied a coherence threshold of 0.3 to mask individual low coherence pixels. We then retrieved surface displacements by projecting the measured line of sight deformation at each point onto the fall line. To do this we defined the unit line of sight vector a to point from the satellite to the target and the unit fall line b to point from target down slope along the steepest gradient. We describe both vectors in a polar coordinate system where θ describes a positive counter-clockwise rotation from x (east), and ϕ describes the angle from positive up (Fig. 4). The full slope parallel deformation D_t could then be retrieved as

$$D_t = \frac{LOS}{cos(\delta)}, \tag{3}$$

where LOS is the measured line of sight deformation and δ is the angle between a and b, which is defined as:

$$cos(\delta) = \frac{a \cdot b}{|a||b|} \tag{4}$$

3.2.3 ~~Amplitude and coherence ratios~~

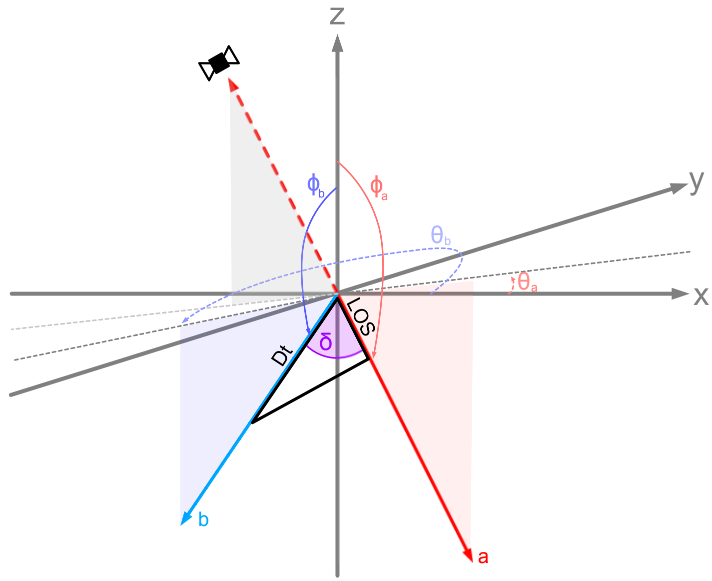

Figure 4. Vector geometries used to project measured ~~line-of-sight~~ line of sight displacements (LOS) onto the fall line (b). For a and b, θ describes the azimuth from x (East) and ϕ describes the angle from positive up. The angle δ between a and b, controls how much of the true deformation is visible in the satellites LOS.

~~To construct a time series of coherence and amplitude evolution, we filtered out all interferograms with mean coherence of less than 0.5 in our area of interest (Fig. 2). This higher threshold was necessary to detect any differences between the unstable part of the slope and the surrounding area. We retained 132 interferograms from the ascending track and 141 interferograms from the descending track after applying this filter criterion.ISCE computes coherence using a 5 x 5 pixel triangular weighted window. For signals s_1 and s_2, coherence is given by~~

$$\gamma = \frac{|\langle s_1 s_2^* \rangle|}{\sqrt{\langle s_1 s_1^* \rangle \langle s_2 s_2^* \rangle}} \qquad 0 \leq |\gamma| \leq 1,$$

~~where * indicates the complex conjugate (Jung et al., 2016) .We created a time series of radar coherence ratio (C_R) by calculating the ratio between the mean coherence over the slide (the area that ultimately failed) and the mean coherence over the surrounding slope (termed Reference Slope, see Figure 3) as:~~

$$C_R = \frac{\overline{\gamma}_{Slide}}{\overline{\gamma}_{RefSlope}}$$

~~Equivalently, we computed the amplitude time series as~~

$$A_R = \frac{\overline{\sigma}^0_{Slide}}{\overline{\sigma}^0_{RefSlope}},$$

~~where $\overline{\gamma}_{Slide}$ and $\overline{\sigma}^0_{Slide}$, and $\overline{\gamma}_{RefSlope}$ and $\overline{\sigma}^0_{RefSlope}$ are the mean values of radar coherence and backscatter over the slide and reference slope, respectively. The reference slope was determined from optical images and a DEM to include the surrounding hillslope with similar aspect and vegetation pattern. Figure 3 shows the evolution of the coherence on the slide and surrounding hillslope for four interferograms acquired in the fall of 2016 and spring 2017.~~

~~Example of coherence filtering for interferogram selection with a threshold of 0.5 within the area of interest (red polygon). The upper row of interferograms is included to compute the coherence ratio, the lower row is not. The computed mean coherence is given above each panel. The 20 May 2017 landslide occurred inside the black outline (corresponding to dashed gray line in Fig. 8). Coherence derived from Copernicus Sentinel-1 data.~~

~~Interferometric coherence of the Mud Creek landslide and surrounding slope in Fall 2016 (a b) and Spring 2017 (c d). The coherence loss in the area from which the May 2017 failure originated is framed by the red rectangle. The reference hillslope is outlined in black. Coherence derived from Copernicus Sentinel-1 data.~~

3.3 ~~Optical data~~

~~To investigate whether coherence changes were~~

3.3 Optical data

To investigate the extent to which coherence variability may have been driven by changes in vegetation cover, we computed a time series of Normalized Difference Vegetation Index (NDVI) ~~,~~ from 22 ESA Sentinel-2 optical images (Tab. 1) acquired between 4 December 2015 and 27 May 2017. NDVI is a measure of vegetation productivity that can be derived from ~~optical satellite imagery . NDVI was computed from~~ the red and near infrared (NIR) channels in optical imagery (bands 4 ~~(red)~~ and 8 ~~(near infrared) of ESA's~~ in Sentinel-2~~(10m resolution)as~~):

$$NDVI = \frac{B8-B4}{B8+B4}\frac{NIR-red}{NIR+red} \tag{5}$$

~~By design, NDVI~~ NDVI makes use of the fact that photosynthetically active vegetation is bright in the near infrared spectrum ($\lambda \sim$800 nm) and dark in the red wavelengths ($\lambda \sim$600 nm; Tucker (1979); Carlson and Ripley (1997)). The index values vary between -1 and 1, where denser and/or more productive vegetation results in more positive values and sparse vegetation or bare ground results in low or negative values. Typical values for dense, healthy vegetation are around 0.6, values for bare ground or minimal vegetation are typically below 0.2 (Jensen, 2009) . We calculated the NDVI for all available cloud-free images back to ~~January 2016~~ December 2015 and then computed our time series in the same manner that we did for ~~the amplitude and~~ coherence ratios:

$$NDVI_R = \frac{\overline{NDVI}_{Slide}}{\overline{NDVI}_{RefSlope}} \tag{6}$$

In addition to the time series of NDVI ratio, we thresholded all NDVI images at a value of 0.25 and investigated the spatial changes through time.

3.4 Precipitation data

Precipitation data were obtained from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climate Network Daily (GHCND) ~~stations.~~ platform. GHCND data provide daily total cumulative precipitation and minimum and maximum air temperature. The Big Sur Station station is located 53 km north-west of Mud Creek at 61 m asl. Data is available from https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USC00040790/detail and were used without any additional processing.

4 Results

4.1 ~~Deformation~~

~~Because InSAR only detects the component of motion in its line of sight, the local incidence angle critically controls how much motion the radar can see. At Mud Creek, the radar's line of sight on the ascending orbit intersects the fall line at a near right angle in most places, impeding the detection of downslope motion. On the descending orbit, the line of sight intersects the fall line at more favorable angles, allowing us to retrieve about 50% of the total displacement.Figure 8 shows the slope parallel displacement obtained from the descending track. The total cumulative displacement on the Mud Creek landslide since April 2015 (beginning of Sentinel-1 measurements) range from ~0.15m to ~0.55m. The displacement time series at three different points on the slope all show moderate spring to early summer speed-ups in 2015 and 2016, followed by a large acceleration in 2017. The area showing measurable displacements is somewhat larger than the area that failed on May 20th, but smaller than the area that consistently showed low coherence in the months preceding the landslide (Fig 8).~~

~~Left: Cumulative line of sight displacements from April 2015 to May 2017 projected onto the fall line. Right: Time series of displacement at three different points within the slide (indicated by the ★, × and + signs). The white line indicates the extent of the slope that failed, the dashed black line the area showing significant displacement, and the dashed grey line the area of low coherence.~~

4.1 ~~Amplitude coherence ratios~~Coherence ratio

The results of coherence ~~, amplitude, and NDVI ratios~~ ratio analysis are shown in ~~Figures 5and ??~~Fig. 5, alongside the NDVI time series and the precipitation record. The 132 good quality interferograms from the ascending orbit form a mostly-continuous time series, though there was a gap in data acquisition in late 2015 and early 2016. The descending track offers a more continuous time series between 2015 and early 2017 (longest temporal baseline = 48 days), but few interferograms ~~in~~ from 2017 passed the coherence threshold. ~~Until early 2017,~~ The coherence ratio hovers around 1 ~~, indicating that changes in coherence affect both the slide and the reference slope similarly~~throughout the dry seasons in both datasets. In spring 2016, following a short period of intense rainfalls, the coherence ratio calculated from ascending data drops to around 0.8 and only recovers slowly. This drop is less distinct in the descending data. Then, coincident with ~~the large increases~~ a large increase in cumulative precipitation ~~, a stark drop in coherence ratio of around 0.4 (or -50%) occurs in early 2017. The amplitude time series on both the ascending and descending tracks show some seasonal trends, but there is no clear difference between~~ in early 2017~~and earlier years. It appears that there is little difference between the backscatter received from the slide body and the surrounding slope in the descending track. Conversely, the backscatter received from the slide body on the ascending track is higher than that of the surrounding slope.~~ , the coherence ratio drops markedly to around 0.6 and does not recover until the catastrophic failure of the landslide.

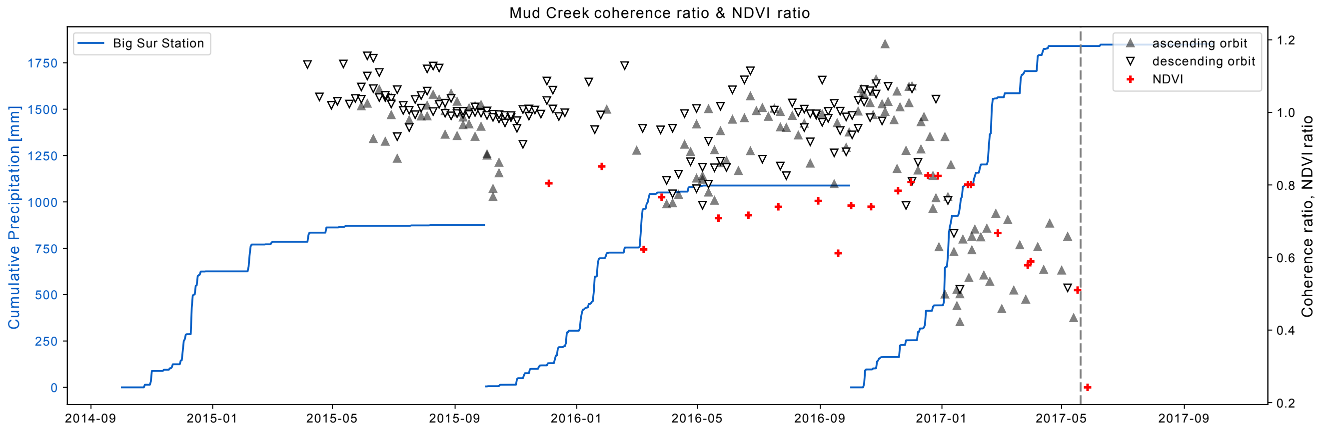

Figure 5. Radar **coherence** ratio plotted against NDVI ratio and cumulative precipitation (at Big Sur Station). The dashed line indicates the timing of the landslide. The coherence-ration hovers around 1 for most of the time prior to the failure, before dropping starkly in January 2017. At the same time, the NDVI ratio begins a gradual decline. A similar behavior for both indices is visible in March 2016.

~~Radar **amplitude** ratio plotted against NDVI ratio and cumulative precipitation (at Big Sur Station). The dashed line indicates the timing of the landslide.~~

4.2 NDVI

The ~~average NDVIratio~~ NDVI, NDVI ratio, and the changes in the spatial pattern also show that processes ongoing on the landslide differed substantially from the surrounding slope. The NDVI ratio of 0.8 prior to 2017 indicates that the Mud Creek slope is generally less densely vegetated than the surrounding ~~hillside. However, starting in early 2017, the gradual decline of the NDVI ratio indicates that vegetation cover within the slide area was degrading. In addition to the ratio time-series, we computed the mean NDVI for the slide area and the reference slope separately to ensure that the evolution of the NDVI ratio is in fact controlled by a decrease of vegetation productivity on the slide and not an increase of productivity on the reference slope (Fig~~hillslope (Fig. 5). This observation is also supported by the raw NDVI time series which indicates that NDVI values on the landslide vary seasonally between around 0.2 and 0.4, while ranging from about 0.25 to 0.5 on the surrounding hillslope

(Fig. 6). These individual time series reveal that the evolution of the vegetation cover on the slide closely paralleled that of the ~~reference slope in~~ surrounding slope throughout 2016, with productivity peaking in April. In early 2017, we observe a clear divergence of the two ~~curves~~time series, as vegetation productivity in the slide area began to decline, before plummeting post-slide. ~~We also observe a single outlier in April 2016, where the NDVI~~ These time series demonstrate that the evolution of the NDVI ratio is in fact controlled by a decrease of vegetation productivity or coverage on the slide ~~exhibited a sudden drop, not seen on the surrounding slope . Incidentally, this drop coincided with the~~ and not an unusual increase of productivity on the reference slope (Fig 6). The gradual decline of the NDVI ratio starting in early 2017 therefore suggests that vegetation cover on the landslide was degrading. When comparing this to the spatial evolution of NDVI values, it is evident that low NDVI regions on the slide were expanding throughout the spring of 2017, driving the decrease in mean NDVI. A low NDVI area, which can be attributed to a steep gully, is consistently present in the center of the slide (see panel typical pattern in Fig. 7). The panel from March 8 in Fig. 7 shows that the drop in NDVI ratio observed in spring 2016 ~~acceleration reported by (Handwerger et al., 2019) .~~ can also be linked to a large expansion of the low NDVI area (Fig. 5). This drop also corresponded to one of the largest rainfall events witnessed that year. The low NDVI ratio in September 2016 is caused by a cloud bank obscuring the toe of the slide, and is therefore not associated with an actual change of vegetation. Then, throughout the spring of 2017, the low NDVI values expanded, driving the decreasing mean NDVI until all vegetation was removed due to the failure of the slope (see post-slide image from 27 May 2017 in Fig. 7).

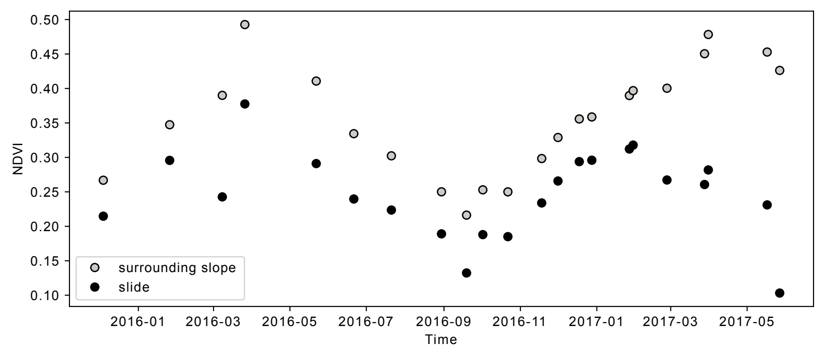

Figure 6. NDVI on the Mud Creek slide body and the surrounding slope. Note that the last data point in May 2017 is from an image acquired after the landslide.

4.3 Deformation

On the descending orbit, the line of sight intersects the fall line at a favorable angle that allows us to retrieve about 50% of the total displacement. To retrieve a more accurate record of true deformation we projected the measured line of sight displacements onto the downslope direction as described in equations 3 and 4.

Figure 7. NDVI on the Mud Creek landslide. The first panel shows the pattern that is typical (example from 26 March 2016). The 8 March 2016 panel corresponds to the dip in NDVI ratio visible in early 2016. The area of low NDVI grows ever larger during the spring of 2017, before much of the vegetation is removed during the landslide (post-slide image from 27 May 2017).

Figure 8 shows the slope parallel displacement obtained from the descending track. The total cumulative displacement on the Mud Creek landslide since April 2015 (beginning of Sentinel-1 measurements) ranges from ∼0.15 m to ∼0.55 m. The displacement time series at three different points show the large acceleration that took place in spring 2017. The time series from the reference region (solid line in Fig. 8) confirms that the area around the landslide was stable throughout the entire time period. At several points in time, the cumulative displacement reverses direction, indicating that unwrapping errors hamper the retrieval of the true displacement. This behavior is particularly obvious during the 2017 speedup, but also during the spring of 2016 (line with stars if Fig. 8). The area showing measurable displacements is somewhat larger than the area that failed on May 20th, but smaller than the area that consistently showed low coherence in the months preceding the landslide (dashed lines in Fig 8).

5 Discussion

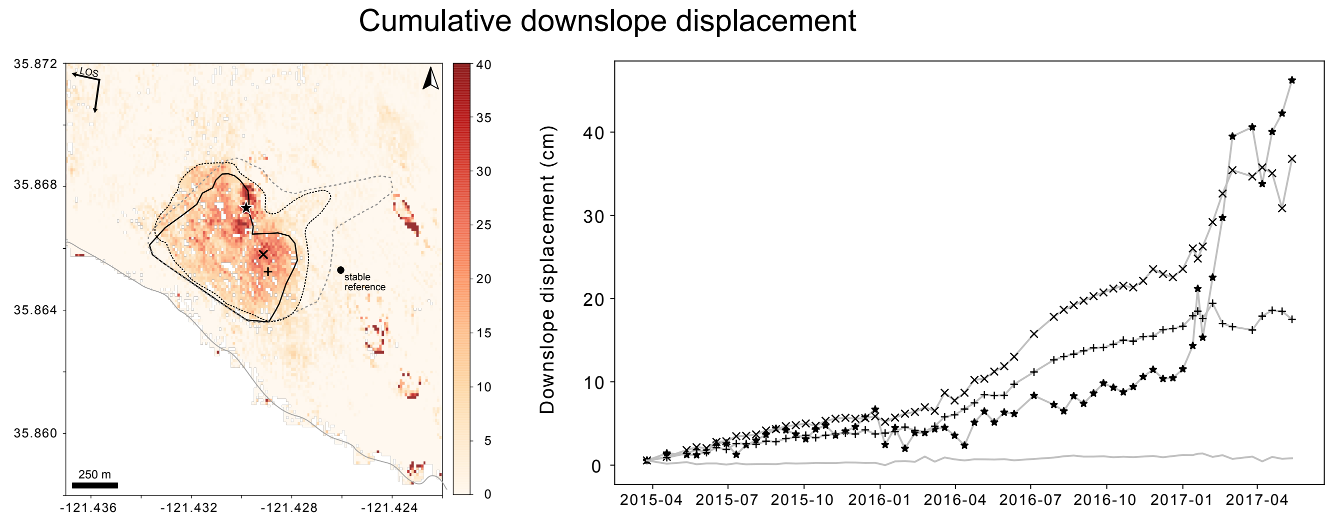

Figure 8. Left: Cumulative line of sight displacements from April 2015 to May 2017 projected onto the fall line. The solid black line indicates the extent of the slope that failed, the dashed black line the area showing significant displacement, and the dashed grey line the area of low coherence. Right: Time series of displacement at three different points within the slide (indicated by the ★, × and + signs) as well as in the region used as stable reference (solid line).

~~Identifying slopes prone to catastrophic failure, or forecasting when a known landslide will fail, remains a largely unsolved challenge.~~ Five months before its final failure, in conjunction with some of the largest rainfall events measured during California's 2016/2017 winter season, the coherence ratio over the Mud Creek landslide dropped ~~by 50%~~suddenly. At the same time, the NDVI ratio began a near linear decline (see Figure 5). These data raise the question of ~~what such observations reveal about the driving processes and /or whether they can be valuable indicators of impending landslides~~how and if they can useful indicators of landslide activity, what challenges this new analysis poses, and what its limitations are.

~~Even where the location of a landslide is known, reliable predictions of the anticipated failure time have only been achieved in a few cases (Intrieri et al., 2019; **?**) , and typically require ground-based measurements of displacement rates. As in many cases, the deformation of the~~

The fact that fewer interferograms from the descending track passed the coherence threshold can likely be explained by the differences in viewing geometries: The ascending track is right-looking, causing the radar waves to intersect the hillslope at a near right angle. Conversely, on the descending track (also right looking), the radar waves intersect the hillslope at an oblique, near surface-parallel angle. This oblique viewing geometry makes the radar waves more susceptible to volume scattering on vegetation (Massonnet and Feigl, 1998) . Indeed, we see wide-spread areas of low coherence during the growing season in the data from the descending track. Unfortunately, the period leading up to the landslide is most impacted by this effect, while data from the ascending track is much less affected. Despite this discrepancy, the pre-failure coherence drop is visible in the data from both orbits. The coherence loss therefore cannot be attributed to geometric differences, but must represent a change on the ground.

The power of the ratio calculation lies in its capability to cancel out negative effects of long temporal baselines, as well as regional atmospheric and environmental changes. If the slope and surrounding hillslope have similar scattering properties, then environmental and atmospheric changes that affect InSAR coherence (e.g., vegetation cycles, precipitation events, ionospheric disturbances) will not differ between a landslide and its surrounding slopes. At Mud Creek, this similarity is given because neither of the slopes are used for agriculture, nor is there any form of human development. Furthermore, both slopes cover a similar altitude range, slope and aspect; optical images suggest they have a very similar vegetation cover (Fig. 1); and the geologic map of the area indicates that the entire area is part of the Franciscan Mélange (California Geologic Survey) . In this manner, as long as coherence is maintained in some part of the area of interest, interferograms with varying temporal baselines can be compared to gain insight into governing processes.

The drop of the coherence ratio in the time series is a clear indicator of ongoing changes by itself, but is useful to consider what factors might be driving these changes in order to understand the value of the coherence ratio with regard to assessing landslide activity. The coherence images (Fig. 3) show clearly that the coherence on the slide dropped drastically, therefore we attribute the effect of the dropping ratio entirely to changing conditions on the slide. However, the change in coherence could be caused by changes to soil moisture, vegetation changes, erosion and active deformation - all of which are processes that may be ongoing on an actively deforming slope that ultimately failed due to increasing pore water pressure (**?**) . As we try to parse out the different influences on coherence ratio, it is important to note that more than one factor may be the leading cause at any given time, and their relationship may vary through time. Disentangling the causes of the coherence drop is therefore by no means straightforward.

The NDVI ratio began its near linear decline in the spring of 2017, concurrent with peak precipitation and the observed drop in the coherence ratio. Fig. 6 clearly shows that the drop of the NDVI ratio can be attributed to changes that are occurring on the slide and not on the surrounding slope. Indeed, during the spring of 2017, more and more pixels in the slide area showed an NDVI of less than 0.25, indicating that the removal or degradation of healthy vegetation was impacting a larger and larger area. However, the pattern seen on 17 May 2017, just three days before the failure, hardly differs from that on 8 March 2016, suggesting that the Mud Creek landslide ~~was only investigated after the failure (Handwerger et al., 2019, 2015) . While this practice provides important insights into landslide mechanics, it does not provide advance warning that can be used to mitigate damage. As Handwerger et al. (2019) show, unwrapping errors~~ had experienced this type of vegetation degradation before. Given this similarity, is likely that the same process led to the low NDVI in 2016 and in 2017. The fact that in 2016 the NDVI ratio recovered within just 18 days (8 March to 26 March) suggests that vegetation was not completely removed. If vegetation was not, or only partly, physically removed, covering of plants with mud from ongoing erosion could explain the low NDVI. Whether the vegetation cover was destroyed or just coated in mud, both processes point to an increased activity of the landslide.

The deformation analysis of the Mud Creek landslide shows a significant acceleration prior to failure. However, the displacement time series presented here fails to pick up the period of acceleration in 2016 reported by **?** . This is not surprising given that unwrapping errors, the effect of which we see throughout the time series, can make measuring the true surface velocities particularly difficult for fast moving and accelerating landslides ~~. Because radar measurements only reveal phase changes in modulo 2π, a displacement of π looks identical to one of 3π.~~ (e.g., ?Dai et al., 2020; Manconi et al., 2018) . Unwrapping errors can be reduced by subtracting the mean landslide velocity prior to the phase unwrapping~~. This~~ , which can reveal the missing phase cycles and help recover more of the true deformation ~~(Handwerger et al., 2015, 2019)~~ (Handwerger et al., 2015; ?) . However, this approach requires assessing each landslide individually, and does not lend itself to automatic processing at large scales. We did not apply a correction to subtract the mean landslide velocity and are therefore not able to recover the full deformation. ~~In particular, we cannot recover the acceleration in 2016 due to unwrapping errors that mask the true acceleration that year.~~ Nevertheless, our ∼0.6 m cumulative surface displacement measurements are in good agreement with the ∼0.8 m reported by ~~Handwerger et al. (2019)~~ ? , and the temporal displacement ~~patters~~ patterns beyond 2016 are nearly identical. ~~Thus acceleration prior to the failure is therefore detectable, even if a landslide velocity model is not applied. This suggests that InSAR-derived surface displacements can be used to identify slope instabilities; however, the significant impact of the unwrapping errors highlight that such an approach is not without challenges and may not yield reliable results. Our time series of coherence ratios indicates that a more systematic analysis of these data might provide valuable information for landslide detection and warning. The premise is that general environmental and atmospheric changes (e.g., vegetation cycles, meteorologic storms, ionospheric disturbances) affecting InSAR coherence should not vary between a landslide and its surrounding slopes. If they do, then we should be able to link that difference to changes on the ground. The observed loss of coherence is likely to be caused by one or more factors influencing coherence : Changes to the dielectric constant of the ground, the local surface geometry, or an acceleration of the slope, and we currently can not parse out the contributions of the different factors in detail. However, we can draw on amplitude, NDVI ratios and displacement to shed some light on the temporal evolution of the coherence ratio : Changes of soil moisture alter the dielectric constant of soil, which can lead to a loss of coherence. Moister soils are typically associated with higher radar backscatter (Oldak et al., 2003; Paloscia et al., 2013) . The amplitude time series indicates that average backscatter from the slide body was slightly higher (ascending orbit) or equal (descending orbit) to that of~~

Several factors likely contributed to the changes of the coherence ratio, but we can draw on NDVI and displacement data to discuss what the most likely drivers are, and how they relate to landslide activity. In 2016, the NDVI ratio showed a notable drop following the largest rain events that year. This was subsequently followed by a visible drop in the coherence ratio, at least in the data from the ascending track. In 2016, however, the ~~surrounding slope. However, there is no discernible trend that sets~~ NDVI ratio quickly bounced back, and the coherence also improved again. In 2017, the NDVI continued to decline and the coherence ratio never rebounded. Both the period in 2016 and the one in 2017 ~~apart from previous years. We interpret these data to show that the Mud Creek slide may have been slightly wetter than the surrounding slope, but that this difference is not significant, and does not seem to persist into~~ were associated with increased displacement). The primary difference between the two periods is that in 2016, the high precipitation events were limited to a short period, while a series of large magnitude rainfall events occurred throughout the spring of 2017. ~~The NDVI ratio began its near linear decline concurrent with an observed the reduction in the~~ This suggests that rainfall is inherently linked to the evolution of the NDVI ratio and the coherence ratio. ~~However, the NDVI decline is gradual, indicating that the change of vegetation cover - and therefore the surface geometry~~

~~- was not sudden. This observation is supported by the reported, continuous sloughing off of vegetation and debris during spring 2017 (?)~~ The NDVI patterns show that vegetation cover degraded near-linearly, but we only have a few snapshots in time, and can't reconstruct the immediate responses to increased precipitation. However, both burying vegetation or removing it will alter the surface geometry in such a way that radar coherence is likely reduced. The removal of vegetation decreases root cohesion ~~(e.g., Schmidt et al. (2001)), promoting~~ (e.g., Schmidt et al., 2001) , which may have promoted additional surface erosion, ~~which would also contribute to an altered surface geometry. Finally,~~ and also contributed to a change of the slope's scattering processes. The high displacement rates observed in early 2017 can also have contributed to the loss of coherence by ~~surpassing the amount that can be unambiguously determined with InSAR. Combined, these data suggest that, initially, the stark coherence loss may have been driven by the acceleration of the slope in early 2017. Following the initial acceleration, the degradation of the vegetation cover throughout the spring of 2017 may be responsible for and /or have contributed to coherence ratio remaining low until the final failure~~overcoming the temporal and spatial aliasing thresholds for displacement measurements.

~~The discrepancies~~ Importantly, there is a noteworthy discrepancy between the low coherence area, the area that exhibits measurable surface displacements and the area that ultimately failed~~indicate that neither displacement nor vegetation degradation can fully explain the low coherence values; since neither of the two changes~~ . The area affected by low coherence is by far the largest, suggesting that, since neither vegetation loss nor large displacements were observed in these peripheral areas of the low coherence region (Fig. 8)~~. This observation highlights the need to estimate the individual contributions of different factors to~~ , soil dielectric property variations are the only remaining factor that may have driven the drop in coherence ratio. This change could be expected to affect the landslide and the stable hillslope similarly, but ultimately the area that failed laid entirely within the low coherence area. It is not possible to fully disentangle the causes of the coherence drop, ~~especially their temporal evolution and interplay.~~ but in the landslide context it seems possible that soil moisture changes were more pronounced on this particular part of the hillside, changing the scattering properties of the ground and possibly driving increased surface erosion, vegetation degradation, and active slope deformation, which in turn, also altered the scattering properties. Combined these changes indicated increased landslide activity and announced the impending failure.

~~A main~~

This is, to our knowledge, the first time that coherence ratios and NDVI ratios were used to assess the activity of a landslide prior to its failure. The main advantage of the coherence ratio is that it does not require the computationally expensive unwrapping step in InSAR processing, and that it reduces some of the difficulties presented by long temporal baselines. Coupling the coherence ratio analysis with the NDVI ratio links the coherence changes to potential physical changes contributing to the instability. Had the Mud Creek landslide been monitored using these indices, both the 2016 and 2017 drops of the coherence and NDVI ratios could have indicated the increasing landslide activity and prompted the deployment of more precise, possibly ground based, measurements. Given that this study presented the first analysis of this kind, many open questions remain and deserve further investigation:

1. Additional (case) studies are needed to determine which types of landslides may exhibit this kind of behavior and how much deviation from the "stable" ratios indicates substantial changes. While coherence changes may affect any hillslope,

regardless of ground cover (with the exception of heavily built up areas), NDVI ratios are not useful in areas that are completely devoid of vegetation (e.g., high alpine or arctic areas). Since NDVI has a tendency to saturate over very dense vegetation (Lillesand et al., 2015) , the limits of this indicator should also be investigated for highly vegetated slopes. Different vegetation indices might be more suitable depending on the situation.

2. Future analyses should determine optimal thresholds for coherence-based filtering thresholds are. In order to select the interferograms that contained enough information for the ratio calculation we applied a coherence threshold of 0.5. For simplicity, we opted for applying the same threshold for both the ascending and descending datasets, but recognize that this threshold was selected somewhat ambiguously and based purely on visual inspection of the interferograms.

3. A major disadvantage of relying on surface displacements for assessing landslide activity remains the viewing geometry. As in the ~~the~~ case of the ascending track at Mud Creek, unsuitable viewing geometries can significantly impede displacement measurements. In contrast, ~~we note that~~ the coherence data from the ascending track - the track that is not well suited to measure surface displacements - ~~provide~~ provided the more continuous time series of coherence ratio during the spring 2017 acceleration. We stress this fact because radar data affected by layover is frequently deemed unworthy of use in these applications (e.g. **?**Wasowski and Bovenga, 2014; Ohki et al., 2020) . The ascending data over Mud Creek is not excessively impacted by this, but the effects are nevertheless visible in the data. Yet the ascending track provides the more useful coherence ratios for this study. Therefore, a systematic analysis of radar coherence may complement traditional InSAR measurements in valuable ways. ~~The radar coherence ratio remained steady during the acceleration phases in 2015 and 2016 which were followed by renewed stabilization of the slide. In 2017, during the acceleration period that preceded catastrophic failure, the coherence ratio experienced a step decrease five months prior to failure, while the NDVI ratio showed a linear decline; it is unclear whether the momentary NDVI drop in 2016 was due to the slope acceleration that year. It is evident that NDVI ratios are limited to vegetated slopes, and a more in-depth analysis of NDVI ratio and coherence ratio at multiple landslide sites is necessary to assess their full value. Nonetheless, both the coherence and NDVI approach are simple to compute and could be applied at large scales. Such techniques would be especially beneficial in areas where InSAR-derived pre-failure acceleration is difficult to resolve.~~

4. The separation of the different factors controlling the coherence drop remains somewhat unsatisfactory. Future studies should be aimed at improving this understanding, potentially with the help of polarimetric SAR data that can separate the different scattering mechanisms (Ferro-Famil et al., 2016) .

5. We focused solely on the temporal evolution of the ratio between areal mean values, but more insight can likely be gained if investigations are carried out at the pixel or cluster-of-pixels level. This insight could also help identifying what is driving the changes in the mean values.

6. Lastly, in order to perform the ratio calculation, the location and extent of the landslide need to be known beforehand. For now, this limits the current applicability of this indicator to previously identified landslides. However, we believe

that intelligent tracking of the behavior of clusters of pixels through time, relative to their surroundings, could be useful for delineating unstable slopes and is worthy of further investigation.

6 Conclusions

Radar coherence has long been used to assess areas of damage after natural catastrophes, but the value of radar coherence ~~as a possible predictor~~ or NDVI as possible indicators for impending landslides has not yet been studied. In this study we showed that time series of radar coherence ratio and NDVI ratio may be able to ~~distinguish a non critical acceleration of a landslide from one leading to failure many months in advance~~serve as a proxy for landslide activity. Comparatively easy to compute, radar coherence ratios have the potential to be generated at large spatial scales to ~~identify~~ monitor unstable slopes. ~~We believe that~~ In particular, if a few criteria are met, the ratio calculation between the surrounding slope and the landslide eliminates interference due to temporal coherence loss, atmospheric disturbances, or vegetation cycles. Our analysis also indicates that this type of analysis can fill data gaps in places where data from only one orbit are suitable for deformation measurements. Nevertheless, questions around whether it is possible to fully disentangle the different factors leading to the pre-failure coherence loss and how common this kind of signal is for different kinds of landslides remain to be resolved. Similarly, it is worth investigating how the presence of more or less vegetation and use of different radar wavelengths influence the results. We also believe that it could be possible to automatically identify drastic drops in radar coherence ratios and NDVI ratio decreases, suggesting that this tool could be used to identify impending failures. All things considered, we strongly believe that the encouraging initial results presented here motivate further investigations of these ~~new~~ parameters.

Code availability. https://github.com/mjacqu/MudCreek

Author contributions. Mylène Jacquemart designed the study, processed and analyzed the data, and wrote the manuscript. Kristy Tiampo supervised the work.

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