We want to thank the reviewers for their continued support, detailed comments, and valuable recommendations. Each suggestion was discussed in detail, and we have rewritten the paper accordingly. And, we have improved the clarity and correctness of phrasing throughout our manuscript. Please find below our detailed response to the comments of the anonymous referees.

Anonymous Referee #1

General comment

The authors integrate remote sensing products (Normalized Difference Vegetation Index, land surface temperature, and precipitation), meteorological observations (nearsurface air temperature and precipitation), and crop yield data to assess the impacts of ENSO on quinoa and potato yield in the Bolivian Altiplano. The purpose of the study is to develop a statistical framework that can be employed to reduce drought impacts on agricultural production in a region where surface data are scarce. The study shows that the remote sensing products listed above are sufficiently accurate when compared against ground observations, and that the positive ENSO phase significantly decreases crop yields. The framework is then employed to identity hotspots that are most vulnerable to droughts. The MS presents a relevant contribution to drought-related risk assessments in a region that is poorly studied. My main concern is related to the bias correction of land surface temperature, as explained in the main comments below. Also, the presentation of the methods section requires some attention. I recommend considering the MS for publication in NHESS after major revision.

Main comments

- The authors assume that land surface temperature (LST) and near-surface air temperature should be equal. This is a misconception as both variables present different processes. LST directly follows from the Stefan-Boltzmann law and therefore depends on outgoing long wave radiation and surface emissivity. Nearsurface air temperature, on the other hand, is affected by other processes, such as turbulent heat fluxes. The authors use near-surface air temperature measurements to "bias correct" remotely-sensed LST using an approach by Zhou and Wang (2016). This does not make much sense, as LST and near-surface air temperature should differ. Furthermore, the cited study by Zhou and Wang (2016) actually uses ground measurements of LST rather than near-surface air temperature to bias correct remotely-sensed LST. I propose three alternative approaches to address this issue: the authors could (i) rerun their analysis using LST directly, (ii) find an approach how to spatially interpolate near-surface air temperature, or (iii) use an already existing air temperature data set that has been published elsewhere (e.g. data from the climate research unit).
  Response: The database used previously in our manuscript was “global monthly land surface air temperature” from the Global Historical Climatology Network and the Climate Anomaly Monitoring System (GHCN and CAMS) defined by Fan and van den Dool (2008). In the revised version we now used the monthly air temperature dataset from University of Delaware developed by Willmott and Matsuura (see http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html). Furthermore, the air temperature database is now properly named along the manuscript.

- I suggest that the authors improve the presentation of the methods section by including the equations employed in their statistical framework (e.g. the NashSutcliffe efficiency (E) coefficient, POD, and FAR).
  Response: The equations used for the statistical analysis were now included in the methods section and explicitly referred to throughout the manuscript.

Detailed comments

- P01L14 Please spell out ENSO before using the acronym.
  Response: The El Niño Southern Oscillation (ENSO) is now spelled out at the first time that it is mentioned in the manuscript.
- P01L17 You write that "droughts can be better predicted using a combination of satellite imagery and ground-based available data". Better than ground-based available data alone? Please be explicit.
  Response: The new version of the manuscript mentions: "The results show that droughts can be monitored using satellite imagery data when ground data are scarce or of poor data quality".
- P01L18 You write that "satellite climate data were associated with" NDVI. This is a very vague formulation to outline your approach. Please be more precise
  Response: The manuscript was modified and the new text includes: "…we tested the performance of satellite imagery products for providing vegetation, land surface temperature (LST), precipitation and air temperature data. With this information, we assessed drought impact on agriculture by associating vegetation with precipitation and air temperature".
- P01L19 You started out your abstract on the topic of drought and are now jumping to "the crop production variability". Please find a more elegant way to include the topic of crop production variability. I would include this above when you describe the research problem.
  Response: Now two main modifications were included in the manuscript to avoid confusion. Firstly, the title was modified to: "Drought impact in the Bolivian Altiplano agriculture associated with El Niño Southern Oscillation using satellite imagery data." This includes agriculture as one of the focal points of our study. Secondly, in the abstract the following text was now included to be more specific about our contribution: "Drought is a major natural hazard in the Bolivian Altiplano that causes large agricultural losses, especially during a positive El Niño-Southern Oscillation (ENSO) phase. However, empirical data for drought assessment purposes in this area are scarce, spatially uneven distributed. Due to these limitations we tested the performance of satellite imagery products for providing vegetation, land surface temperature (LST), precipitation and air temperature data on a local level. With this information, the Normalized Difference Vegetation Index (NDVI) and LST were used to classify drought events, and associated with past ENSO phases. It was found that the most severe drought events generally occur during positive ENSO phase (El Niño years). We found a decrease in vegetation is mainly driven by low precipitation and high temperature rates, and we identify areas where losses will be most pronounced under such conditions. The results show that droughts can be monitored using satellite imagery data when ground data are scarce or of poor data quality. The results can be especially beneficial for emergency response operations and for enabling a pro-active approach to disaster risk management against droughts."

- P01L19 You are jumping back and forth between methods and results. I think you could improve the readability of your abstract when you first outline your approach and then the results
  Response: The abstract was modified, please see our response above.
- P01L21 I would replace "indicate" with "identify".
  Response: Identified is now used instead.
- P02L02 I would include a reference here, e.g. UNDP, 2011: Tras las huellas del cambio climatico en Bolivia: Estado del arte del conocimiento sobre adaptacion al cambio climatico agua y seguridad alimentaria. United Nations Development Program - Bolivia, 144 pp
  Response: The references UNDP, 2011; Garcia and Alavi, 2018 were now included in the text.
- P03L14 You could include a reference for SAMS here, e.g. Zhou, J., and K. M. Lau, 1998: Does a monsoon climate exist over South America? J. Climate, 11, 1020- 1040.
  Response: The references Garreaud et al., 2003; Zhou and Lau, 1998 were included.
- P03L19 Please explain more clearly how exactly the gap filling was done.
  Response: Data gaps were no longer filled, only in-situ precipitation and temperature data sets with less than 10% of missing data were considered for the analysis. This analysis was carried out relating the in-situ data with the satellite-based data of precipitation and temperature for pair-wise time series. This is mentioned in the section 2.2 Validation of satellite-based data products. We included more information to avoid confusion.
- P03L25 You mention the resolution three times. Please avoid redundancy
  Response: Now, the resolution is mentioned only once.
- P04L14 Reformulate. I suggest you write "An E equal to 1 corresponds ..."
  Response: E is no longer used as a statistical measurement as other measures as suggested are now introduced.
- P04L08 I suggest you provide the equations for the Nash-Sutcliffe efficiency (E) coefficient, POD, and FAR
  Response: All the equations used for the statistical accuracy measures were included in the revised manuscript. Please see Table 1.
- P06L10 This paragraph suggests that land surface temperature (LST) and nearsurface air temperature should be equal. Please refer to my general comment above to address this misconception.
  Response: Air temperature, no LST, was used as a predictor. However, it was wrongly named. Now, we have re-written the text and it is properly named in the manuscript (see also response to the main comments).
- P06L28 Delete "and the" or restructure sentence.
  Response: “and the data set spans” was deleted from the text.
- P07L16 This sentence is vague. Do you mean NDVI grid cells? Also, NDVI does not "simulate" crop yield. Please rephrase.
  Response: This sentence was removed.
- P07L20 Please define accumulated degree days.

Response: ADD is no longer used as a predictor, and the analysis now includes the 3-month time series of air temperature during the growing season instead. We explain the reasoning for that in more detail in the text.

- P07L22 Better than what?
  Response: The text was modified to: "For this, only the NDVI grids at the agricultural land were selected".
- P07L26 Spell out and define GDD here.
  Response: GDD is no longer used in the analysis.
- P11L28 Please refer to my general comment above.
  Response: Please see the main comment response.
- P11L30 Typo, replace p = 001 with p = 0.01.
  Response: The typo was corrected.
- P12L03 Please refer to my general comment above.
  Response: Please see the main comment response.
- P15L18 I would move any discussion on insurance policy and drought mitigation to the discussion section.
  Response: This information was moved to discussion section.
- P16L15 Avoid vague formulations such as "There are numerous cases in many countries". Also, it is not accurate to say that the impacts of ENSO are particularly strong in the mid-latitudes.
  Response: This sentence was removed.
- Figure 01 please specify the percentiles, min, max, and outliers of the boxplots in the Figure caption. The same comment applies to Figure 5.
  Response: Now included, e.g. lower and upper boundaries 25th (Q1) and 75th (Q3) percentiles, respectively, line inside box is median, lower and upper error lines 1.5 times the interquartile rage (Q3 - Q1) from the top or bottom of the box, white circles data falling outside 1.5 times the interquartile rage.

Anonymous Referee #2

GENERAL COMMENT

The paper is focused in the study of drought risk generated by climatic variables during ENSO occurrences and it is oriented to agricultural issues and related impacts on Bolivian Andes. For the last, the authors used potato and quinoa crop measurement data, to be related with temperature and precipitation information on ENSO composite periods. Additionally, the document assessed the detection of specific drought hotspot areas in base the NDVI vegetation index. Crops were related with NDVI variability, and the last was linked with climate variables as precipitation and accumulated degree day data. In general, the document is oriented to impacts on agriculture generate by droughts during strong El Niño events.

MAIN COMMENTS

- The authors didn’t clarify their risk definition, for example, in front to an extreme drought even during any kind of warm ENSO phase, the risk can be very low or cero if the direct affected population has very low vulnerability. Then, the mention of risk implies knowledge about the conception of risk, vulnerability and hazardous events (i.e., the danger amount), which are not well described in the current document.
  Response: The reviewed manuscript focuses on drought impact in the Bolivian Altiplano agriculture associated with El Niño Southern Oscillation using satellite imagery data. The aim is to provide information to support disaster risk management using satellite imagery. It is tested/compared to empirical observations so that it can be used for risk reduction of crop production losses. We focus on the severity of drought events. The severity drought is described in the manuscript (please see the results section, Tables 4 and 5 and appendix Fig. A1-A3).
- Lack of good bibliography review.
  Response: Previous related studies were reviewed in more detail and relevant information is included in the manuscript, please see reference section.
- P1 section 1. The general idea is the impacts of ENSO in agriculture and food security, but there is not so much to risk.
  Response: As mentioned above, considering that the manuscript focuses on drought impact on agriculture associated with ENSO. The manuscript title and content now describe more accurately the study approach.
- P3 L4. The title is covering a lot of issues. Risk is not only studied on agricultural context. My suggestion is to change the title to something like “Agricultural drought impacts during the ENSO over the Bolivian Altiplano”.
  Response: Thank you for the suggestion.The title was modified to “Drought impact in the Bolivian Altiplano agriculture associated with El Niño Southern Oscillation using satellite imagery data”.
- P3 L23. CHIRPS is a good dataset for precipitation information, since it is a mixed observation product (satellite products, station data, etc.), but here is necessary to indicate the problems

using it over Andes or over South America. Several papers are pointing out that the CHIRPS across the Andes overestimate/underestimate in lower/higher values, respectively.

Paredes-Trejo et al. 2016. Intercomparison of improved satellite rainfall estimation with CHIRPS gridded product and rain gauge data over Venezuela. https://doi.org/10.20937/ATM.2016.29.04.04

Paredes-Trejo et al. 2017. Validating CHIRPS-based satellite precipitation estimates in Northeast Brazil. https://doi.org/10.1016/j.jaridenv.2016.12.009

Rivera et al. 2018. Validation of CHIRPS precipitation dataset along the Central Andes of Argentina. https://doi.org/10.1016/j.atmosres.2018.06.023

Response: Thank you for the references. They were very helpful. The manuscript now indicates the uncertainties of using satellite-based precipitation data, and the recommended references are included in the results section.

- P4 L3. The LST-NDVI association is usually used for drought monitoring, then why didn't the authors explain nothing about it in the introduction and/or in the section 2.1?

  Karnieli et al., 2010. Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations. https://doi.org/10.1175/2009JCLI2900.1

  Response: The manuscript now includes more information about NDVI and LST as relevant drought indicators. Moreover, the classification of drought using NDVI and LST is now included in detail as well (see sections 2.3 and 3).

- P5 L5. Since the raw data have cyclicity/periodicity parts, then the 0.7 Spearman correlation should represent a very low association or linearity. Before to start the comparison, it is necessary that the authors remove the cyclicity/periodicity parts from the assessed information.
  Response: To avoid errors from periodicity, the accuracy measures of the satellite-based data products of precipitation and air temperature were defined for each month of the time series (see sections 2.3 and 3).

- P6 L10. The LST definition is different that the gauged air temperature from weather stations. LST is defined by Stephan-Boltzmann law, and on the other hand, the air temperature is defined by climate patterns and process. Moreover, as before indicated, the LST-NDVI relationship is a good method for monitoring drought, more than air temperature – NDVI. The authors should work with the LST but need to improve the correction procedure with some in ground LST measurements or other alternative way.
  Response: The database used previously was "a global monthly land surface air temperature" from the Global Historical Climatology Network and the Climate Anomaly Monitoring System (GHCN and CAMS) defined by Fan and van den Dool (2008). For the modified manuscript, we used the monthly air temperature dataset from University of Delaware developed by Willmott and Matsuura (see http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html). Now, the air temperature database is properly named along the manuscript.

- P7 L8. The crop yield vs NDVI is given values on 0.6 Spearman correlation, and it is yielding a little ambiguous result, the authors should bring information like, for example, how much is the explained variance of this relationship? i.e., How much does the NDVI explain the yield?
  Response: The reviewed manuscript does not include the association of crop yield and NDVI as a technique to discard NDVI grids. In contrast, we now assume that NDVI generally simulates properly the crop production. This is because the elimination of NDVI grids from the agricultural land could ignore relevant information. As well, we want to avoid some uncertainties originated from the crop yield dataset. For instance, the crop yield data do not take in consideration the crop rotation that are represented by different crops in the same area across sequenced growing seasons. We include the limitations as well as advantages using this approach in the discussion section and also provide some ways forward in that regard.
- P7 section 2.4. Was only a set of 2 predictors that were assessed in the regression analysis? if not, which are the other discarded predictors in the regression analysis? more than see the statistical results, the Authors should explain the physical reasons why the others preselected predictors were considered as potential predictors and why they were discarded.

  Response: This text is now included in the manuscript: "For the study, we assumed that NDVI simulates the stages of the crop phenological stages that is from September to April (Fig. 1). Precipitation was selected as predictor for its relevance on water availability for vegetation growth. Precipitation is the main source of water in the Altiplano because only 9 percent of the Bolivian cropped surface area is irrigated (INE, 2015). Air temperature is a relevant variable due to its involvement on photosynthetic and respiration processes (Karnieli et al., 2010)." We also discussed the results in more detail.
- P9 section 3. The data analysis should be done after to remove the cyclicity/periodicity of the data, to be comparable between them.
  Response: To avoid errors originated from cyclicity/periodicity, now the analysis is developed for each month for the accuracy measures of satellite/based data products and the classification of drought. The stepwise regression between NDVI and climate variables were developed using a standardized 3-month time series. "Previous to the stepwise regression analysis, the 3-month time series of NDVI, satellite precipitation and satellite air temperature were standardized".
- P10 L7. This could be moved to conclusion section.
  Response: The text was modified (see sections 3 and 4).
- P10 L8. "all dataset had acceptable bias" this affirmation is something subjective since the bias can be between 15% to 35%, then it is far to be considered as an acceptable bias. More than the references indicated for the authors (those can show values acceptable in other context), Can the authors show any way or calculation to corroborate that that range of bias is "acceptable"? Another option, in my point of view, is removed this assumption.
  Response: Now the text includes: "Summarizing these observations we conclude that CHIRPS-rainfall dataset is an adequate alternative in case of lack of gauged data or in case of poor data quality. However, it should be noted that such data still must be used with caution considering the uncertainties due to the under or overestimation of precipitation along the heterogeneous topography of the Altiplano (see Paredes-Trejo et al., 2016; Paredes-Trejo et al., 2017; Rivera et al., 2018)."

And:
“In conclusion, the satellite air temperature data product perform adequately from November to April. Similar to the precipitation data, the application of satellite air temperature data must take into account the potential errors due to the estimation uncertainties, mainly during winter season”.

- P11 L27. Again, the LST temperature has a different physical definition than air temperature. Moreover, the LST- ENSO relationship is given as the ENSO alters the air temperature patterns globally, and that air temperature influences vegetation and agricultural productivity (Glennie and Anyamba, 2018), then on ground level, additionally that air temperature, the vegetation cover, albedo, and soil properties (and others) are affecting the ground temperature generated by emitted radiation on the ground. This means that the ENSO-LST and ENSO- air temperature teleconnections have different mechanisms, then the correction of LST with air temperature has not sense since we expect to assess the crop yields. Hence, the suggestion that the LST underestimation could be due to elevation and/or cloud cover is not correct too. Glennie and Anyamba, 2018. Midwest agriculture and ENSO: A comparison of AVHRR NDVI3g data and crop yields in the United States Corn Belt from 1982 to 2014.
https://doi.org/10.1016/j.jag.2017.12.011
Response: As mentioned above the database used in the analysis was air temperature, however it was misnamed, now it is properly named along the text. Moreover, now we employed another air temperature data base that is the monthly air temperature dataset from University of Delaware developed by Willmott and Matsuura (http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html).

- P12 L25-L26. This phrase is ambiguous. Something that the authors can do is to calculate the explained variance per each predictor, and it associates with location coordinates.
Response: This text was removed, and now the results show the findings using the spatial coordinates (see Fig. 5).
- P13 L5-L6. Although the lag values are expected to be between 3 or 4 months, the lag differences between precipitation and vegetation per location can be explained on base to local landscape elements (e.g., Yarleque et al. 2016). Yarleque, C., M. Vuille, D. R. Hardy, A. Posadas, and R. Quiroz (2016), Multiscale assessment of spatial precipitation variability over complex mountain terrain using a high-resolution spatiotemporal wavelet reconstruction method, J. Geophys. Res. Atmos., 121, 12,198–12,216, doi:10.1002/2016JD025647.
Response: Thank you for the useful reference, it is now included in the results section of the manuscript.

- P13 L11-L12. “The hours of sun required for crop development could be the explanation for these results” It is true in part, see me previous comment. On this Andes region is necessary consider aquifer or ground water level changes (i.e., moisture on ground level) from Mountainous regions to flatter/lower elevation areas.
Response: The manuscript now mentions the findings of Yarleque et al. 2016.

- P14 L4. Here was linked a generated index with sea surface temperature anomalies against the crop yield signal with anomalies+ periodicity/cyclicity?. If this is the case, then I expect that the results bring a kind of non-physical statistical information.
  Response: Now the analysis includes the classification of drought using NDVI and LST. The drought events were analyzed and compared with ENSO phases. The classification of drought was developed for each month to avoid errors from periodicity.

- Figure 5. In this figure is given boxplots with only the 1982-1983 strong El Niño case as outlier, the rest of cases for quinoa and potato are given a non-statistical difference with other years, since the rest of cases are intercepting the range of the boxplots, i.e., between the maximum and minimum possible values, contradicting the conclusions of the authors.
  Response: This figure is no longer in the manuscript. More information to avoid confusion in regards to results found was included.

- P16 L1. How is the "magnitude of assistance" calculated/estimated?
  Response: This sentence was modified to "Our approach can enable a pro-active approach to disaster risk management against droughts."

DETAILED COMMENTS

- P6 L7. Four or three? P6 L7. "but not the satellite not and" changes to "but not the satellite and". P8 L5. "potato was 4◦C and 3◦C for quinoa" changes to "potato and quinoa were 4◦C and 3◦C, respectively" P8 L10. What's "5 percent level" exactly mean? P9 L7. "with" changes to "during". P9 L11. Add "strong" before that "El Niño" P9 L12. Add "strong" before that "El Niño". P12 L7. Remove "is". P12 L11. ". And" Changes to ", and". P14 L7. "warm" changes to "strong". P15 L2. Add "strong" before that "El Niño". P15 L9. Add "strong" before that "El Niño". P15 L20. Remove "is".
  Response: All the detailed comments from page 6 to page 15 were modified following the referee suggestions.

Drought ~~risk in the~~ impact in the Bolivian Altiplano agriculture associated with El Niño Southern Oscillation using satellite imagery data

Claudia Canedo-Rosso[1,2], Stefan Hochrainer-Stigler[3], Georg Pflug[3,4], Bruno Condori[5], and Ronny Berndtsson[1,6]

[1]Division of Water Resources Engineering, Lund University, P.O. Box 118, SE-22100 Lund, Sweden
[2] Instituto de Hidráulica e Hidrología, Universidad Mayor de San Andrés, Cotacota 30, La Paz, Bolivia
[3] International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361 Laxenburg, Austria
[4] Institute of Statistics and Operations Research, Faculty of Economics, University of Vienna, Oskar-Morgenstern-Platz 1, 1090 Wien, Austria
[5] Inter-American Institute for Cooperation on Agriculture (IICA), Defensores del Chaco 1997~~Instituto Nacional de Innovación Agropecuaria y Forestal (INIAF), Batallón Colorados 24~~, La Paz, Bolivia.
[6] Center for Middle Eastern Studies, Lund University, P.O. Box 201, SE-22100 Lund, Sweden.

Correspondence to: Claudia Canedo-Rosso (canedo.clau@gmail.com ~~and claudia.canedo_rosso@tvrl.lth.se~~)

Abstract. Drought is a major natural hazard in the Bolivian Altiplano that causes large agricultural losses ~~to farmers~~, especially during a positive El Niño-Southern Oscillation (ENSO) phase~~s~~. ~~However, e~~Empirical data for drought assessment ~~risk estimation~~ purposes in this area are scarce and spatially uneven distributed. Due to these limitations~~, similar to many other regions in the world,~~ we tested the performance of satellite imagery ~~data~~ products for providing vegetation, land surface temperature (LST), precipitation and air temperature data on a local level. ~~The results show that droughts can be better predicted using a combination of satellite imagery and ground-based available data.~~ With this information, ~~Consequently, the satellite climate data were associated with the Normalized Difference Vegetation Index (NDVI) in order to evaluate the crop production variabilityWthat~~ the Normalized Difference Vegetation Index (NDVI) and LST were used to classify drought events, associated with past ENSO phases. ~~Moreover, NDVI was used to target specific drought hotspot regions. Furthermore~~It was found that~~,~~ the most severe drought events generally occur during positive ENSO phase (El Niño years).~~,~~ ~~a significant~~ We found that a decrease in ~~crop yields~~vegetation is mainly driven by low precipitation and high temperature, and we ~~indicate~~ identified areas where agricultural losses will be most pronounced under such conditions. The results show that droughts can be monitored using satellite imagery data when ground data are scarce or of poor data quality. The results can be especially beneficial ~~can be used~~ for emergency response operations and for enabling~~e~~

a pro-active approach to disaster risk management against droughts.~~ This includes economic-related and risk reduction strategies such as insurance and irrigation.~~

Keywords: Drought~~ risk management~~, agriculture, ENSO, NDVI, land surface temperature, climate variables, precipitation, and air temperature~~NDVI, Quinoa and pPotato yield~~.

1. Introduction

Agricultural production is highly sensitive to weather extremes, including droughts and heat waves. Losses due to such~~ extreme~~ hazard~~ous~~ events pose a significant challenge to farmers as well as governments worldwide (UNISDR, 2009, 2015). Worryingly, the scientific community predicts an amplification of these negative impacts due to future climate change (IPCC, 2013). Especially in developing countries such as Bolivia, drought is a major natural hazard and~~ Bolivia~~ Bolivia has experienced large socio-economic losses in the past due to such events (UNDP, 2011; Garcia and Alavi, 2018). However, the impacts vary on a seasonal and annual timescale, in regards to the hazard intensity, ~~and ~~as well as the existing capacity to prevent and respond to droughts (UNISDR, 2009, 2015). Regarding the former, the El Niño Southern Oscillation (ENSO) plays an especially important role in several regions of the world, including the Bolivian Altiplano, as it drives losses of~~in~~ agricultural crops, and causes increased food insecurity (Kogan and Guo, 2017). Most important rainfed crops in the region include quinoa and potato (Garcia et al., 2007). Generally speaking, agricultural productivity in the Bolivian Altiplano is low due to adverse weather and poor soil conditions (Garcia et al., 2003). On the other hand, low agricultural production levels can also be associated with the ENSO climate phenomena (Buxton et al., 2013). For this area, droughts are generally driven by the ENSO warm phases (Thompson et al., 1984; Garreaud and Aceituno, 2001; Vicente-Serrano et al., 2015). Previous research has addressed the influence of ENSO on agriculture in South America and the globe (see Iizumi et al., 2014; Ramirez-Rodrigues et al., 2014; Anderson et al., 2017). ~~Moreover, Anderson et al. (2017) synthetized published studies on this topic. The~~These studies were calling for ~~suggest that ~~a better understanding of the association between ENSO and agriculture to ~~could ~~improve~~ the~~ crop management practices and food security.

~~In this regard, the Sustainable Development Goals (SDGs) state that priorities for adaptation to climate change include water and agricultural dimensions. These, in turn, can be related to extreme natural hazardous phenomena including floods, droughts, and higher temperatures (UN, 2016).~~ The implementation of drought risk management approaches is now seen as fundamental (see e.g., the Sustainable Development Goals or the Sendai Framework for Risk Reduction) for ~~developing a strategic plan processes and the planning of mitigation policy measures for~~

sustainable development in vulnerable regions, including Latin American countries such as Bolivia (Verbist et al., 2016). To lessen the long-term impacts of these extreme events, the national government in Bolivia has taken several steps, e.g., to allocate budgets for emergency operations to compensate part of the losses occurred.~~, which are usually evaluated ex-post (i.e. after the event).~~ Most of these measures are implemented ex-post (i.e., after a disaster event). However, based on ENSO forecasting, an El Niño event can be predicted 1 to 7 months ahead (Tippett et al., 2012) and consequently, there is an ~~lso~~ opportunity to implement additional ex-ante policies (i.e., before the event) to reduce societal impacts to droughts, increase preparedness, and generally improve current risk management strategies.

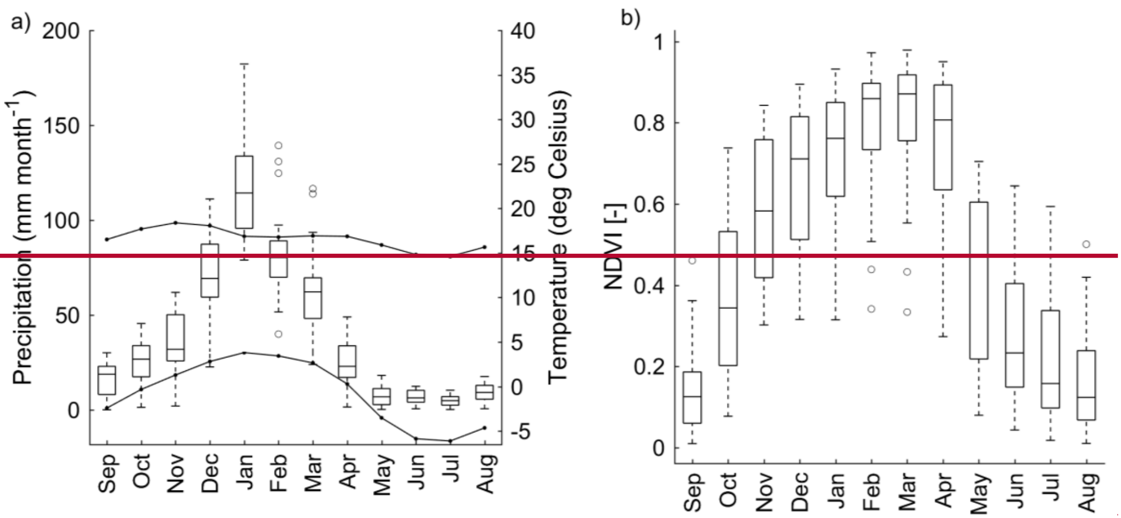
~~This paper addresses the corresponding question how a risk based approach can be used to determine the potential need of resources during droughts and provide ways forward how to determine hotspot areas where it is most likely that such resources would be needed. One major constraint for developing countries, when it comes to analyse~~One major constraint for drought risk management in Bolivia ~~current and future drought occurrences,~~ is the scarce and uneven ~~and scarce~~ distribution of weather and ~~crop~~ agricultural production related ground data. To circumvent this problem, we ~~suggest to use~~test ~~rainfall, land surface temperature, and vegetation~~ satellite-based data products (compared to available empirically gauged data) ~~so as~~ to provide~~have~~ a full coverage (in respect to~~of~~ land area) for drought ~~risk~~ assessment and its spatial distribution ~~in the study area~~across the region. ~~Furthermore, these data are combined with empirically gauged precipitation~~ and ~~, temperature~~ at~~and crop yield data on the ground level to enhance the knowledge and provide consistent relationship between agricultur~~al~~e production and climate variability.~~ Due to the particular importance of ENSO for drought risk management~~Finally~~, we~~the approach is used to~~ additionally assess the~~drought risk~~ impacts ~~on agriculture~~ associated with ENSO on agriculture for the Bolivian Altiplano ~~that is which was found to be significantly important to be considered within any drought risk management strategy~~. Furthermore, we give indications what climate variables may be most important in which regions to predict drought losses that can further be used for hotspot selection. ~~We provide ways forward to tackle these challenges using a risk based approach.~~ The paper is organized as follows, section 2 ~~will~~ presents the methodology applied and data used, and ~~while~~ section 3 presents the ~~will~~ corresponding results found. Section 4 puts the results into a context of drought impact and hotspot selection with conclusion.~~presents the results. Section 4 gives a discussion in regards to risk management strategies and finally, section 4 concludes and provides an outlook to the future.~~

2. Data Used and Methodology

2.1 Ground data and satellite imagery

The methodology applied is very much related to the data scarce situation for the Bolivian Altiplano and we therefore start with an introduction of available datasets that are used for our purposes. In regard to climate~~Climate-wise~~, the Altiplano has a pronounced southwest-northeast precipitation gradient (200–900 mm year^{-1}) during the wet season occurring from November to March (Garreaud et al., 2003). Over 7~~6~~0% of total precipitation occur during summer months (from December to February~~DJF~~, see Fig. 1a) in association with the South American Monsoon ~~(SAM) (see Fig. 1a)~~(see Zhou and Lau, 1998; Garreaud et al., 2003). Time series of monthly precipitation at ~~23~~ 12 locations as well as mean, maximum, and minimum temperature at 8~~11~~ locations from September 1981 to August 2015 were ~~obtained~~available from the National Service of Meteorology and Hydrology (SENAMHI) of Bolivia (see Table A1). ~~Initially, the available precipitation data set included 65 gauges but only 23 were used as they had~~ These data sets have less than 10% of missing data. ~~(chosen as cut-off point for use in the analysis). Data gaps were filled with mean monthly values from the full dataset.~~

As already indicated, precipitation and temperature gauge locations are unevenly distributed and mainly concentrated in the northern Bolivian Altiplano. To improve the spatial coverage of ~~rainfall~~ climate related data, monthly quasi-rainfall time series from satellite data ~~were therefore included in our study. T~~ the Climate Hazards Group InfraRed Precipitation with station data (CHIRPS) were included in our study. ~~from the quasi-global rainfall dataset was used.~~ CHIRPS represents a 0.05° spatial resolution satellite imagery and ~~is~~ a quasi-global rainfall dataset from 1981 to the near present ~~with a satellite resolution of 0.05°~~ (Funk et al., 2015). The advantage of using CHIRPS is the high~~er~~ spatial resolution of data, ~~i.e., the resolution of 0.05°,~~ obtained with resampling of TMPA 3B42 (with 0.25° grid cell). The spatial resolution represents a better option for agricultural studies as well and therefore is most appropriate for our approach (CHIRPS is described in detailed at http://chg.geog.ucsb.edu/data/chirps/).



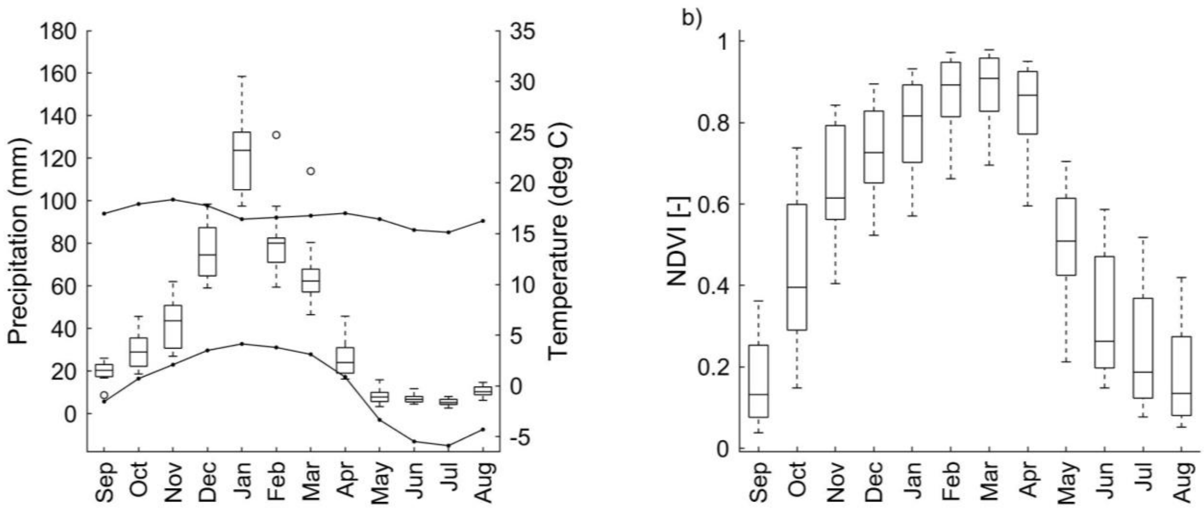


Fig. 1. (a) Gauged ~~M~~mean monthly total precipitation and average maximum and minimum temperature from September 1981 to August 2015~~ of the 23 gauged stations~~. (b) ~~The m~~Mean monthly NDVI at the same spatial locations. Lower and upper box boundaries 25th (Q1) and 75th (Q3) percentiles, respectively, line inside box is median, lower and upper error lines 1.5 times the interquartile range (Q3-Q1) from the top or bottom of the box, white circles data falling outside 1.5 times the interquartile rage.

Additionally, satellite monthly mean ~~land surface~~ air temperature ~~(LST)~~ was obtained from the Physical Sciences Division (PSD) of the US National Oceanic and Atmospheric Administration (NOAA, https://www.esrl.noaa.gov/psd/) defined by Willmott and Matsuura~~Global Historical Climatology Network and the Climate Anomaly Monitoring System (GHCN and CAMS, https://www.esrl.noaa.gov/psd/data/gridded/data.ghcncams.html) from the US National Oceanic and Atmospheric Administration (NOAA) defined by Fan and van den Dool (2008)~~. The satellite air temperature dataset ~~LST~~ has a resolution of 0.5° and was ~~it is conveniently also~~ available during the study period from September 1981 to August 2015.

Apart from climate datasets, NDVI was assembled from the Advanced Very High Resolution Radiometer (AVHRR) sensors by the Global Inventory Monitoring and Modelling System (GIMMS) at semi-monthly (15 days) time step~~s~~ with a spatial resolution of 0.08°. NDVI 3g.v1 (third generation GIMMS NDVI from AVHRR sensors) was available from September 1981 to August 2015. The NDVI is an index that presents a range of values from 0 to 1, bare soil values are closer to 0, while dense vegetation is close to 1 (Holben, 1986). NDVI 3g.v1 GIMMS provides information to differentiate valid values from possible errors due to snow, cloud, and interpolation~~-~~. These errors were removed from the dataset and replaced with the nearest neighbour value.

Additionally, Land Surface Temperature (LST) was obtained from the Global Land Data Assimilation System (GLDAS) by the Noah Land Surface Model L4 monthly version 2.0. The LST dataset has a resolution of 0.25° and it was available for the study period from September 1981 to August 2015. Agricultural land in the Bolivian Altiplano covers about 20,000 km², and it was spatially identified based on the land use map developed by the Autonomous Authority of the Lake Titicaca (for the northern Altiplano) in 1995 at a scale of 1:250,000 (UNEP, 1996), and the Ministry of Development Planning in 2002 using Landsat imagery and ground information at a scale 1:1,000,000 (geo.gob.bo, for the southern Altiplano).

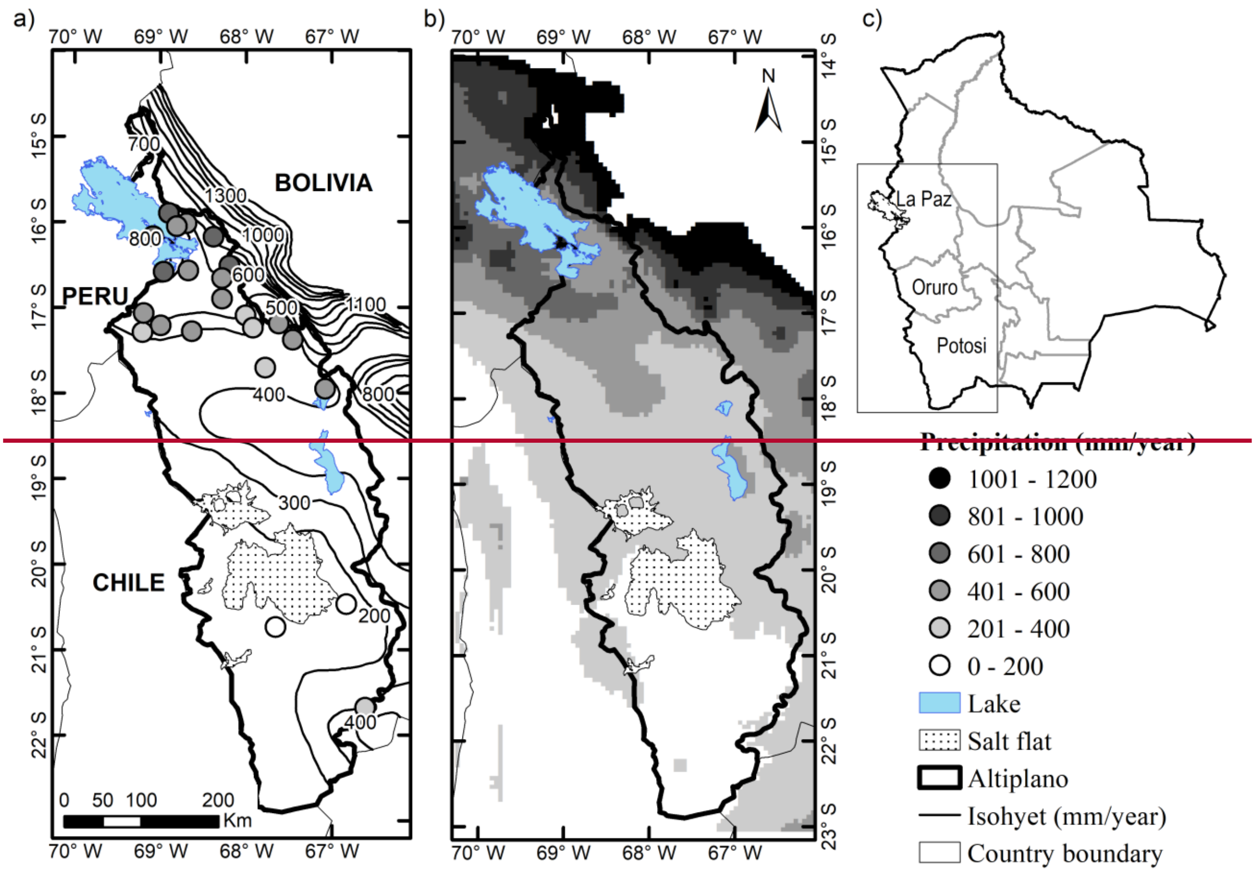
2.2 Validation of satellite-based data ~~rainfall and temperature~~ products ~~using gauged data~~

The performance of the satellite-based data ~~products~~(compared to empirical ground data, see Fig. 2) to accurately estimate amount of rainfall~~s~~ (~~i.e.,~~for example to assess rain detection capability) was based on statistical measures for monthly pair-wise time series, including categorical analyses and follows the methodology applied in previous studies in this region for comparison reasons ~~as suggested in the literature~~ (Blacutt et al., 2015; Satgé et al., 2016). The mean error (ME), ~~also called~~ bias, and mean absolute error (MAE) were~~as~~ calculated based on Wilks (2006).

~~Additionally, the Nash-Sutcliffe efficiency (E) coefficient was calculated based on Nash and Sutcliffe (1970).~~ These measures evaluate the prediction accuracy of the satellite data compared to ~~the~~ gauged data. The ME and bias show~~s~~ the degree of over- or underestimation (Duan et al., 2015)~~, and the E coefficient evaluates the prediction accuracy compared to observations~~. In contrast, as measuring the absolute deviation, MAE shows only non-negative values. The~~An~~ ME, bias, and MAE ~~equals to one that corresponds to a~~have perfect match correspond ~~equal~~ to zero between gauge observation and satellite-based estimate~~ and zero indicates that the satellite estimations are as accurate as the mean of observed data. Negative values indicate that the observed mean is better than satellite-based estimate, see Nash and Sutcliffe (1970) for more details~~. Furthermore, and similar to Blacutt et al. (2015) and Satgé et al. (2016), the Spearman's rank correlation was computed to estimate the goodness of fit to observations. To evaluate results, as ~~done~~ in similar studies, correlation coefficients larger or equal to 0.7 ~~with a significance level of 0.01~~ were considered as reliable (Condom et al., 2011; Satgé et al., 2016). The ME, bias, and MAE were calculated, respectively according to Eqn. (1), (2), and (3) (Table 1).

Table 1. Accuracy measures for satellite data performance evaluation. Here, N is the number of samples, S_i is the satellite-based dataset for month i, and G_i is the gauged dataset for the same month. H is a hit, F is a false alarm, and M is a miss.

Statistical indicator	**Abbreviation**	**Units**	**Equation**	
Mean error	ME	mm, ºC	$\sum(S_i - G_i) / N$	(1)
Bias	Bias	%	$\sum(S_i - G_i) / \sum G_i \times 100$	(2)
Mean absolute error	MAE	%	$\sum\lvert(S_i - G_i) / G_i\rvert / N \times 100$	(3)
Probability of detection	POD	-	$\mathrm{H} / (\mathrm{H} + \mathrm{M})$	(4)
False alarm ratio	FAR	-	$\mathrm{F} / (\mathrm{H} + \mathrm{F})$	(5)



a)
b)
c)
70° W
69° W
68° W
67° W
14° S
15° S
16° S
17° S
18° S
19° S
20° S
21° S
22° S
23° S
BOLIVIA
PERU
CHILE
700
1300
1000
800
600
500
1100
400
800
300
200
400
0 50 100 200
Km
N
La Paz
Oruro
Potosi
Precipitation (mm/year)
1001 - 1200
801 - 1000
601 - 800
401 - 600
201 - 400
0 - 200
Lake
Salt flat
Altiplano
Isohyet (mm/year)
Country boundary

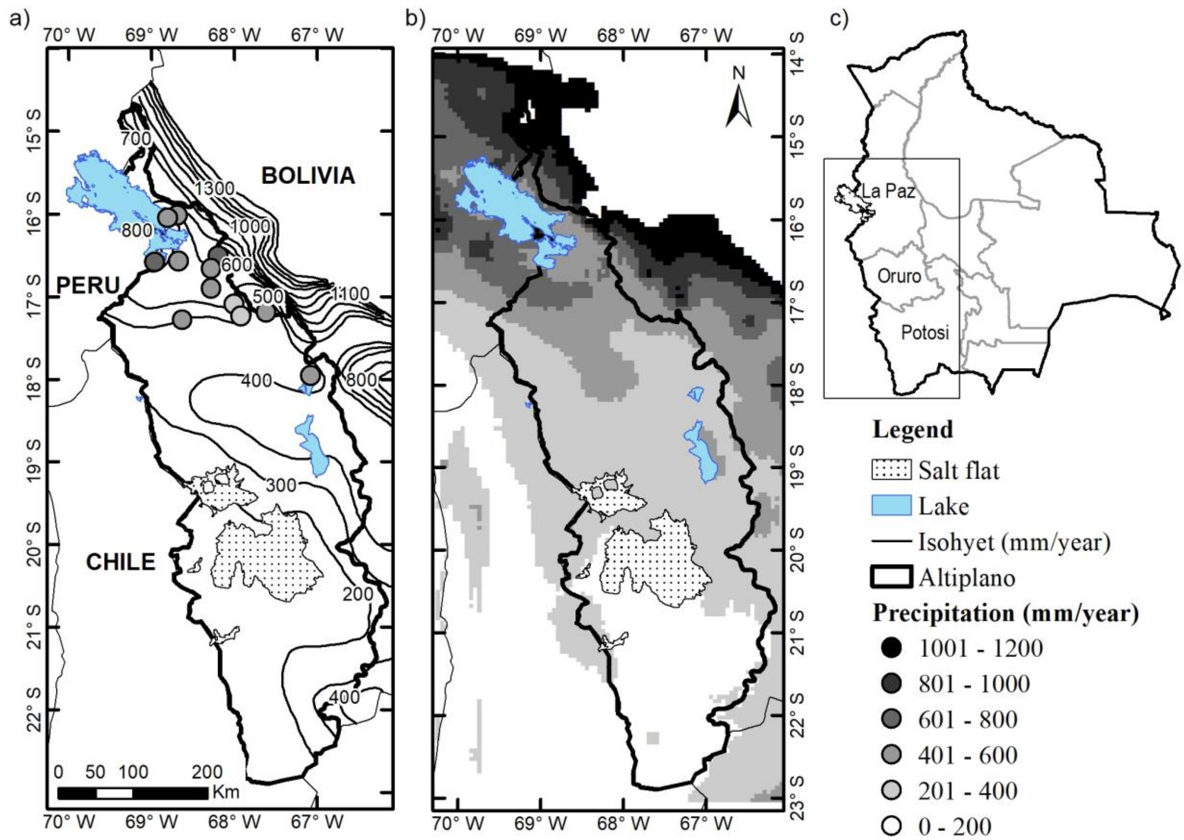


Fig. 2. M~~The m~~ean of ~~the ~~total annual precipitation from September 1981 to August 2015 for: (a) gauged precipitation data (circles) and isohyets (solid line), (b) the CHIRPS satellite rainfall product, and (c) Bolivia, and the major political divisions of the Bolivian Altiplano: La Paz, Oruro and Potosi~~, where crop yield data ~~are~~~~is available in the Altiplano~~.

Two statistical indicators based on a contingency table were computed for the categorical statistics, namely Probability of Detection (POD) and False Alarm Ratio (FAR). The POD indicates whati~~ch~~ fraction of the observed events that was correctly estimated, and FAR indicates the fraction of the predicted events that did not occur (Bartholmes et al., 2009; Ochoa et al., 2014; Satgé et al., 2016). The POD and FAR range from 0 to1, where 1 is a perfect score for POD, and 0 is a perfect score for FAR. ~~The categorical statistic measures~~These measures were used to evaluate the satellite estimations. Here, the rainfall amounts are considered as ~~discrete ~~binary values, i.e., rain occurrence or absence. Based on this approach, ~~four ~~three ~~scenarios ~~counting variables were taken into account: the number of events when the satellite rain estimation and the rain gauge report a rain event (hit or H), when only the satellite reports a rain event but ~~is a~~no rain on the ground is observed (false alarm or ~~(~~F), and when only the rain gauge reports a rain event but not the satellite ~~not~~ and therefore is a miss (M). The POD and FAR were calculated, respectively according to Eqn. (4) and (5) (Table 1).

Besides the precipitation data, ~~also~~ satellite temperature data were validated using ground data. The ~~LST~~ satellite air temperature was correlated with the mean gauged temperature at the same spatial location. The mean temperature of the gauged data was calculated using the arithmetic mean between the maximum and minimum temperature. ~~The relationship enables to correct the LST with a linear regression equation (Zhou and Wang, 2016).~~ The regression performance was evaluated using the monthly pair wise time series to define the Spearman's rank correlation, relative ME, ~~or~~ bias, and MAE~~and the E coefficient~~.

2.3 Drought associated with ENSO

Healthy vegetation usually shows enlarged near infrared and reduced visible red band, and shows a low surface temperature due to the absorption of thermal infrared radiation (Kogan and Guo, 2017). Therefore, vegetation indices and land surface temperature (LST) are widely used for water and energy balance approaches (see Moran et al., 1994; Corbari et al., 2010; Sánchez et al., 2012; Helman et al., 2015). Previous findings indicate a negative (positive) relationship between LST and NDVI caused by limited moisture (energy-temperature) availability for vegetation growth (Karnieli et al., 2010). Drought spells typically present low NDVI and high LST due to vegetation deterioration and higher contribution of the soil signal (Kogan, 2000). Here, we study the relationship between LST and NDVI using the Vegetation Health Index (VHI, Eqn. (8)) developed by Kogan (1995) that combines the Vegetation Condition Index (VCI, Eqn. (6)) and Temperature Condition Index (TCI, Eqn. (7)). VCI is a normalized NDVI that allows to seek the variability of the signal, showing an increased VCI when NDVI increases. (Kogan, 1995; Kogan, 2000; Kogan and Guo, 2017). In contrast, the TCI formulates a reverse ratio compared to the VCI, decreasing when LST increases, assuming that higher land surface temperatures suggest a decreasing soil moisture causing stress of the vegetation canopy.

Table 2. Drought classification indices.

Drought index	**Acronym**	**Equation**	
Vegetation Condition Index	VCI	$(NDVI_i - NDVI_{min}) \,/\, (NDVI_{max} - NDVI_{min})$	(6)
Temperature Condition Index	TCI	$(LST_{max} - LST_i) \,/\, (LST_{max} - LST_{min})$	(7)
Vegetation Health Index	VHI	$0.5\ VCI + 0.5\ TCI$	(8)

where NDVIi, NDVImax and NDVImin (LST, LSTmax and LSTtmin) are monthly NDVI (LST) and the month absolute maximum and minimum from September 1981 to August 2015, respectively. We took a mean of VCI and TCI assuming that they equally contribute to the VHI.

The VCI, TCI, and VHI was defined for each month during the growing season (from September to April). We assumed the occurrence of drought event when the indices were lower than 40%. The classification of drought was established based on the severity of the event in which five classes were defined: extreme (≤10), severe, (≤20), moderate (≤30), mild (≤40), and no (>40) drought (Bhuiyan and Kogan, 2010).

The drought events were further classified based on the occurrence of El Niño and La Niña events (Table 3). The classification ENSO was obtained from Null (2018). El Niño and La Niña events were identified from 5 consecutive overlapping 3-month mean sea surface temperature for the Niño 3.4 region (in the tropical Pacific Ocean). A moderate El Niño (La Niña) was defined as 5 consecutive overlapping 3-month periods at or above the +1.0 º to + 1.4 ºC anomaly (-1.0 º to -1.4 ºC), strong El Niño (La Niña) event for a threshold between +1.5 º to +1.9 ºC anomaly (-1.5 º to -1.9 ºC anomaly), and a very strong El Niño event for a threshold equal or greater than +2 ºC anomaly (https://ggweather.com/enso/oni.htm). For this study, a neutral or weak phase was defined as a threshold between -0.9 º to +0.9 ºC anomaly.

Table 3. El Niño and La Niña phases~~.~~ (from Null (2018)).

El Niño			**La Niña**	
Moderate	**Strong**	**Very Strong**	**Moderate**	**Strong**
1986-87	1987-88	1982-83	1995-96	1988-89
1994-95	1991-92	1997-98	2011-12	1998-99
2002-03		2015-16		1999-00
2009-10				2007-08
				2010-11

~~2.3 Crop yield simulation based on NDVI data~~

~~As indicated above, quinoa and potato are the main crops in the Bolivian Altiplano and they are still gaining importance. The quinoa growing season is from September to April and for potato it is from October to March. Yield data from 1981 to 2015 for quinoa and potato were obtained from the Bolivian National Institute of Statistics (INE, https://www.ine.gob.bo) for the administrative regions La Paz, Oruro, and Potosi (Fig. 2). The annual crop yield datasets represent production (t) in relation to area (ha) at regional level. No historical crop yield data on local scales are available yet which is a major limitation for any risk-based approach and needs to be addressed in~~

~~the future. Nevertheless, we suggest that the coarse distribution of the crop yield data can be improved using the NDVI. Besides improving the crop yield resolution, the NDVI also allows to analyse the variability of vegetation at a monthly time scale. This makes it possible analyse the phenology of the studied crops through to the growth phases. NDVI estimates the vegetation vigour (Ji and Peters, 2003) and crop phenology (Beck et al., 2006). NDVI was assembled from the Advanced Very High Resolution Radiometer (AVHRR) sensors by the Global Inventory Monitoring and Modelling System (GIMMS) at semi-monthly (15 days) time steps with a spatial resolution of 0.08º. NDVI 3g.v1 (third generation GIMMS NDVI from AVHRR sensors) and the data set spans from September 1981 to August 2015. Note, the NDVI is an index that presents a range of values from 0 to 1, bare soil values are closer to 0, while dense vegetation has values close to 1 (Holben, 1986). NDVI 3g.v1 GIMMS provides information to differentiate valid values from possible errors due to snow, cloud, and interpolation errors. These errors were eliminated from the dataset and replaced with the nearest neighbour value.~~

~~Relationships between crop yield and NDVI for agricultural land area of the Altiplano were developed using Spearman's rank correlation, based on a similar approach by Huang et al. (2014). The maximum semi-monthly NDVI of March and April for every year was identified. Only March and April were considered because this period represents the maximum phenological development of quinoa and potato crops. The maximum NDVI of each grid was compared to the annual crop yield at La Paz, Oruro, and Potosi. The NDVI grids and crop yield correlations equal or larger than 0.6 (Spearman correlation, p = 0.05) were considered as adequate for crop yield estimation, and only these grids were considered for further use. As will be discussed further below, a regression approach was applied for selected NDVI grids and corresponding climate variables (precipitation and temperature). In doing so, the agricultural land in the Bolivian Altiplano was delimited based on the land use map for Bolivia developed by Raul Lara Rico from the Ministry of Rural Development and Land of Bolivia in 2010 (geo.gob.bo) using Landsat imagery and ground information at a scale 1:1,000,000.~~

2.4 Regression of vegetation and climate variables

~~Only the NDVI grids that properly simulated the crop yield were related to climate variables. Thus, the~~A stepwise regression approach was used to quantify the dependency between vegetation and satellite-based climate variables (precipitation and temperature; Eqn. ~~1~~10) further to be used for hotspot selection. In more detail,~~. T~~ the~~ final~~ results presented here are a combination of forward and backward selection techniques to increase the robustness of the results (in terms of explanatory power, i.e., variability explained, as well as variable selection, i.e., same variable selected across a range of possible models). The independent variable considered was ~~the~~ NDVI, and the dependent variables were selected to include precipitation and air temperature ~~accumulated precipitation and accumulated degree days (ADD)~~ (for the same spatial location across the study region). We assumed that NDVI represents the crop phenological stages of the growing season that is from September to April (Fig. 1). Precipitation was selected as predictor due to its relevance for water availability for vegetation growth. Precipitation is the main source of water in the Altiplano because only 9% of the Bolivian cropped surface area are irrigated (INE, 2015). Air temperature is a relevant variable due to photosynthetic and respiration processes (Karnieli et al., 2010). Firstly, the NDVI was related to CHIRPS rainfall datasets. Secondly, ~~the ADD~~air temperature was included in the analysis. For this, only the NDVI grids for agricultural land were selected. ~~that better simulated the crop yield of quinoa and potato were used (see section 2.3).~~

~~.~~Since, agricultural production data are scarce in the region, we suggest that crop yield data can be improved using the NDVI. Besides improving the crop yield resolution, the NDVI also allows to analyse the variability of vegetation at a monthly time scale. This makes it possible to analyse the phenology of the studied crops through to the growth phases. NDVI estimates the vegetation vigour (Ji and Peters, 2003) and crop phenology (Beck et al., 2006). The final regression model therefore is

$$NDVI = \beta_0 + \beta_1\ precipitation + \beta_2 air\ temperature \qquad (10)$$

$$\cancel{NDVI = \beta_0 + \beta_1 accumulated\ precipitation + \beta_2 accumulated\ degree\ days \qquad (1)}$$

~~Both precipitation and temperature were represented as accumulated values (for temperature using the GDD). The mean monthly temperature was multiplied by the number of days of each month to obtain daily values. GDD was computed only considering the months of the growing season for each year. To calculate the ADD, the accumulated value of the Growing Degree Day (GDD) multiplied by the number of days of each month was computed. The GDD is defined as the difference between mean and base temperature. The mean temperature is the arithmetic average between maximum and minimum temperature, and T_b is the minimum threshold or base temperature. Base temperature of potato was 4°C and 3°C for quinoa (Jacobsen and Bach, 1998). If T_b is greater than T_{mean}, then GDD is equal to 0. For the ADD calculation we considered crop phenology, September to April were used to calculate the ADD for quinoa, and from October to April for potato.~~

For the forward selection, the variables were entered into the model one at a time in an order determined by the strength of their correlation with the criterion variable (only including variables if they present~~are~~ a ~~significant~~confidence level of~~on the~~ 95%~~ percent level~~). The effect of adding each variable was assessed during its entering stage, and variables that did not significantly add~~ed~~ to the fit of the model were excluded (Kutner et al., 2004). For backward selection, all predictor variables were entered into the model first. The weakest predictor variable was then removed and the regression fit re-calculated. If this significantly weakened the model then the predictor variable was re-entered, otherwise it was deleted. This procedure was repeated until only useful predictor variables (in a statistical sense, e.g., significant as well as model fit) remained in the model (Rencher, 1995). The results were compared with ~~other~~ results from ~~the~~ literature regarding ~~to check for suitability of results with~~ phenology and weather-related characteristics ~~dimensions~~ of ~~plants~~crops.

It should be noted that the ~~cumulative precipitation was calculated for a period of 12 months from September to August of the following year for all locations. The~~ precipitation in the Altiplano shows a marked rainy season from November to March. The ~~highest~~ peak of precipitation is in December and January (Fig. 1a). And, NDVI displays a~~the highest~~ peak in March and April (Fig. 1b). The lag between the ~~max~~ precipitation and ~~max~~ NDVI is reasonable since vegetation requires time to grow (e.g., Shinoda, 1995; Cui and Shi, 2010; Chuai et al., 2013). Considering this lag-time, ~~The~~ the ~~accumulated precipitation and~~ 3-month time series of NDVI was regressed with the 3-month time series of the climate variables (satellite-based data products of precipitation and air temperature) during the growing period~~with a lag of two, three, and four month lag was developed~~ for the ~~agricultural~~ agricultural land~~area~~. First, the NDVI and the climate variables were related considering the overlapped 3-month time series, and afterwards a relation was developed considering a lag from 1 to 4 months between NDVI and climate variables, resulting 22 regressions per NDVI grid. The regressions were developed for each NDVI grid separately, associated with the nearest precipitation and air temperature dataset. Previous to the stepwise regression analysis, the 3-month time series of NDVI, satellite precipitation and satellite air temperature data were standardized.

~~2.5 Crop yield relationship with ENSO~~

~~The Oceanic Niño Index (ONI) is usually used to identify El Niño (warm) and La Niña (cool) years (http://www.cpc.ncep.noaa.gov/). ONI is the 3-month running mean of Extended Reconstructed Sea Surface Temperature (ERSST v5) anomalies in the El Niño 3.4 region. The El Niño 3.4 anomalies represent the average equatorial SSTs in the equatorial Pacific Ocean (5°N to 5°S latitude, and 120° to 170°W longitude). Five consecutive overlapping three month periods at or above +0.5°C anomaly represent warm events (El Niño), and at or below the -0.5 anomaly cold (La Niña) events. This threshold was further broken down into weak (with a 0.5 to 0.9 SST anomaly), moderate (1.0 to 1.4), and strong (≥ 1.5) events (http://ggweather.com/enso/oni.htm). In our study we considered the categories neutral/moderate (with a 0 to 1.4 SST), strong El Niño (≥ 1.5) and strong~~

~~La Niña (≤ -1.5) years (Appendix Table A2). The classification considered three consecutive overlapping 3-month periods at or above the +1.5°C anomaly for warm (El Niño) events and at or below the -1.5°C anomaly for cold (La Niña) events. The ENSO year in this study starts in September-October-November and ends in August-September-October for each year from 1981 to 2015. Subsequently, the crop yield of quinoa and potato was compared with strong El Niño years. This relationship was analysed using parametric two sample t-test as well as the non-parametric Wilcoxon rank sum test. In more detail, the two sample t-test and Wilcoxon rank sum compare two independent data samples, with the difference that the first compares samples that assume a normal distribution, and the second is a non-parametric test which is based on the ranking of empirical values (Wilks, 2006). The null hypothesis of the two sample t-test was that crop yields during El Niño and neutral/moderate years have equal means. The null hypothesis of the Wilcoxon rank sum test was the crop yield during El Niño and neutral/moderate years are samples from continuous distributions with equal medians. Both tests compute two-sided p-value. When the hypothesis is equal to 1, the null hypothesis is rejected at 5% significance level. And the null hypothesis is accepted when it is equal to zero.~~

3. Results ~~and Discussion~~

~~3.1 Validation of satellite imagery using gauged data~~

Validation of the satellite rain data using empirical precipitation data from the weather stations was done for the ~~23~~ 12 locations where gauge precipitation data were available (see Fig. 2 and Table A1). ~~Interestingly, the spearman rank correlation between ground observed precipitation and satellite rain product datasets was significant (P<0.001) for all locations.~~ The qualitative methods discussed in section 2.2 for the CHIRPS rainfall estimates show differences between summer (from December to March) and winter season (from June to August). CHIRPS data show better accuracy during summer. The precipitation during the austral summer is highly relevant because it concentrates the 70% of the annual rainfall (Garreaud et al., 2003) and it occurs during the growing season. During May, CHIRPS data show lower accuracy compared to the other months. The precipitation from May to August is almost null in the study area (Fig. 1) and it will be further described as the dry season. This season presents stable atmospheric conditions with few precipitation events (Garreaud et al., 2003).

Interestingly, the spearman rank correlation between monthly gauged precipitation and satellite rain product datasets was significant (p-value <0.05) for all locations. The correlation coefficients (r) vary from 0.5 to 0.8 (mean = 0.7). The ME and bias disclose an underestimation of precipitation estimation during October, November, and April, and an overestimation during the summer season (mean = 5 mm and 7%, respectively) with a peak in February. For the MAE coefficient, CHIRPS estimations are more accurate during the rainy season (mean = 31%). In contrast, CHIRPS data indicate poor accuracy during the dry season (mean MAE = 92%). From June to August, CHIRPS data present an underestimation of the gauged precipitation (mean bias = -39%). Summarizing these observations, we conclude that the CHIRPS-rainfall dataset is more accurate during the rainy season, and it represents an adequate alternative in case of lack of gauged data or in case of poor data quality. However, it should be noted that such data still must be used with caution considering the uncertainties due to the under or overestimation of precipitation along the heterogeneous topography of the Altiplano (see Paredes-Trejo et al., 2016; Paredes-Trejo et al., 2017; Rivera et al., 2018).

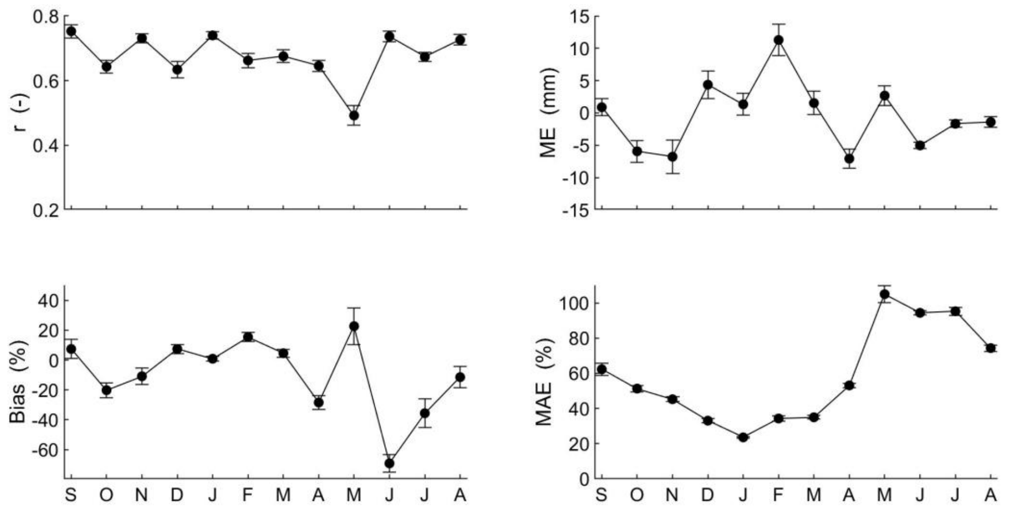
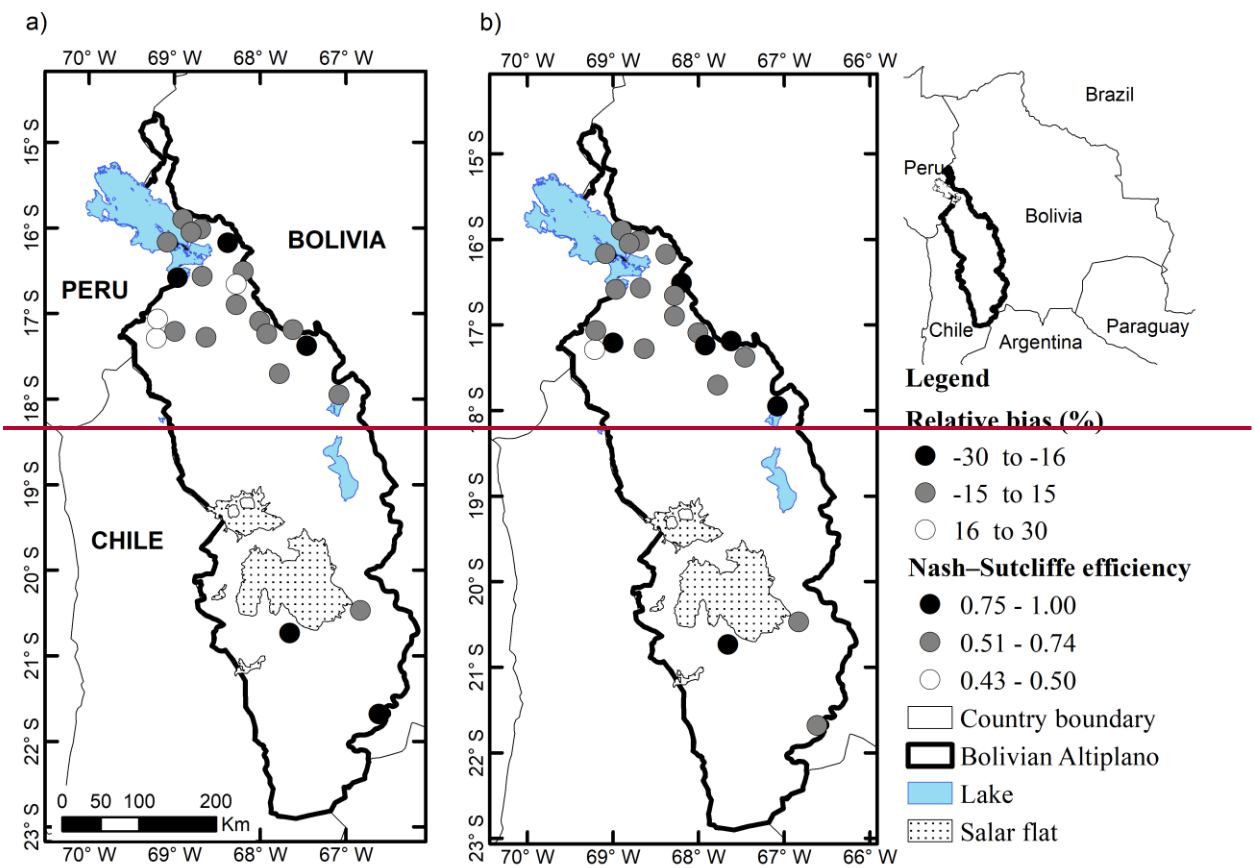


Fig. 3. Monthly accuracy measures of CHIRPS-rainfall data product. Mean monthly values are represented by black circles, and bars represent the standard error of the mean.

~~The correlation coefficients were higher than 0.7, except for Colcha K [6] (brackets indicate the position of the station detailed in Table A1), that presented a significant (P<0.001) correlation of 0.66. Hence, the findings suggest that CHIRPS shows a significant positive relationship with empirical data. However, still the satellite datasets should be used with caution and its applicability for hydrological analysis applications tested. In addition, El Alto Aeropuerto [10], Oruro Aeropuerto [13], and Viacha [23] present the highest correlation coefficient with values higher than 0.9 (P<0.001). The datasets from the airports in Bolivia have higher data quality (e.g. Hunziker et al., 2018) and CHIRPS gives the best fits with the El Alto Aeropuerto [10] and Oruro Aeropuerto [13] for the~~

~~statistical performance evaluation as described above, including the categorical tests mentioned. In summary, our results suggest a high degree of confidence in the CHIRPS performance compared to empirical data using the Spearman correlation coefficient as a performance measure. The ME (bias) between satellite and gauged data showed a range from -15 to 15% for most of the stations (Fig. 3a), representing a very good fit~~ (Moriasi et al., 2007; Shrestha et al., 2017)~~. However, the bias for Berenguela [4], Santiago de Machaca [20], and Viacha [23] was about 25%. Furthermore, the bias for Colcha K [6], Conchamarca [8], Hichucota [12], and San Juan Huancollo [17] was about -18%. The dataset for San Pablo de Lipez [18] had a bias of -29%. Previous studies indicate a bias from -25 to 25% representing a satisfactory fit (see Moriasi et al., 2007). Other studies have included a bias from -30 to 30% as satisfactory fit (see Shrestha et al., 2017). In conclusion, all datasets had acceptable bias.~~



~~Fig. 3. (a) The relative mean error or bias (%) and (b) the Nash–Sutcliffe efficiency coefficient of the CHIRPS rain data compared with the gauged precipitation from September 1981 to August 2015.~~

~~The Nash–Sutcliffe efficiency coefficients (E) were larger than 0.5 for all stations except Berenguela [4] with a coefficient of 0.43 (Fig. 3b). As a consequence, the E coefficients showed that the mean square error is lower than the variance of the gauged data for all stations, including Berenguela. The E coefficients were larger than 0.75 for Achiri [1], Colcha K [6], El Alto Aeropuerto [10], Oruro Aeropuerto [13], Patacamaya [14], and Salla [15]. These datasets presented a very good fit between the CHIRPS and gauged precipitation, and the others also showed good fits, except for Berenguela [4] (see Moriasi et al., 2007).~~

~~The categorical statistics were used for a precipitation event (larger than 0 mm/month). The results of the Probability of Detection (POD) measure showed a range from 0.92 to 1, indicating that the satellite rain product correctly estimates above 0.92 for the fraction of gauged precipitation events. Additionally, the False Alarm Ratio (FAR) showed values from 0 to 0.3 for most stations, except Colcha K [6] and Uyuni [22] that had a FAR of about 0.5. Both stations are located in the southern Bolivian Altiplano, close to the Uyuni salt flat. CHIRPS generally overestimated rainfall with about 5 to 10 mm/month for both regions during the dry season (from April to October). Therefore, using a threshold of precipitation events larger than 10 mm/month resulted in a decrease of FAR to 0.2 and 0.3 for Colcha K [6] and Uyuni [22], respectively. Hence, in general the CHIRPS estimations presented a reasonably good fit compared to gauged data. The best fit was for the gauged datasets at the airports (El Alto Aeropuerto [10] and Oruro Aeropuerto [13]) that have better data quality, and consequently the validation showed better performance there. The datasets with a unsatisfactory fit included Colcha K [6] (with a correlation lower than 0.7) and Berenguela [4] (with an E lower than 0.5). The bias for San Pablo de Lipez [18] can be seen as acceptable depending of the ranking used. For the categorical analysis, all stations presented a good POD and FAR, except for Colcha K [6] and Uyuni [22] that tended to overestimate the precipitation during the dry season. In general, CHIRPS rainfall product properly estimated the actual conditions in the study area. However, for developing other hydrological studies we suggest to compare with the available gauged data before applying the CHIRPS datasets, in order to identify possible errors, and datasets with larger uncertainty or confidence.~~

Moving from rainfall to temperature, the inter-annual temperature at the 8~~11~~ locations varied considerably between summer (~~DJFM~~from December to March) and winter (~~JJA~~from June to August~~S~~), including a larger variance for the minimum temperature (Fig. 1a). ~~Regions close to the Lake Titicaca present lower inter-annual variability (Copacabana [9]). In contrast, Uyuni [22] showed larger inter-annual oscillations.~~ The mean monthly air temperature from satellite data was compared with mean temperature of gauged data. The ~~LST~~ satellite air temperature underestimated the mean gauged temperature, and this error could be due to the high elevation and cloud coverage. The spearman correlation at the ~~11~~ 8 stations displayed coefficients from 0.~~8~~ 1 to 0.~~9~~ 7~~(p=001)~~. From November to April, air temperature satellite-based estimations show significant correlations (p-value <0.05). Large correlations are shown during summer season (mean = 0.7), while the other months show rather weak correlations ~~values~~. ME and bias show a slight underestimation from October to April (mean = -0.5 and -4% respectively), and an overestimation from May to August (mean = 0.3 and 12% respectively). Finally, MAE is about 10% from September to April, higher values develop~~n~~ during winter season (mean = 32%). In conclusion, the satellite air temperature data product performs better from November to April. Similar to the precipitation data, the application of satellite air temperature data must take into account the potential errors due to the estimation uncertainties, mainly during winter season. ~~This permitted to correct the LST with linear regression. The regression results presented a range of coefficient of determination from 0.7 to 0.9 for all stations, meaning that the variability of gauged temperature is reasonably well explained by the LST. The results of linear regression approaches were applied to define the adjusted LST, that is the raw LST times 0.88 plus 5.7 degrees Celsius. The adjusted LST and the mean gauged temperature data showed acceptable relative bias (±25%) and E (≥0.5) coefficients for all stations. The same linear equation regression approach was used to correct the datasets of LST for all the studied area.~~

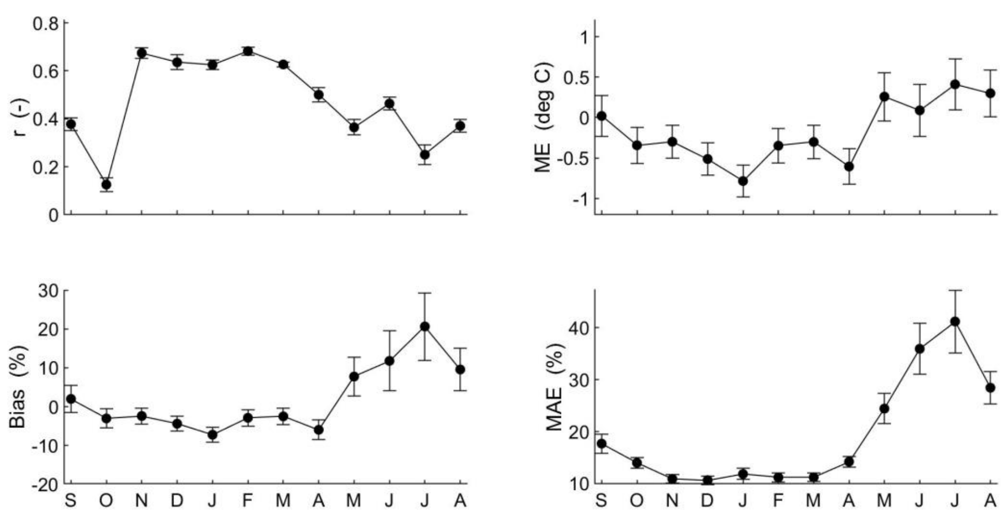


Fig. 4. Same as Fig. 3 but for accuracy measures of satellite-based air temperature data product.

As discussed above, the VCI, TCI, and VHI were calculated during the growing season. The sowing period depends on the initial soil moisture content, therefore the beginning of the growing season oscillates from September to November (Garcia et al., 2015). For this reason, the drought severity was classified considering the mean of VCI, TCI, and VHI for the agricultural land during November-April. Figure A1 shows mean monthly VCI from November 1981 to April 2015. The major drought events (severe or extreme) are visible in 1982-83, 1983-84, and 2009-10. Followed by moderate drought events during 1987-88, and 1993-94, and several mild events. Figure A2 shows the mean monthly TCI, where the major drought events (severe or extreme) occurred in 1982-83, 1987-88, 1997-98, 2004-05, and 2009-10. Followed by moderate drought events during 1981-82, 1983-84, 1994-95, 2006-07, and 2008-09, and several mild events as well. Finally, Fig. A3 shows the VHI results, in which the major drought events occurred during 1982-83, 2004-05, and 2009-10.

Further, we related drought indices with the ENSO phases (Table 4). Extreme, and severe droughts were generally found during El Niño phase. The extreme drought of 1982-83, coincided with a very strong El Niño phase. For this event, the largest economic losses caused by droughts during the study period were reported (Table 5). Followed by the very strong El Niño phase of 1997-98, which reported the second largest economic losses. Besides these two main drought events, the strong El Nino 1987-88 coincided with an extreme/moderate drought (TCI$\leq$10%, VCI$\leq$30%) classification. During this period, large economic losses were reported as well (Table 5). In contrast, the strong El Niño 1991-92 showed low severity (mild drought VCI$\leq$40%), and no economic losses were reported. This indicates that despite El Niño phenomenon is generally associated with drought in the Altiplano, there are several other mechanisms that drive a drought occurrence and determine its severity. For instance, dry (wet) and warm (cool) conditions during El Niño (La Niña) phases are generally shown in the tropics (Garreaud et al., 2003). However, an anomalous location and intensity of zonal wind anomalies could cause disturbances of the warming and cooling air patterns causing rainfall anomalies on the Altiplano (Garreaud and Aceituno, 2001). This is the case of the dry La Niña 1988-89 that showed a mild drought classification (TCI$\leq$40%).

Table 4. Drought indices classification during ENSO phases.

ENSO	**Drought**	**VCI**	**TCI**	**VHI**
El Niño	Extreme		1982-83, 1987-88, 1997-98	
	Severe	1982-83, 2009-10	2009-10	1982-83, 2009-10
	Moderate	1987-88	1994-95	
	Mild	1986-87, 1991-92	1986-87	1994-95, 1997-98
La Niña	Mild	1995-96, 2007-08, 2010-11	1988-89	
Neutral/	Extreme		2004-05	

weak	Severe	1983-84		
	Moderate	1993-94	1981-82, 1983-84, 2006-07, 2008-09	2004-05
	Mild	1981-82, 1996-97, 2003-04, 2008-09	1984-85 1990-91 1993-94 2014-15	1981-82, 1983-84, 1990-91, 1993-94, 2005-06, 2008-09

One severe (1983-84) and one extreme (2004-05) event occurred during a neutral/weak ENSO. The severe drought (VCI ≤ 20%) occurred during a neutral phase of 1983-84. This coincides with the findings of Vicente-Serrano et al. (2015), that analyzed the standardized precipitation/evaporation index in Bolivia, which is an alternative technique to characterize a meteorological drought. The extreme drought (TCI ≤ 10%) of 2004-05 occurred in November and December. From January to April of 2004-05 the VCI and VHI were above 40%, and there were no claims of drought losses in the Altiplano for this particular year (Table 5). Besides these two events, moderate and mild droughts also occurred during non El Niño phases.

Table 5 shows that five drought events were reported during a neutral ENSO phase. In 2012-13, the largest impact occurred, affecting about 80 000 people in the Altiplano (Desinventar, 2020). Despite that the mean of the drought indices indicates no drought during this period (VCI, TCI, and VHI >40%), some spatial locations in the study region indicated the occurrence of a drought event in November and December (21% and 29% of the total studied grids showed mild and moderate droughts for the TCI and VCI respectively).

Table 5. Drought impact in Bolivia (from (EM-DAT, 2020), BID (2016), and CAF (2000)).

Year	**ENSO phase**	**Affected people**	**Total damage ('000 US$)**
1982-83	El Niño	3 083 049	917 200
1987-88	El Niño		48 400
1989-90	Neutral	283 160	
1997-98	El Niño		279 310
1993-94	Neutral	50 000	
1999-00	La Niña	20 000	
2003-04	Neutral	55 000	
2007-08	La Niña	27 500	
2009-10	El Niño	62 500	100 000
2012-13	Neutral	340 355	
2013-14	Neutral	51 180	

~~3.2 Regression of NDVI and climate variables~~

Regarding the relationship between vegetation and climate variables, we note that ~~T~~the precipitation season ~~is~~ occurs mainly during the austral summer months (from ~~DJFM~~December to March), and the vegetation development shows a lag with a maximum development ~~around~~ of about March and April (Fig. 1). The NDVI (Fig. 1b) shows a similar growing pattern as the crop phenology in the region, which starts in September and ends in April. ~~Also, the m~~Maximum and minimum temperature varies~~y~~ during the year. ~~The latter shows even larger variability, with h~~Higher temperature~~s~~ during the austral summer ~~. And this could~~ leads to higher evapotranspiration ~~that might~~ and a decrease ~~the~~ of water retained in the root zone. With this presumption, ~~we analysed the relationship between NDVI and climate variables. In a first step, the relationship between the maximum NDVI during the major phenological development months (i.e. March-April) and the corresponding annual crop yield between 1981 and 2015 was defined. A total of 26 and 76 NDVI grids estimated properly the quinoa and potato yield, respectively (Fig. 4). These are locations were NDVI showed a good correspondence with quinoa and potato yield, a correlation equal or larger than 0.6 (spearman correlation, p = 0.05) was used as a threshold for acceptable performance.~~

~~In a next step,~~ stepwise linear regression models were tested using 3-month time series of ~~s~~ ~~the~~ NDVI as dependent variable and ~~grids~~3-month time series of satellite-based data product of precipitation and air temperature as independent variables (Eqn. (10)). The stepwise regression was defined considering the overlapped 3-month time series, and the 3-month time series with a lag from 1 to 4 months ~~and accumulated CHIRPS rainfall datasets~~ at the same spatial location over the agricultural land.

The results of the stepwise regression show larger coefficient of determination (R^2) in the northern and central Bolivian Altiplano, starting from the southern Lake Titicaca and moving southwards to the Lake Poopó, and close to the rivers paths. Lower R^2 is shown along the southwestern Bolivian Altiplano, that could be explained through the large variance of the NDVI, which may depend to on other factors besides precipitation and temperature, including crop management. ~~with a lag of two, three, and four months and which were found statistically significant at the 0.01 level. The coefficient of determination (R^2) oscillated from 0.4 to 0.7 in both cases. Additionally~~N~~, stepwise linear regression for NDVI as independent variable, and the accumulated precipitation and ADD as dependant variables was performed (Eqn. (1)).~~ Figure 5 shows the R^2 of the best fit regression in the Bolivian Altiplano for the three-month period of NDVI and the climate variables (precipitation and temperature) during the beginning and end of the growing season. It can be seen that the NDVI depends largely on the studied climate variables. This may be due to the crop´s sensitivity for water stress during specific stages of the growing season.~~,~~ For instance the~~and the~~ most sensitive stages of the quinoa crop are the emergence, flowering, and grain development (see Geerts et al., 2008a; Geerts et al., 2009), and the near absence of irrigation practices in most of these regions.

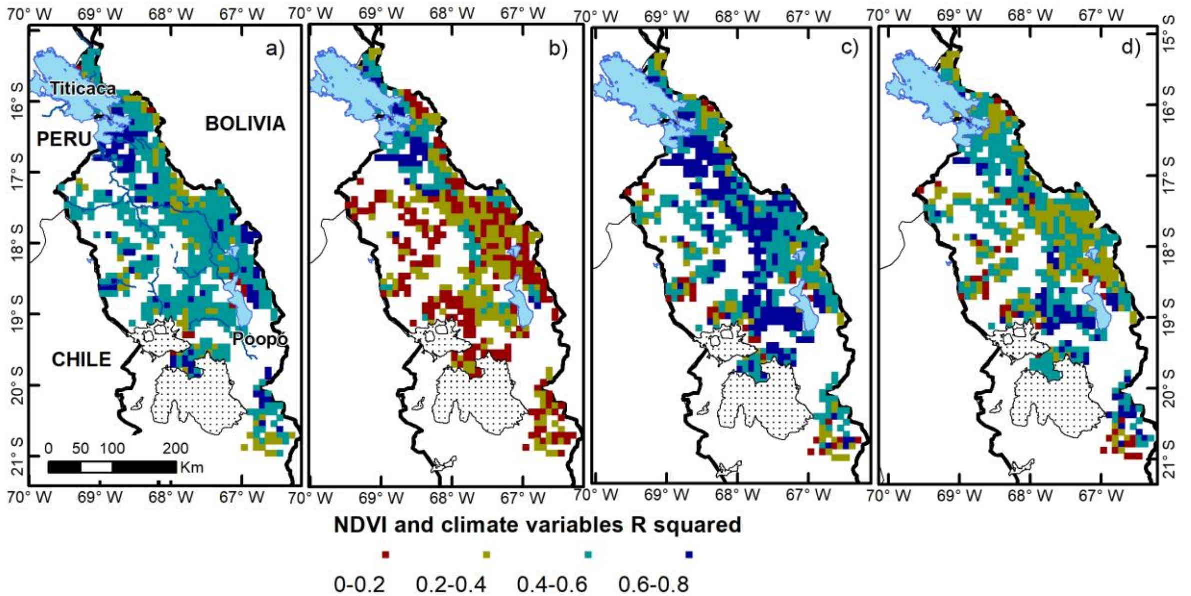
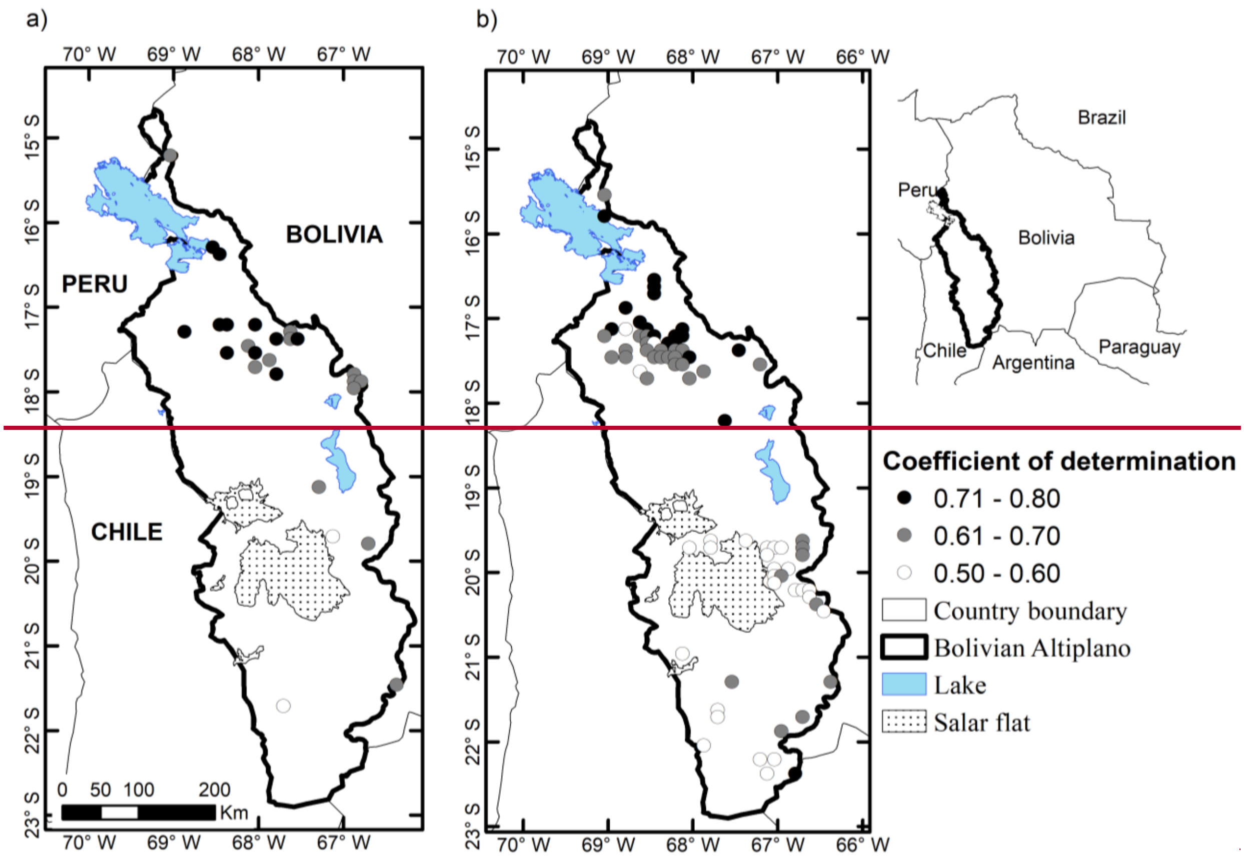


Fig. 5. Coefficient of determination (R^2) of NDVI for the 3-month time series for a) SON, b) OND, c) MAM and d) MAM and the climate variables (satellite precipitation and air temperature products) for SON, SON, FMA, and MAM respectively. The significant regression coefficients for precipitation (air temperature) cover: a) 45% (98%), b) 64% (91%), c) 95% (96%), and d) 23% (98%) of the total studied grids that represent the agricultural land.

In more detail, the stepwise regression results for the overlapping 3-month time series of NDVI and climate variables for SON (September, October, and November) show statistically significant coefficients for precipitation and air temperature at 45% and 98% the agricultural area in the Bolivian Altiplano with a median of 0.2 and 0.7, respectively (Fig. 5a). This indicates that the NDVI increases with more rain and higher air temperature. Interestingly, the significant regression coefficients of NDVI for OND (October, November, and December) associated with precipitation and air temperature for SON cover 64% and 91% of the agricultural area, and have a positive median of 0.3 and 0.4, respectively (Fig. 5b). A time-lag of one month shows larger spatial coverage of response of vegetation to precipitation anomalies. Here, the largest coefficient of determination are shown in areas surrounding the Lake Titicaca. Moreover, the response of the NDVI for MAM (March, April, and May) to the studied climate anomalies for FMA (February, March and April) covers 95% and 96% of the agricultural land for precipitation and air temperature, respectively (Fig. 5c). This mostly shows coefficients of determination ranging from 0.4 to 0.8, and positive regression coefficients for precipitation and air temperature have a median of 0.5 and 0.4, respectively. The hours of sun required for crop development could be the explanation for the time-lag between vegetation and the climate variables. In addition, the lag differences between vegetation and precipitation can be explained by topography, land cover, ground-water, and soil properties (Yarleque et al., 2016). Finally, the regression for NDVI and climate variables for the overlapped 3-month time series of MAM shows significant coefficients at 23% and 98% of the agricultural land, with a median of 0.4 and 0.6 for precipitation and air temperature, respectively (Fig. 5d). Hence, the vegetation response to precipitation is limited for the last overlapped 3-month time series of the growing season. However, it should be noted that air temperature remains an important variable.

To summarize, while acknowledging some important limitations, we found the CHIRPS dataset adequate to be used for drought risk assessment in case of severe data scarcity for the Bolivian Altiplano. Furthermore, we found that the vegetation variance can be explained by precipitation and air temperature. More specifically, we point out the relevance of precipitation as the main water source for vegetation development and air temperature as a driver of photosynthetic processes. Precipitation is particularly important at the early and late phenological stages, in which crops are more sensitive to water shortage. This is the case for the main crops in region, i.e., quinoa and potato. For the quinoa crop, the most sensitive phases to water stress are the emergence, flowering, and grain development (see Geerts et al., 2008a; Geerts et al., 2009). The most sensitive phases of the potato crop to water stress is the tuber initiation and bulking (van Loon, 1981; Alva et al., 2012). On the other hand, air temperature is relevant for vegetation productivity, and overall, we found a positive relation between vegetation and air temperature. However, in prolonged dry periods, high air temperature could increase the evapotranspiration rates, and in consequence, decrease the soil moisture (Huang et al., 2019). This scenario could impact negatively the vegetation, as this is the case of the drought events of 1982-83 and 1997-98, where large production losses were reported (Santos, 2006). ~~The results also showed statistical significance for all locations included in the study. The R^2 oscillated from 0.5 to 0.8. It should be noted that the R^2 is generally larger in the northern and central Bolivian Altiplano, where the total precipitation is also larger. These are strong indications that precipitation and temperature explains the variability of the crop yield, and the influence is more notable in the northern and central Bolivian Altiplano. Figure 4 shows the coefficient of determination resulting from stepwise regression between NDVI, and precipitation, and temperature with a four-month lag.~~



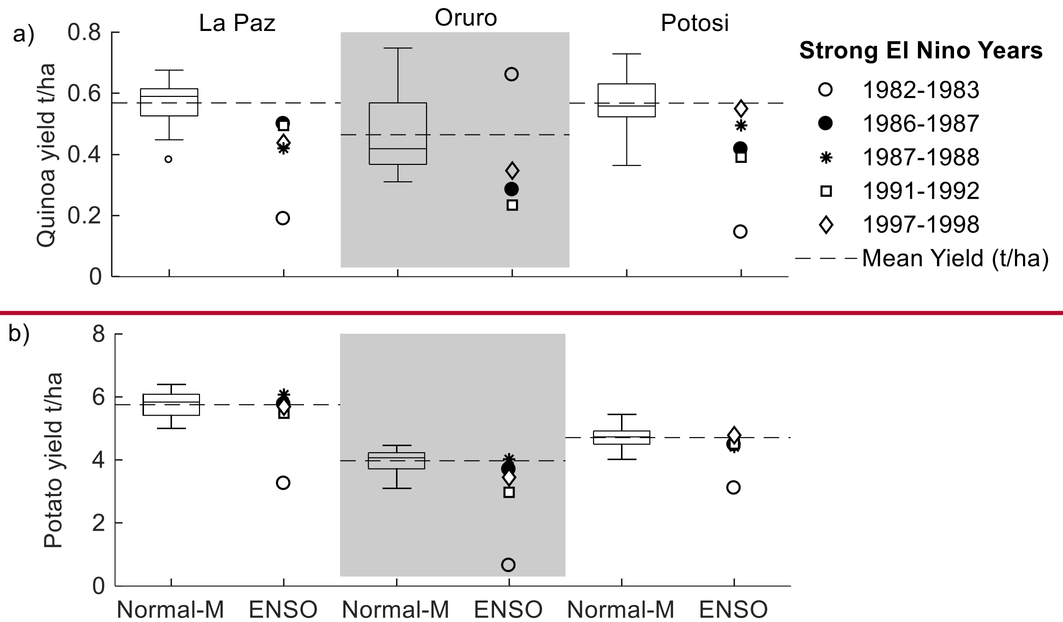
~~Fig. 4. The circles show the spatial location where NDVI properly estimates the (a) quinoa and (b) potato yield. And the graduated colours show the coefficient of determination (R^2) of the stepwise regression between NDVI as the predictand, and precipitation and temperature as the predictors with a lag of 4 months.~~

~~The regression models with only precipitation as dependent variable showed a larger coefficient of determination for three and four-month lag. In northern and central Bolivian Altiplano (16 to19 ºLS) larger R^2 was found with a three-month lag and in the southern Bolivian Altiplano (20 to 22º LS) with a fourth-month lag. The results are related to different sowing time and starting period of the rainy season in the areas. In the northern Bolivian Altiplano the rainy season extends longer in time than in the southern Altiplano, where the rainy season is mainly concentrated to the austral summer months (DJF, Fig A1). Regression with precipitation and temperature as~~

~~dependent variables showed larger coefficients of determination for a four-month lag. The hours of sun required for crop development could be the explanation for these results.~~

~~3.3 Relationship between ENSO and crop yield~~

~~After a reasonable relationship between NDVI and the satellite based climate datasets the next question to be tackled is relation to ENSO phases (as well as possible strategies to mitigate effects of these). As indicated, the relationship between ENSO and crop yield was analysed using two sample t-test and Wilcoxon Rank-Sum Tests for La Paz, Oruro, and Potosi (see Fig. 2c). To test the relationship, crop yield during neutral/moderate years was compared with crop yield during El Niño years (warm ENSO phase) (see Table A2). The results showed that quinoa yield during warm ENSO phase and neutral/moderate years presents a significant difference at 95% confidence level except for Oruro (Table A3). The yield during neutral/moderate years is higher with about 0.2 t/ha compared to El Niño years. The quinoa yield production during El Niño years is lower than the mean yield for neutral/moderate years, except for Oruro during 1982-1983 (Fig. 5). This finding contradicts previous studies that reported large agricultural losses during 1982-1983 and 1997-1998 (Santos, 2006). On the other hand, the quinoa yield has constantly increased during the last years, mainly in Oruro. This could be explained by employment of advanced crop management strategies (e.g., selected crop varieties and application of agricultural innovations), as this region is one of the largest producer in Bolivia and the world (Ormachea and Ramirez, 2013).~~



~~Fig 5. The boxplot of the (a) quinoa and (b) potato yield for normal and moderate years (Normal-M) for La Paz, Oruro, and Potosi. And the crop yield during strong El Nino years (markers). The mean of the crop yield during the normal and moderate years (dashed line).~~

~~Despite the quinoa's high tolerance to environmental stress including droughts~~ (Jacobsen et al., 2003; Jacobsen et al., 2005)~~, it generally showed larger losses during El Niño events than potato (Fig. 2). The risk for crop yield reduction could be reduced here with irrigation during the sensitive phases of the quinoa crop development. A strategy like deficit irrigation could be employed~~ (Geerts et al., 2008b; Talebnejad and Sepaskhah, 2015)~~. Another strategy to mitigate the crop yield reduction is implementation of crop varieties more resistant to water stress (e.g. Sun et al., 2014).~~

~~The t-test and Rank-Sum test results showed that potato yield during neutral/moderate and El Niño years is significantly different at 95% confidence level except for La Paz (Table A3). The results showed that production during neutral/moderate years is higher in Oruro and Potosi. All regions showed lowest potato yield during strong El Niño for 1982-1983, with a yield reduction of 40, 80, and 30%, as compared to mean yield during normal/moderate years in La Paz Oruro and Potosi, respectively. The yield reduction during other El Niño events seems to have a larger effect in Oruro. Besides El Niño events during 1982-1983, potato yield in La Paz showed lower vulnerability to this phenomenon. This could be explained by closeness to the Lake Titicaca and other water bodies that might be used as a water source during precipitation deficit. Similar strategies for drought mitigation~~

~~(e.g., irrigation and resistant crop varieties) could be implemented in order to avoid large crop losses. However, knowing that a very strong El Niño could lead to large agricultural losses, insurance policy could be assigned to farmers in order to manage the risk before the occurrence of a drought event. For the implementation of any drought mitigation strategy, identification, evaluation, and monitoring of drought risk are crucial. What is important is our findings that ENSO must be taken explicitly into account in such considerations.~~

4. ~~Summary and conclusions~~ Discussion and Conclusion

We employed a satellite dataset product and tested its empirical accuracy as well as performance to similar (but with coarser resolution) datasets available for the Bolivian Altiplano region. Afterwards spatio-temporal patterns of satellite precipitation and air temperature anomalies were explored based on monthly time series during the period of September 1981 to August 2015. Drought severity was evaluated based on a drought classification scheme using NDVI and LST. Finally, association between the spatial distribution of NDVI with precipitation and air temperature was examined. Using these datasets, it was shown that drought risk (measured through various drought indices) increases substantially during El Niño years (Table 4 and 5), and as a consequence the socio-economic vulnerability of farmers will likely increase during such periods. ENSO forecasts as well as drought severity (through drought indices) can help to determine possible hotspots of crop deficits during the growing season. Through empirical relationship with climate variables on the local scale our approach can enable a pro-active approach to disaster risk management against droughts. As it was shown here, ENSO warm phase related characteristics are especially important in the context of extreme drought events and could therefore be incorporated within early warning systems as standard practice. Despite these challenges for development of drought early warning systems (see FAO, 2016, 2017), applications have been successful in the past (e.g., Global Information and Early Warning System (GIEWS) of FAO, and Famine Early Warning System (FEWS) of USAID). Monitoring and predicting ENSO can therefore significantly contribute to reduce the risk of disasters. This study is a first attempt to provide an assessment of drought impact on agriculture in relation to the ENSO phenomenon for the Bolivian Altiplano. We focused on where vegetation is more affected by droughts over agricultural land and how this can be clarified using satellite imagery. It is important to note that the variance of drought indices (as well as NDVI) to a large extend is explained by precipitation and air temperature anomalies in the studied region. The agriculture in this semi-arid region is ecologically fragile and the main water source is precipitation, and thus crop production is considerably affected by precipitation anomalies. However, while an overall response of vegetation variance to precipitation and air temperature is evident, it is important to consider other variables, such as evapotranspiration and soil moisture to improve risk-based models. Another important issue is the time-lag of the response of vegetation to precipitation and air temperature anomalies, which shows a hysteresis of 1-2 months. These findings provide information for future drought risk management and early warning system applications. In addition, with such information agricultural models can be set up and risk management plans with better accuracy determined.

~~We employed a satellite dataset product and tested it for accuracy as well as performance to similar (but with coarser resolution) datasets available for our region. Using these datasets, it was shown that during El Niño years the crop yield reduces considerably (Fig.ure 5 Table A3), and as a consequence the socio-economic vulnerability of farmers, will likely increase during such periods. Furthermore, it was found that NDVI can be related to crop yield and therefore, NDVI canould be used to target specific hot spots depending on NDVIs availability at a local scale. As a consequence, ENSO forecasts as well as possible magnitudes of crop deficits canould be established that which may be beneficial for emergency authorities, including identification of possible hotspots of crop deficits during the growing season. Our approach can help to determine the magnitude of assistance needed for farmers at the local level but can also enable a pro-active approach to disaster risk management against droughts. This may include not only economic related instruments such as insurance but also risk reduction instruments such as irrigation and resistant crop varieties as discussed above. In fact, risk management based financing is gaining increasing attraction in real-world settings as it has several advantages. However, it should be acknowledged that large challenges still remain (see French and Mechler, 2017).~~

~~The drought severity could be measured via time shifts from normal conditions of climatic parameters such as precipitation. As in our case, we not only elucidated shifts but also the difference in risk for El Niño and neutral/moderate years. However, one of the main challenges of drought risk analysis is data scarcity, e.g., low density or unevenly distributed stations for hydro-meteorological data networks, poor data quality due to missing data, and restricted use of data between government agencies or other institutions. As it was shown here, ENSO warm phase related characteristics are especially important in the context of extreme drought events and should therefore be incorporated within early warning systems as standard practice. Despite these challenges for development of drought risk assessment, applications have been successful in the past. There are numerous cases in many countries and as in our case, particularly in the mid-latitudes where weather patterns are strongly influenced by ENSO. Monitoring and predicting ENSO can therefore significantly contribute to reduce the risk of disasters.~~

~~This study is a first attempt to provide an agricultural drought risk assessment in relation to the ENSO phenomenon for the Bolivian Altiplano. Our study provided valuable information for drought risk reduction, primarily by finding information of hotspots where crop yield is more affected by droughts and how this can be clarified using satellite imagery. However, while an overall good fit between climate, ENSO, and crop yield variables was found, it is important to consider other variables, such as evapotranspiration and soil moisture to improve risk-based models. With such information also agricultural models canould be set up and risk management plans with better accuracy determined.~~

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APPENDIX

Table A1. Spatial location of the studied weather stations where gauged precipitation data ~~is~~ are available, the stations that also present temperature maximum and minimum data indicate T on the column of temperature.

No	Station name	Latitude	Longitude	Altitude	Temperature
[1]	Ayo Ayo	-17.1	-68.0	3888	
[2]	Calacoto	-17.3	-68.6	3830	T
[3]	Collana	-16.9	-68.3	3911	T
[4]	El Alto Aeropuerto	-16.5	-68.2	4034	T
[5]	El Belen	-16.0	-68.7	3833	T
[6]	Oruro Aeropuerto	-18.0	-67.1	3701	T
[7]	Patacamaya	-17.2	-67.9	3793	
[8]	Salla	-17.2	-67.6	3500	
[9]	San Juan Huancollo	-16.6	-68.9	3829	
[10]	Santiago de Huata	-16.1	-68.8	3845	T
[11]	Tiahuanacu	-16.6	-68.7	3863	T
[12]	Viacha	-16.7	-68.3	3850	T

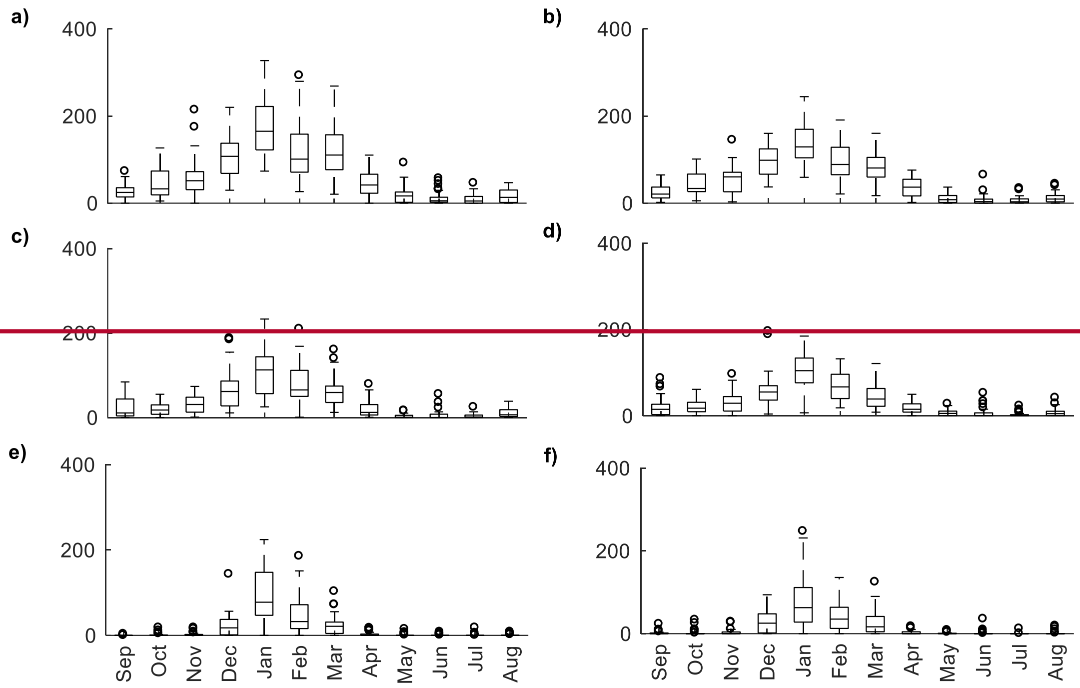
~~N$_o$~~	~~Station name~~	~~Region~~	~~Latitude~~	~~Longitude~~	~~Altitude~~	~~Temperature~~
~~[1]~~	~~Achiri~~	~~La Paz~~	~~-17.21~~	~~-69.00~~	~~3880~~	~~T~~
~~[2]~~	~~Ancoraimes~~	~~La Paz~~	~~-15.90~~	~~-68.90~~	~~3882~~	
~~[3]~~	~~Ayo Ayo~~	~~La Paz~~	~~-17.09~~	~~-68.01~~	~~3888~~	~~T~~
~~[4]~~	~~Berenguela~~	~~La Paz~~	~~-17.29~~	~~-69.21~~	~~4145~~	
~~[5]~~	~~Calacoto~~	~~La Paz~~	~~-17.28~~	~~-68.64~~	~~3830~~	~~T~~
~~[6]~~	~~Colcha K~~	~~Potosí~~	~~-20.74~~	~~-67.66~~	~~3780~~	
~~[7]~~	~~Collana~~	~~La Paz~~	~~-16.90~~	~~-68.28~~	~~3911~~	~~T~~
~~[8]~~	~~Conchamarca~~	~~La Paz~~	~~-17.38~~	~~-67.46~~	~~3965~~	
~~[9]~~	~~Copacabana~~	~~La Paz~~	~~-16.17~~	~~-69.09~~	~~3870~~	
~~[10]~~	~~El Alto Aeropuerto~~	~~La Paz~~	~~-16.51~~	~~-68.20~~	~~4034~~	~~T~~
~~[11]~~	~~El Belen~~	~~La Paz~~	~~-16.02~~	~~-68.70~~	~~3833~~	
~~[12]~~	~~Hichucota~~	~~La Paz~~	~~-16.18~~	~~-68.38~~	~~4460~~	
~~[13]~~	~~Oruro Aeropuerto~~	~~Oruro~~	~~-17.95~~	~~-67.08~~	~~3701~~	~~T~~
~~[14]~~	~~Patacamaya~~	~~La Paz~~	~~-17.24~~	~~-67.92~~	~~3793~~	~~T~~
~~[15]~~	~~Salla~~	~~La Paz~~	~~-17.19~~	~~-67.62~~	~~3500~~	
~~[16]~~	~~San Jose Alto~~	~~La Paz~~	~~-17.70~~	~~-67.78~~	~~3746~~	~~T~~
~~[17]~~	~~San Juan Huancollo~~	~~La Paz~~	~~-16.58~~	~~-68.96~~	~~3829~~	
~~[18]~~	~~San Pablo de Lipez~~	~~Potosí~~	~~-21.68~~	~~-66.61~~	~~4256~~	
~~[19]~~	~~Santiago de Huata~~	~~La Paz~~	~~-16.05~~	~~-68.81~~	~~3845~~	
~~[20]~~	~~Santiago de Machaca~~	~~La Paz~~	~~-17.07~~	~~-69.20~~	~~3883~~	
~~[21]~~	~~Tiahuanacu~~	~~La Paz~~	~~-16.57~~	~~-68.68~~	~~3863~~	~~T~~
~~[22]~~	~~Uyuni~~	~~Potosí~~	~~-20.47~~	~~-66.83~~	~~3680~~	~~T~~
~~[23]~~	~~Viacha~~	~~La Paz~~	~~-16.66~~	~~-68.28~~	~~3850~~	~~T~~

~~**Table A2.** The classification of strong El Niño (≥ 1.5 deg C), strong La Niña (≤ -1.5 dec C) and neutral/moderate (-1.4 to 1.4 dec C) years for the period 1981 to 2015.~~

Strong El Niño	Neutral and moderate	Strong La Niña
1982-83	1981	1988-89
1986-87	1984-1985	1998-99
1987-88	1989-1990	2007-08
1991-92	1992-1996	2010-11
1997-98	2000-2006	
	2008-2009	
	2011-2014	

~~**Table A3.** T-test and Wilcoxon rank sum test for quinoa and potato yield during El Niño years and neutral/moderate years. If the hypothesis is equal to 1 it means that we rejected the null hypothesis at a confidence level of 95%.~~

		T test 2 sample			Wilcoxon rank sum test		
		Hypothesis	P value	t-stat	Hypothesis	P value	z-stat
Quinoa	La Paz	1	~0	4.2	1	0.01	3.0
	Oruro	0	0.13	1.6	1	0.05	2.0
	Potosi	1	~0	3.4	1	0.04	2.5
Potato	La Paz	0	0.10	1.7	0	0.54	0.61
	Oruro	1	~0	3.4	1	0.02	2.4
	Potosi	1	0.02	2.6	1	0.05	2.0



~~**Figure A1.** Boxplot of the total monthly precipitation in the Bolivian Altiplano at the northern Altiplano: (a) Copacabana [9], (b) El Alto Aeropuerto [10], central Altiplano: (c) Oruro Aeropuerto [13], (d) Patacamaya [14], and southern Altiplano (e) Colcha K [6], and (f) Uyuni [22].~~

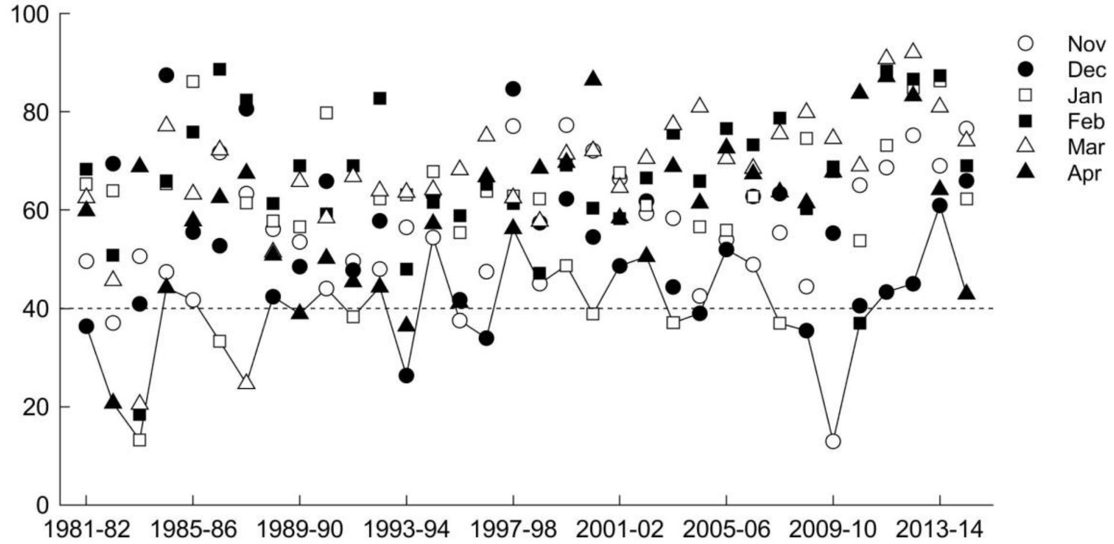


Fig. A1. Monthly mean VCI (%) from November 1981 to April 2015. Values below 40% (dashed line) represent a drought event.

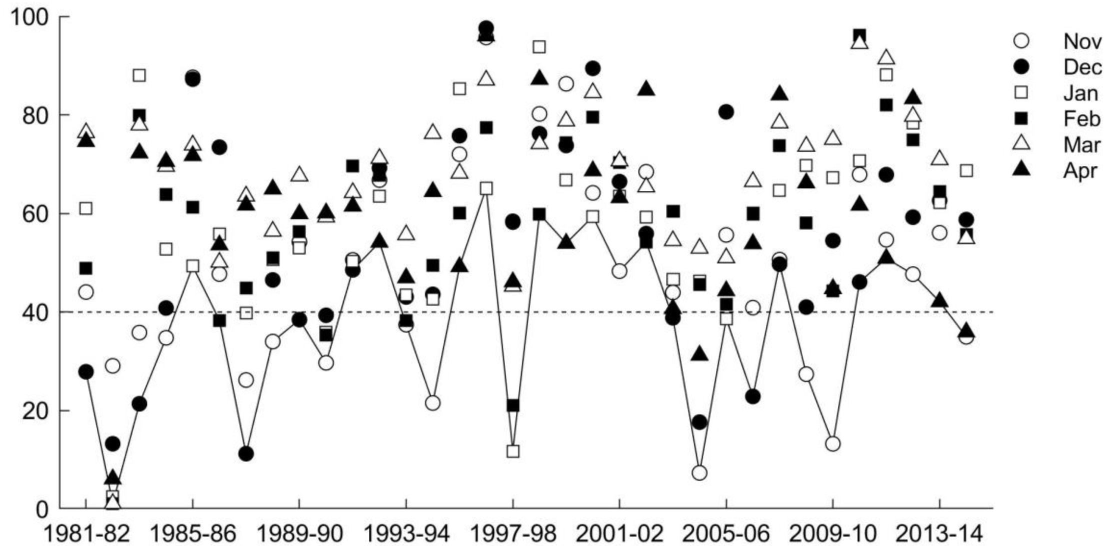


Fig. A2. Same as Fig. A1 but for the TCI.

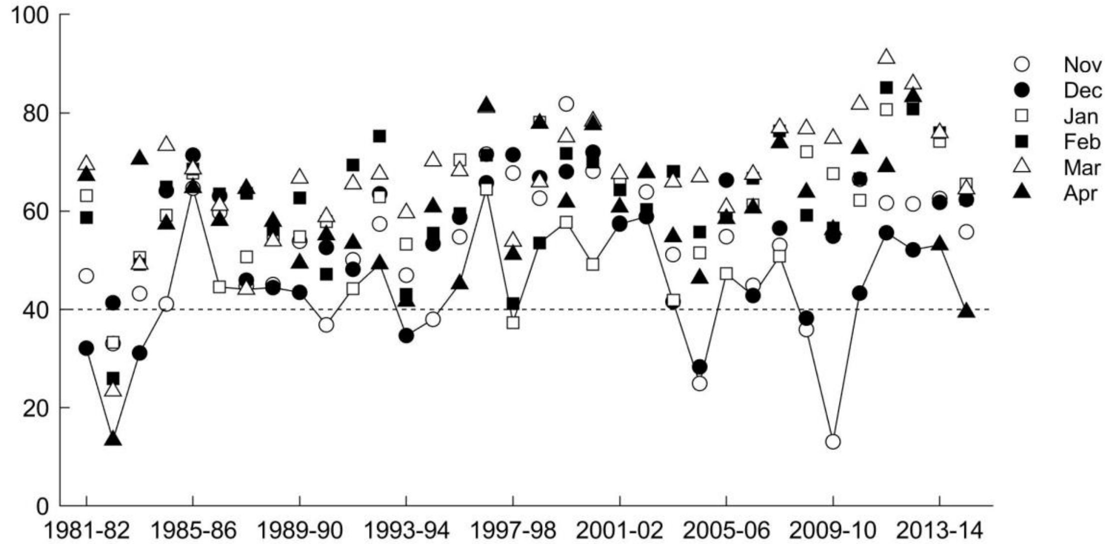


Fig. A3. Same as Fig. A1 but for the VHI.