Response to reviewer #1

1- General Comments

Réveillet et al. have restructured the manuscript with the new title "Impact of forcing on sublimation simulations for a high mountain catchment in the semi-arid Andes" fundamentally with respect to the reviewer's comments. The focus on the differences in sublimation depending on the forcing by AWS data or WRF model output is presented much more comprehensively in the updated version.

In general, the manuscript can be optimized by highlighting and rating the most important parameters, their representation in the different products (AWS, WRF) and their impact on processes controlling sublimation rates in the final conclusions. In addition, the advantage of using WRF data (I assume the application in forecast) should be pointed out with respect to the presented outlook.

The manuscript is worth for publishing after corrections according to the comments hereafter.

Authors' response: Thanks again to the reviewer for new insightful comments that have helped to strengthen the final paper.

2- Specific Comments

(1) The snow depth (SD) in Fig. 3 is presented in m w.e. First, I assume that this is SD in meter, and not the SWE. In section 4.2 the RMSE error is given by 0.15 m. This is about the same magnitude as the total snow depth in 2014, and considerable in relation to SD in 2015. Please discuss the ration of RMSE to total snow depth in order to rate the overall performance of SD simulations.

Authors' response: Thank you for pointing out this mistake, m w.e. have been changed to m.

The RMSE mentioned in section 4.2 corresponds to the mean of the RMSE computed at each station. When forced by the AWS-forcing, it ranges between 0.06 and 0.19 m w.e. (indicated in Figure 5) corresponding to 11 and 26 % of the maximum snow depth at each station. In particular large RMSE computed for 2014 corresponds to 63 %. Details are reported in the Table below and the % is now given in section 4.2:

Simulated snow depths using the AWS-forcing (Figures 5 a-f) are in good agreement with measured snow depth values (mean *k*=0.14 and mean *RMSE*=0.15 m, corresponding to 36% of the maximum mean snow depth). Note that the largest RMSE corresponds to 63% of the maximum snow depth.

[…]

Simulations performed with the WRF-forcing indicate lower performances in simulating snow depth evolution at the AWS (Figure 5 g-m; mean *k*=0.12, and mean *RMSE*=0.20 m, corresponding to 39% of the maximum mean snow depth, and the largest RMSE corresponds to 76 % of the maximum snow depth).

AWS	Max Snow measured (m)	RMSE AWS-forcing	%	RMSE WRF-forcing	%
La Gloria	0.45	0.14	31%	0.34	76%
Vega Tapado	0.35	0.17	59%	0.16	27%
Colorado Alto	0.35	0.18	63%	0.15	43%
La Laguna	0.59	0.17	28%	0.30	51%
Tapado	0.56	0.06	11%	0.07	13%
Tapado Alto	0.74	0.19	26%	0.19	26%
Mean	0.51	0.15	36%	0.20	39%

(2) Within this study multiple parameters and processes are shown influencing the simulated sublimation. In addition to the high uncertainty in precipitation (and thus SD, SCA, SCD) also the roughness value is shown to have a high impact on results. Likewise, the ground level wind can be assumed to control turbulent heat fluxes considerably. On page28 line 24 several sources of uncertainty are mentioned. I would like to encourage the authors to present on the basis of the results and the discussion a final ranking of the largest uncertainties and their impact on simulated sublimation in the conclusion. Please also state which potential and advantages are expected by improving WRF using AWS data assimilation vs using MicroNet interpolation of AWS data (re-analysis or fore-cast? see last sentence (iii)).

Authors' response:

More information are now given in the conclusion, according to your comment. It now reads:

"Sublimation simulated in this study is associated with several sources of uncertainty related to the forcing chosen and the model calibration. Regarding the calibration, the roughness value is the key concern to properly simulate the turbulent fluxes and result showed strong sensitivity to this value. Nevertheless, without measurements to properly calibrate this value, it appears to be the main source of model calibration uncertainty. Results presented here highlight precipitation as the main forcing uncertainty, due to measurement errors and lack of spatial representation as precipitation data was only available for two stations. Precipitation uncertainties directly impact snow on the ground, and therefore indirectly sublimation rates. Uncertainties in wind speed were likely the second source of error in sublimation results, which needs to be better constrained in future studies. Therefore, this study highlights that this uncertainty has a strong impact on sublimation and further work is suggested to *(i)* improve measurements uncertainties, *(ii)* increase the number of sensors over the catchment, and *(iii)* incorporate AWS measurements into the WRF model and use data assimilation to improve model outputs. CEAZA is currently working on point *(iii)* to provide improved WRF outputs for the semi-arid Andes of Chile. This study has highlighted the current difficulties in using standard WRF model outputs in a semiarid, Andean catchment. Moving forward, it would be highly advantageous to improve WRF model performance in mountainous areas where high relief and difficult access often limits AWS distribution to valley floors, therein limiting the accuracy of interpolation techniques for terrain sensitive variables, such as precipitation and wind speed and direction."

3- Detailed Comments (P = page, L = line)

P1 L21: To complete the information in the brackets add the catchment size

Authors' response: Done:

"…this study aims to simulate melt and sublimation rates over the instrumented watershed of La Laguna (513 km^2, 3150–5630 m a.s.l., 30°S 70°W), during two hydrologically contrasting years (i.e. dry *vs.* wet)."

P1 L25: Here and throughout the text: please try to avoid the slash (here: melt/sublimation). It might be confusing if this is "and" or "or". In this case it also can be read as the ratio of melt divided by sublimation.

P1 L28: Here more detailed information on the processes (SW radiation, sensible heat flux, …) causing higher melt rates would be desirable.

P1 L29: One sentence might be added on the overall applicability of WRF output for forcing the snow-pack simulation.

"Results of simulations indicate first a large uncertainty in sublimation to melt ratios depending on the forcing as the WRF data has a cold bias and over-estimates precipitation in this region. These input differences cause a doubling of the sublimation to melt ratio using WRF forcing inputs compared to AWS. Therefore, the use of WRF model output in such environments must be carefully adjusted so as to reduce errors caused by inherent bias in the model data. For both input datasets, the simulations indicate similar sublimation fraction for both study years, but ratios of sublimation to melt vary with elevation as melt rates decrease with elevation due to decreasing temperatures. Finally results indicate that snow persistence during the spring period decreases the ratio of sublimation due to higher melt rates."

P5 L9: Do you have experience or any data on how the temperature and RH measurements of the HOBO weather stations perform in comparison to the permanent AWS. Are the HOBO temperature sensors ventilated? Please add one or two sentences.

Authors' response: No direct comparison data are available in the study area. The temperature sensors are not ventilated, however relatively constant wind allows natural ventilation of the sensors. We agree that the HOBO's sensors performances are lower than for Campbell Scientific sensors and have added a sentence to indicate this in the text (se below). Nevertheless, we still think that the main source of error is from the interpolation more than the measurements.

"Although the lower accuracy of HOBO weather sensors compared to the permanent stations represent a source off errors in the forcing data, errors resulting from the spatial interpolation of forcings are likely to be much greater than these."

P12 L18: AWS 2014 vs 2015

Authors' response: Done

P12 L24: Replace "larger number of clouds" by "higher degree of cloud cover"

Authors' response: Done

P12 L30: Please present the relative difference in addition to the absolute value. Please also state that this sums up to a factor of three for highest elevations (see Fig. 4d).

Authors' response: This information has been added, according to your comment:

"and higher precipitation (annual cumulative difference larger than 1 m w.e. and a difference ranging between a factor of 1.6 to 3.4 depending on the elevation (Figure 4d))."

P14 L1: What is the temperature along the precipitation event on June 21st 2015? Can the temperature threshold between rain and snow be also a reason for the overestimation of snow depth?

Authors' response: It is unlikely that rainfall causes the difference, as no rainfall has been observed, or calculated, in the catchment. The overestimation of snow depth is likely due to the results of the interpolation calculation, which is based on relatively low snowfall rates at the La Laguna AWS compared with higher elevations. We have further clarified this point in the text.

"Interpolation results in overestimation of the simulated snow depth during 2015, probably due to an over-estimation of the precipitation for the large event on June 21st 2015 (Figure 3) caused by large differences in measured precipitation at the La Laguna and Tapado AWSs especially. Nevertheless, the start and the end date of the snow season are in good agreement with observations (maximum difference of 3 days observed at La Gloria site). Note that this comparison probably over-estimates the accuracy as snow depths are compared at the exact location of meteorological forcing. Larger uncertainties are expected at the interpolated locations."

Authors' response: We have added the following explanation to the Discussion (Section 5.1.2, p23-24):

The large variation of the SCA resulting from the WRF driven model results (Figure 5) is likely related to the higher frequency of relatively small precipitation events modeled by WRF than are recorded by the AWS. These small events cover the catchment with a relatively thin layer of fresh snow, which sublimates relatively quickly causing the SWE to decrease to < 3 mm w.e. at lower elevations, causing high variability in modeled SCA.

P20 L9: For 2015 the modelled turbulent fluxes…

Authors' response: Done

P24 L15: Please mention here why it would be advantageous to correct the regional WRF model output in contrast to use the MicroMet interpolation of station values.

Authors' response: The following text has been added to the end of the Conclusion (Section 6):

"This study has highlighted the current difficulties in using standard WRF model outputs in a semiarid, Andean catchment. Moving forward, it would be highly advantageous to improve WRF model performance in mountainous areas where high relief and difficult access often limits AWS distribution to valley floors, therein limiting the accuracy of interpolation techniques for terrain sensitive variables, such as precipitation and wind speed and direction. "

P27 L13: Referring to the title, sublimation rates have been the specific focus. Of course the snow depth and SCA do play an important role as they result from precipitation, which is highly uncertain (see conclusions).

Authors' response: The first sentence now reads: The main objective of this study was to investigate the impact of forcing data on modeled mass and energy balance to explain sublimation ratios.

P27 L15: Since sublimation is most sensitive to the roughness value, wind at the ground level also plays an important role once a snow cover exists. Please add this information.

Authors' response: According to your comment, and in agreement with reviewer #2, a discussion about the role of the wind has been added. See response to Reviewer #2.

P28 L15: Delete "years" at the end of the sentence.

Authors' response: Done

Figure 3:

- It's not clarified in the caption if hourly wind speed or daily mean values of wind speed are presented. I would suggest to present hourly values to enable a better estimate of potential wind transport and sublimation rates from the graph.

Authors' response: The wind rose are result of combining hourly wind speed and velocity data. The word 'hourly' has been added to the caption.

Figure 10

- Caption: Revise "Cumulated" by "Stacked".

Authors' response: Done.

Response to reviewer #2

1- General comments

The manuscript is much improved from the initial submission. The paper now focuses more on the differences in sublimation when using different forcing datasets, with a smaller focus on differences in sublimation due to interannual climate variability and elevation. The new and amended figures highlight useful information and the results have been structured in a logical fashion.

The interpretation and discussion around the central result of the paper (increased sublimation rate and ratio when using WRF output) is, however, still lacking and deserves much more attention. The assertion that differences in snow cover are driving the differences is not compelling and is not supported by all the results. For instance, it does not explain why sublimation is still higher in 2015 when the snow-covered area is similar between WRF and AWS simulations. Colder temperature and lower RH will tend to favour sublimation over melt, but these factors do not explain the larger magnitude of both the sensible and latent heat for WRF simulations across all elevations in both years.

I would suggest that wind speed is one of the key reasons for differences in sublimation that needs discussion. Figure 4 shows large differences in wind speed between AWS and WRF forcing (average ~2 vs ~5 ms-1). The turbulent fluxes are very sensitive to variations in wind speed in this range, especially if stability corrections are employed. Figure 9 shows both latent and sensible heat fluxes are increased in WRF simulations compared to AWS simulations, indicating that wind speed is driving an increased magnitude of turbulent fluxes (and hence sublimation). Another piece of evidence that wind speed is driving increased sublimation is the increased sublimation in 2015 for AWS simulations, which have higher wind speed than in 2014.

The interpretation in the results and discussion (including sections 4.3.2, 5.1, 5.1.2 and specific comments) needs revised to align with the new results presented.

In addition, some of the methods that are central to the key results need further description. In particular: the calculation of turbulent fluxes, extrapolation of radiation, definition of mass balance terms, validation of surface temperature (see specific comments).

Authors' response: Thanks again for new insightful comments that have helped to strengthen the final paper. Response of the comments mentioned here are detailed below.

One further area of concern is the discrepancy between the total precipitation and total ablation simulated by each forcing dataset. In 2015, snow covered area starts and ends the year close to 0 (Figure 6) implying that all the snow that fell during the year has been lost in the year. Both forcing datasets result in a similar magnitudes of SCD and ablation rate with elevation (figures 7 and 8) as well as catchment average total ablation (figure 10), which appears to be around 0.4 m w.e.. Yet the precipitation in WRF is between 0.20 to 1 m w.e. larger than the AWS forcing. What has happened to this extra precipitation in the WRF simulations? Has it fallen as rain? Please explain.

Authors' response: There is no extra precipitation with regards to ablation results, there is a zero sum for all modeled years for both WRF and AWS driven outputs. The confusion may lie with the graphical representation, which does not include relative percentage of the catchment. For example, in Figure 8, if the elevation is summed directly, it appears that the ablation rates for 2015 are very similar, however when summed over the snow-covered area they equal precipitation amounts (Table R1).

Table R1: Total values (m^3 w.e.) calculated in each simulation over the entire catchment

	2014				2015			
	Precipitation	Melt	Sublimation	Precipitation-Ablation	Precipitation	Melt	Sublimation	Precipitation-ablation
AWS	4174.5	3013.3	1161.2	0	22775.4	12167.5	10608.4	0
WRF	24354.4	4315.5	20038.9	0	54509.9	16046.4	38463.5	0

2- Specific comments:

P1ln24 "melt/sublimation ratios" Please be consistent with the terms used in the rest of the manuscript i.e. "ratio of sublimation to total ablation (sublimation+melt)"
P1ln25 "due to…" This statement needs revising in line with the major comment above. It is not clear that the increased precipitation increases the sublimation ratio. In fact, this is at odds with the last sentence in the abstract.
Authors' response: Corrected, please see response to reviewer 1. The new text is:
"Results of simulations indicate first a large uncertainty in sublimation to melt ratios depending on the forcing as the WRF data has a cold bias and over-estimates precipitation in this region. These input differences cause a doubling of the sublimation to melt ratio using WRF forcing inputs compared to AWS. Therefore, the use of WRF model output in such environments must be carefully adjusted so as to reduce errors caused by inherent bias in the model data. For both input datasets, the simulations indicate similar sublimation fraction for both study years, but ratios of sublimation to melt vary with elevation as melt rates decrease with elevation due to decreasing temperatures. Finally results indicate that snow persistence during the spring period decreases the ratio of sublimation due to higher melt rates."

P8ln10 Given the overestimation of wind speed in the WRF output, it would be worth checking that the data used were in fact supplied at 2m height - standard WRF outputs for surface wind speed are given at 10m and will be markedly higher than 2m wind speed.
Authors' response: We can confirm that the 10 m WRF output were logarithmically-scaled to the 2 m height before inclusion into MicroMet, similar to the way the data from the La Laguna AWS was treated (scaled from 10 m to 2 m height). The text now reads "The model outputs are at 2 m above the surface (note that wind output was logarithmically scaled from 10 m to 2 m height) and are available at 22 km resolution over Chile, 7 km resolution at the regional scale, and 3 km resolution over the La Laguna catchment (Figure 1)."

Section 3.1 or 3.2 Please describe in more detail the mass balance terms used. I.e. does 'sublimation' include evaporation from a melting surface? Does melt include melt that is refrozen in the snowpack or only that which drains from the snowpack? This will make a big difference to the sublimation ratio.
Authors' response: Further clarification have been added, and the edited text in Section 3.2 now reads:
"After validating the model, the sublimation ratio and sublimation and melt rates were computed over the catchment for the two years. The sublimation rate corresponds to the mass sublimated per unit of time and does not include evaporation from meltwater. The sublimation ratio is defined as a percentage, and equal to the sublimation divided by the total ablation (i.e. sublimation plus melt rates). The melt rate corresponds to meltwater that runs off from the snowpack. Whilst the model calculates refreezing, the final melt rate described here does not include snow melt that refreezes in

P10ln30 Please describe in more detail the relevant aspects on the turbulent flux parameterisation in SnowModel (i.e. surface temperature calculation, stability correction, whether the option to enhance turbulent fluxes for patchy snow was used etc). This is a key aspect of the methods the deserves more attention.

Authors' response: Unfortunately the model does not include the possibility to separately evaluate patchy snow. Regarding the other information, it has been added as follows:

"Note that the surface temperature is solved iteratively by closing the energy balance (Liston and Elder 2006). In addition, under stable atmospheric conditions, turbulent fluxes are modified based on a Richardson number correction (Liston and Hall, 1995)."

P12ln30 The variation of LW and SW with elevation in Figure 4f,g does not make sense - if Ta and RH are lower with WRF, then LW should be less but the WRF values are very similar to the AWS values in each year. Similarly, the SW values for WRF and AWS data are very close for each year, despite larger differences in RH between WRF and AWS than between each year for each data source. Can the authors check the lines are labelled correctly and revise comments regarding differences in LW and SW.

Following on from the above point, section 3.2.1 needs to describe (at least in general) how short and longwave fluxes are extrapolated. From reading Liston and it seems that cloud cover is estimated using RH, then predetermined cloud extinction coefficients are used to calculate SW and LW across elevations. Was the option to 'assimilate' the observations used in this study? Neither of these is particularly standard practice when SW and LW observations are available to distribute LW and SW across a catchment, and these inputs will have a large bearing on the simulated energy and mass balances.

Authors' response: MicroMet was used in 'assimilation mode' for both AWS and WRF datasets to calculate SWi and LWi , and so used available measurements to distribute these variables across the catchment. It should be noted that in the case of LWi, the data range and observed pattern compare well to observed measurements shown in the paper under review, and to measurements shown in MacDonell et al. (2013b) in the Huasco catchment (the catchment immediately to the north of the study site). It should be noted that as the area only experiences relatively low levels of cloud cover, radiative forcings are relatively "easy" to simulate. However, variables such as temperature, humidity, wind and precipitation are more complex, especially in a mountainous region. Unfortunately we only have measurements in valley floors, and so it is more difficult to assess exactly the best practice to spatially distribute these parameters.

We have included a statement in the methods section clarifying that we assimilate the data: "Radiation values for LWi and SWi are assimilated and specified using the default parameterization (Liston and Elder 2006a)."

P13ln10 It is good to see the validation of the surface temperature (albeit at one site only), and it would be useful to include this at the beginning of section 4.2 or at least the supplementary material, given that a correct estimation of surface temperature is key to a correct simulation of melt vs sublimation. The surface temperature simulated with WRF should also be included on this figure too – I expect it will be lower than the AWS measurements given the predominance of sublimation.

Authors' response: As suggested we have added the WRF results and included the surface temperature comparison in the supplementary information:

D – Surface temperature

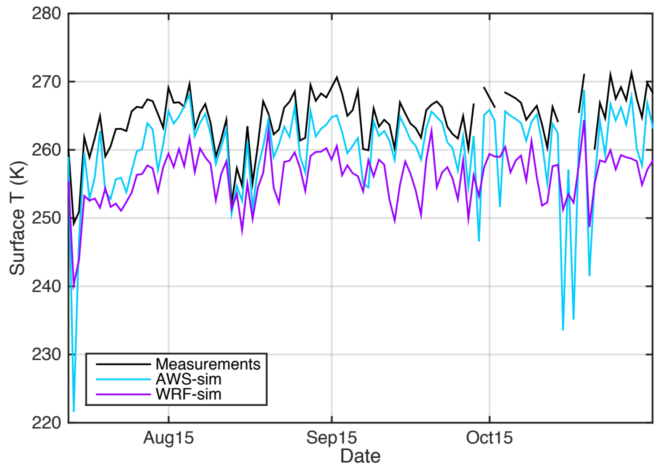

Figure S3: Observed and modeled surface temperature at Tapado AWS. Measurements correspond to the surface temperature computed from the outgoing long wave measured by the station. Cyan line correspond to the simulated surface temperature using the AWS-forcing and the purple one the WRF-forcing.

P22ln6 "This [larger turbulent fluxes in WRF vs AWS for 2014] can be explained by the larger snow cover simulated by WRF-forcing with snow cover in the entire catchment while the AWS-forcing only results in snow at higher elevations. Since the fluxes are computed over snow surfaces only, WRF increases the contribution of warmer, low elevation areas." Figure 8 shows that the differences in turbulent fluxes are similar at all elevations, which does not support this statement. In 2015, the snow cover is similar between WRF and AWS simulations, yet turbulent fluxes and sublimation are still much larger in the WRF simulations – suggesting that snow cover duration is not driving the differences in sublimation. Please remove or revise this statement.

Authors' response: During the revision we realized that the text referred to Figure 8 instead of Figure 9, and have changed the text accordingly. In addition, we have adjusted the scale to facilitate the direct comparison of the four plots. In doing so, it becomes clearer that there is a difference in turbulent heat fluxes at different elevations. However, we agree that snow cover duration is not the only control, and that wind differences are likely to contribute. As we added additional explanation here, we decided it was more appropriate to include the text in the Discussion (Section 5.1.2), and so the paragraph now reads:

"In 2014 the turbulent fluxes are dominant for the WRF forcing but not for the AWS forcing (Figure 9 a,c). This can be partially explained by the larger SCA simulated by WRF-forcing with snow cover in the entire catchment while the AWS-forcing only results in snow at higher elevations. Additionally, WRF-forcing indicates colder, drier and windier condition than the AWS-forcing (Figure 4). Lower RH and higher wind speed will directly increase the latent heat flux, and potentially sublimation ratio, depending on surface temperature (see Figure S3 in Supplementary Material for surface temperature comparison)."

P24ln26 "On the other hand biases in wind speed, incoming LW and SWi and air pressure are low for both years (results not shown)." Figure 4 now wind speed, LWi and SWi, this comment needs revised. A large bias in wind speed is shown in the figure and needs discussing.

Authors' response: The comment regarding the bias in wind speed has been corrected, and section 5.1.2 has been rewritten.

sublimation rate and ratio (especially in 2015, Figure 10)." This comment is confusing as SCD in 2015 was similar between AWS and WRF simulations, hence it cannot be the driver for differences between WRF and AWS. Please revise.

Authors' response: We agree that the text is unclear, we have edited the paragraph, which now reads:

"The SCD also has a significant influence on sublimation. For 2014, the differences in SCD between the two forcings were 100 days below 4500m, and close to 50 days above this elevation (Figure 7a). Snow that persists until later in the year (austral Spring and Summer) results in an increased total melt rate and can influence the sublimation ratio (especially in 2015, Figure 10). This is the only explanation for the larger melt fraction observed with AWS-forcing compared to WRF-forcing at low elevations, given the cold bias in WRF-forcing (Figures 8c and 4b). Since a larger SCD can be related to larger precipitation amount, precipitation uncertainties likely play a significant role and the sublimation estimation."

P25l8 "This is the only explanation for the larger melt rate observed with AWS-forcing compared to WRF-forcing at low elevations, given the cold bias in WRF-forcing (Figures 8c and 4b)." Figure 10c shows that in 2014 the low elevation areas show a similar melt rate between WRF and AWS simulations so it is unclear what is meant here. The cold bias in WRF forcing would tend to favour lower melt, which would explain the higher melt with AWS forcing. Please revise.

Authors' response: The paragraph has been clarified to talk about melt fraction as opposed to rates and the impact of snow permanence until the austral Spring and Summer months. Please see previous response.

3- Editorial comments:

Figure 4f,g – please check the lines are labelled correctly.

Authors' response: Yes, see comment above.

Figure 5a – should the legend read "AWS sim" rather than "WRF sim"

Figure 5 caption – correction to colours – "vs. observed (red)…" and "Grey shaded areas.."

Authors' response: Done

Figure 8a ylabel – "…(%) for 2014"

Figure 8 caption – "… forcing for 2014 (a) and 2015 (b). Simulated annual average total ablation (sublimation and melt) …

Authors' response: Done

Figure 9 – common x limits would make it easier to compare between years as well as with elevation.

Authors' response: Done

Figure 11 – common y limits would make it easier to compare between forcing datasets.

Authors' response: Done

Impact of forcing on sublimation simulations for a high mountain catchment in the semi-arid Andes

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Abstract. In the semi-arid Andes of Chile, farmers and industry in the cordillera lowlands depend on water from snowmelt, as annual rainfall is insufficient to meet their needs. Despite the importance of snow cover for water resources in this region, understanding of snow depth distribution and snow mass balance is limited. Whilst the effect of wind on snow cover pattern distribution has been assessed, the relative importance of melt versus sublimation has only been studied at the point-scale over one catchment. Analyzing relative ablation rates and evaluating uncertainties are critical for understanding snow depth sensitivity to variations in climate and simulating the evolution of the snow pack over a larger area and over time. Using a distributed snowpack model (SnowModel), this study aims to simulate melt and sublimation rates over the instrumented watershed of La Laguna (513 km^2, 3150–5630 m a.s.l., 30°S 70°W), during two hydrologically contrasting years (i.e. dry *vs.* wet). The model is calibrated and forced with meteorological data from nine Automatic Weather Stations (AWS) located in the watershed, and atmospheric simulation outputs from the Weather Research and Forecasting (WRF) model. Results of simulations indicate first a large uncertainty in sublimation to melt ratios depending on the forcing as the WRF data has a cold bias and over-estimates precipitation in this region. These input differences cause a doubling of the sublimation to melt ratio using WRF forcing inputs compared to AWS. Therefore, the use of WRF model output in such environments must be carefully adjusted so as to reduce errors caused by inherent bias in the model data. For both input datasets, the simulations indicate similar sublimation fraction for both

study years, but ratios of sublimation to melt vary with elevation as melt rates decrease with elevation due to decreasing temperatures. Finally results indicate that snow persistence during the spring period decreases the ratio of sublimation due to higher melt rates.

1. INTRODUCTION

In the semi-arid Andes, glaciers and seasonal snow cover are the dominant water sources, as rainfall is episodic and insufficient to meet user demand. The region is characterized by very low precipitation amounts that are largely limited to winter months (i.e. June, July and August), and are erratic. Large interannual variability is observed, as the area is strongly affected by El Nino South Oscillations (ENSO) (e.g. Falvey and Garreaud, 2007; Garreaud, 2009; Montecinos et al., 2000). In broad terms, during El Niño periods the semi-arid Andes are characterized by warm air temperatures and higher precipitation totals, whereas La Niña periods are on average colder with less precipitation (e.g. Ducan *et al.,* 2008). Whilst snowmelt comprises the bulk of available water (Favier et al., 2009), due to low humidity, high solar radiation and strong winds, sublimation is a significant ablation process, especially at high elevations (Ginot et al., 2001; Gascoin et al., 2013; MacDonell et al., 2013). Consequently, quantifying snow mass balance processes are crucial for predicting current water supply rates, and for informing future projections.

Despite the importance of snow cover for water resources in this region, there is currently a limited understanding of snow depth distribution and mass balance, largely due to the difficulty of accurately measuring and modeling both accumulation and ablation processes in this area (Gascoin et al., 2011). Temperature index models have been shown to be inadequate to evaluate mass balance processes in the semi-arid Andes, due to the importance of the latent energy flux (Ayala et al., 2017). However, an energy balance model requires a larger input dataset that is often not available in Andean catchments due to the logistical difficulty of Automatic Weather Station (AWS) installation and maintenance. Therefore, the evaluation of alternative methods for acquiring distributed meteorological information is required. Options include the use of interpolation/extrapolation strategies (e.g. *MicroMet,* Liston and Elder, 2006b), reanalysis (NCEP, Kalnay et al., 1996) or atmospheric model outputs (e.g. Weather Research and Forecasting (WRF) model, Skamarock and Klemp, 2008). For the semi-arid Andes, both *MicroMet* extrapolation based on AWS data (Gascoin et al., 2013) and atmospheric models (e.g. Favier et al., 2009; Mernild et al., 2017) have been used to force snow models. However, none of these studies have quantified the uncertainties related to forcing data.

The relative importance of melt and sublimation to total ablation has been studied at both the point-scale (MacDonell *et al.,* 2013) and catchment scale (Gascoin *et al.,* 2013) in one catchment in the semi-arid Andes.

MacDonell *et al.* (2013) estimated that the sublimation fraction was 90% at high altitude (>5000m a.s.l.) in an extreme environment with predominantly sub-freezing temperatures and strong local wind speeds. Using a distributed snowpack model Gascoin *et al.* (2013) found that the total contribution of sublimation (static-surface and blowing snow sublimation) to total ablation in the Pascua-Lama area (29.3° S, 70.1°W; 2600 - 5630 m a.s.l.) was 71%. However, this value was obtained for one snow season, and the precipitation was estimated from snow depth measurements as precipitation gauge data were unreliable. The sensitivity of sublimation to meteorological forcing and in particular to precipitation uncertainties was not evaluated.

The objective of this study is to assess the uncertainties related to modeling snow evolution in the semi-arid Andes using AWS and WRF-model generated meteorological datasets during two contrasting years. From this analysis, the snow mass balance for one relatively wet and one dry year will be compared, and an evaluation of the impacts of model choices on sublimation and melt rates in dry mountain areas will be discussed.

To address this aim, the model SnowModel described in Liston *et al.* (2006) will be applied to the La Laguna catchment in the semi-arid Chilean Andes during 2014 and 2015. These two years were selected because in this region, 2015 was considered to be a strong *El Nino* event, associated with warm and wet conditions, whereas 2014 was drier and colder and considered a neutral year (Ceazamet; http://origin.cpc.ncep.noaa.gov, Figure S1 in the supplementary information). We hypothesize a significant sublimation ratio for winter 2014, due to drier and cooler conditions which should inhibit melt. Regarding 2015, higher precipitation totals could lead to *(i)* increased snow depths and snow persistence at the end of the winter season (i.e. in August, September), favoring melt and therefore decreasing the sublimation ratio or *(ii)* increased sublimation in the spring can increase the saturation vapor pressure at the snow surface, providing more energy for sublimation (Herrero and Polo, 2016). This uncertainty regarding the impact of snow cover duration on sublimation highlights the need for further research.

2. STUDY SITE AND DATA

2.1 Study site

La Laguna watershed is located in the semi-arid Andes of Chile in the Elqui Valley (30°S, 70°W), 200km East of La Serena, close to the border with Argentina (Figure 1a). As it is easily accessible this catchment is the most instrumented within the region with an unusually high density of AWS, especially during 2014 and 2015.

The catchment covers an area of 513 km^2 and elevations range from 3150 to 6200 m a.s.l. (Figure 1b). At these elevations, only minimal vegetation in the form of shrubs is observed, so we do not consider vegetation in this study. The study area includes rock glaciers and glaciers. Tapado Glacier is the largest of these with an area of

2.2 km^2 (Figure 1b). This catchment was selected since it is an important water resource in the Elqui valley. Indeed it feeds water to the La Laguna reservoir (38.10^6 m^3 capacity), which is part of the strategic irrigation system in the Elqui Valley. Nevertheless the precipitation amount is very low. The mean annual precipitation measured at la Laguna station is 200 mm a^{-1} and precipitation events are episodic with less than 10 events per year. In this region, most of these events (90%) occur during the winter period (Figure S1, Rabatel et al., 2011), as snow fall. This seasonal difference is mainly due to differences in the position and intensity of a high-pressure cell in the eastern Pacific Ocean. During the summertime the high-pressure cell limits advection, while during the winter it moves further North, allowing the moisture-laden depressions to reach the study site (Garreaud et al., 2011). Seasonal precipitation variability and frequency are also complicated by individual storm trajectories (e.g. Sinclair and MacDonell, 2016) which can cause large differences in relative precipitation distribution across the catchment, a phenomenon also described in central Chile (Burger et al., 2019).

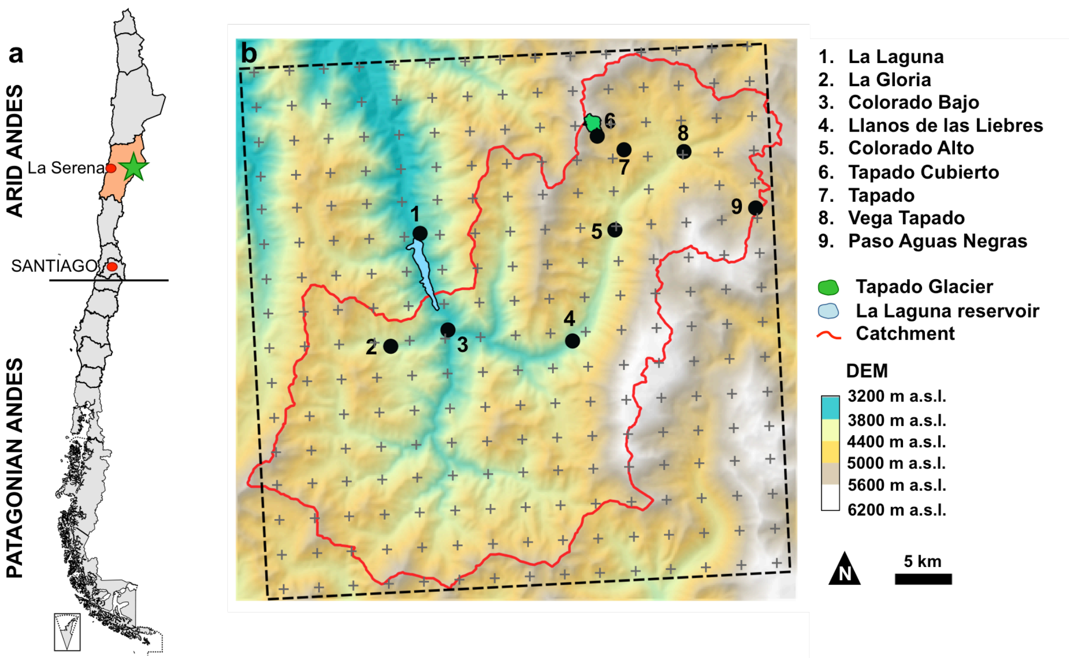

Figure 1: a) Map of Chile with Coquimbo Region colored orange and the catchment location identified with a star. b) DEM (SRTM, 100m) of La Laguna catchment. Red line corresponds to the catchment delineation, black dashed line to the WRF domain containing the virtual WRF stations (grey crosses). Blue area is La Laguna reservoir and greed area is the Tapado Glacier. AWS stations are the 9 black points.

2.2. Data

2.2.1 Digital elevation model

The digital elevation model (DEM) used in this study was derived from the CGIAR hole-filled 3 arc-second SRTM DEM resampled to 100 m resolution by the cubic method. The 100 m resolution was chosen to facilitate alignment of the model grid with the 500 m resolution MODIS products (see below).

2.2.1 Meteorological data

a/ Automatic weather station measurements

Meteorological data from nine Automatic Weather Stations (AWS) are available in the catchment (Figure 1b) over the study period 2014-2015. La Laguna, Tapado and Paso del Agua Negra AWSs are scientific grade permanent stations maintained by CEAZA (www.ceazamet.cl) with hourly measurements. In addition, five HOBO® weather stations (Colorado Bajo, La Gloria, Llano de Las Liebres, Colorado Alto and Vega Tapado) were installed in March 2014 and set to record meteorological data every 30 minutes. The Tapado Cubierto station was installed in 2013 on the debris-covered part of the glacier and provides measurements at hourly intervals. Although the lower accuracy of HOBO weather sensors compared to the permanent stations represent a source off errors in the forcing data, errors resulting from the spatial interpolation of forcings are likely to be much greater than these. More details regarding available measurements and the time periods for which these are available are provided in Figure 2. Tapado records are reported in Figure 3 as an example of the weather conditions in this catchment.

Due to the complexity of precipitation measurement (e.g. MacDonald and Pomeroy, 2007), datasets were post-processed. First, filters were applied to eliminate outliers (i.e. negative values and values larger than 30 mm h^{-1}). Second, satellite images (MODIS Aqua and MODIS Tierra) were used to remove recorded precipitation events on sunny days, which were probably due to wind transport. These precipitation events were only removed if five cloud-free images were available (i.e. the two for the day: one the afternoon before and one the next morning). In total, three precipitation events lower than 2 mm w.e. were removed with this method.

At Tapado, measurements are recorded at two Geonor weighing precipitation gauges, of which one is shielded (Alter Shield) and one is unshielded. After being filtered, the cumulative difference at the two gauges was 9.1 mm for 2014 (i.e. 10%; 97.1 mm for unshielded gauge 1 and 106.2 mm for shielded gauge 2) and 5.4 mm for 2015 (i.e. 1% ; 457.5 mm for gauge 1 and 462.9 mm for gauge 2) with a maximum hourly difference of 1.1 mm, however the relative bias between the sensors is neither constant nor unidirectional. As the difference between the two sensors was relatively small, the mean of the two datasets was used as the reference precipitation value, and a maximum uncertainty of 10% was estimated.

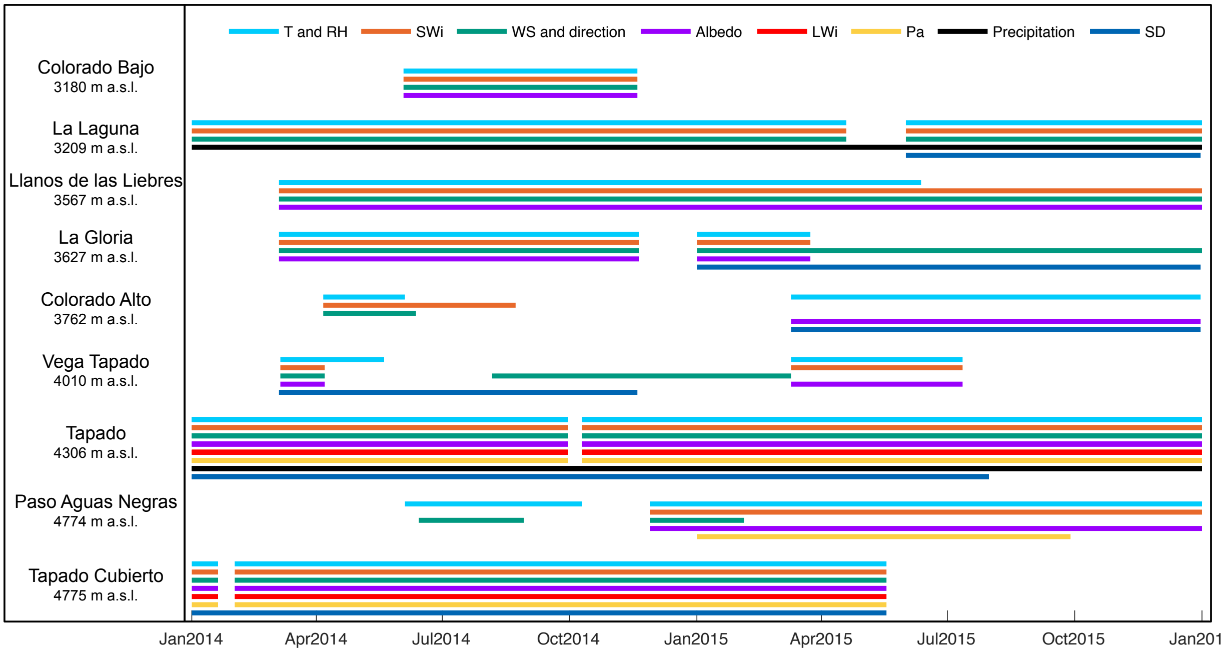

Figure 2: Date of available measurements from the nine AWSs used to calibrate and validate the model. T is the air temperature, RH the relative humidity, SWi and LWi the incoming short and long wave radiation respectively, WS the wind speed and Pa the atmospheric pressure and SD the snow depth.

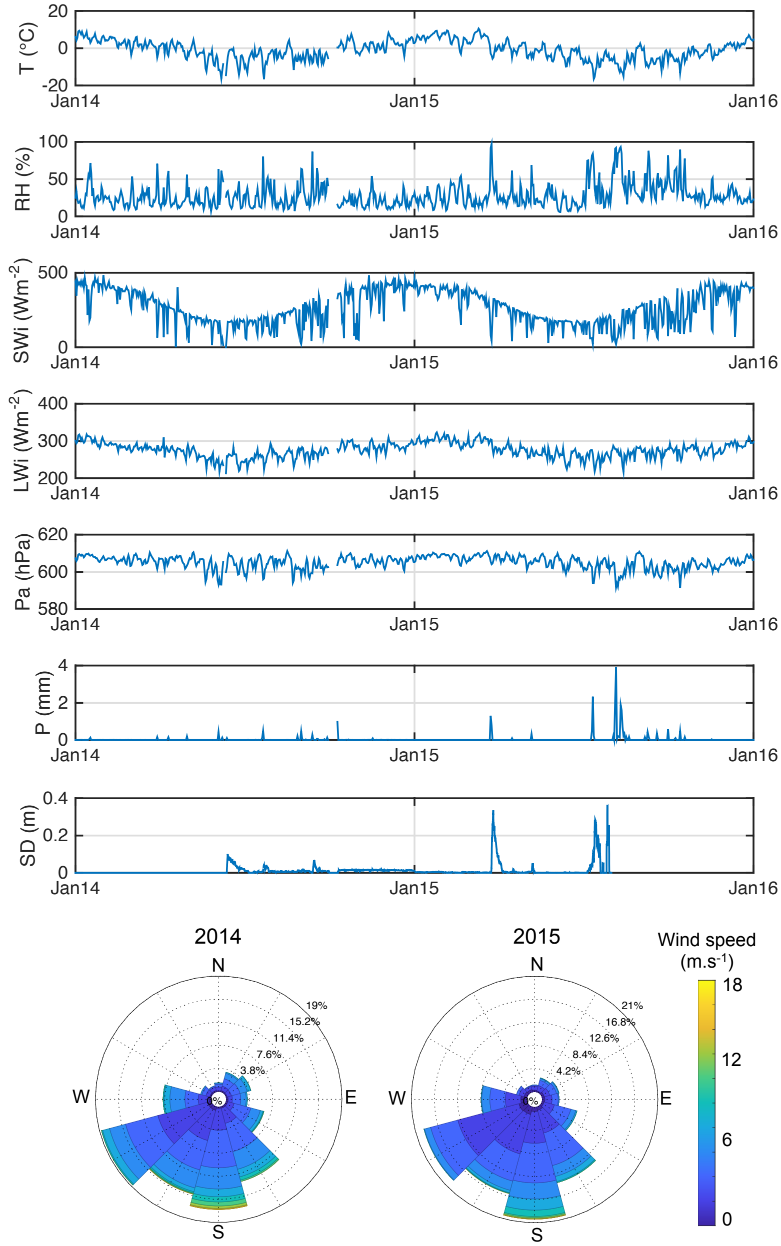

Figure 3: Example of meteorological conditions of the study area. Daily air temperature (T), relative humidity (RH), incoming shortwave (SWi) and longwave (LWi) radiation, air pressure (Pa), precipitation (P), snow depth (SD) and hourly wind speed and direction (wind roses) measured at the Tapado AWS from 1 January 2014 to the 31 December 2015. Note that SD measurements are available until the 1st of August 2015.

b/ WRF model outputs

The Weather Research and Forecasting (WRF) model was used to force SnowModel. WRF is usually used to predict weather for atmospheric research and operational weather forecasting. Using reanalysis-data as boundary conditions, this model is able to provide hourly meteorological data such as air temperature, relative humidity, incoming radiation, wind speed and direction, atmospheric pressure and precipitation. In this study WRF was forced by 6 hourly data from the National Center for Environmental Prediction (NCEP) reanalysis data, at 1° grid resolution (Kalnay et al., 1996), as well as daily surface temperature of the ocean at 0.083° of resolution. WRF model has been run using the model version 3.7.1 (Skamarock and Klemp, 2008), with default parameterizations (this choice is discussed in Section 5.1). The model has been run over a time period covering the entire study period (from April 2013 to April 2016). The model outputs are at 2 m above the surface (note that wind output was logarithmically scaled from 10 m to 2 m height) and are available at 22 km resolution over Chile, 7 km resolution at the regional scale, and 3 km resolution over the La Laguna catchment (Figure 1). The hourly 3 km outputs (T, RH, WS and direction, P, SW, LW, Pa) over the catchment represent the virtual stations that have been used in this study.

2.2.3 Local snow depth data

In 2014, three AWSs provided snow depth measurements at an hourly time step (Vega Tapado, Tapado and Tapado Cubierto; Figure 2). Over the 2015 winter, snow depth measurements were available at five stations (La Gloria, Colorado Alto, Tapado, La Laguna and Tapado Cubierto). The snow depths were measured with ultrasonic sensors and require post-treatment because they are particularly prone to measurement errors and typically produce a noisy signal (Lehning et al., 2002). Therefore, the control procedure described in Lehning et al., (2002) was applied to clean the signal, and in particular to eliminate spikes, check for outliers and physical limits.

2.2.4 MODIS snow products

MOD10A2 (Terra) and MYD10A2 (Aqua) snow products version 5 were downloaded from the National Snow and Ice Data Center (Hall et al., 2006; Hall and Riggs, 2007) for the period 1 January 2014 – 1 January 2016. The binary snow products were projected on a 500 m resolution grid in the same coordinate system as the DEM. Missing values, mainly due to cloud obstruction, were interpolated using the algorithm of Gascoin et al. (2015).

3. METHOD

3.1 SnowModel description

The physically-based model SnowModel (Liston and Elder, 2006b) was used to simulate the snow depth evolution over the entire catchment. SnowModel has already shown acceptable performance in the challenging context of semi-arid mountains, including the Andes (Gascoin *et al.* 2013, Mernild *et al.* 2017) and the High Atlas (Baba et al., 2018a, 2018b). It is a spatially distributed snowpack evolution modeling system composed of four submodels briefly described below.

Micromet is a physically-based meteorological distribution model developed specifically to produce high-resolution, spatially-distributed atmospheric forcing data. This model requires precipitation, wind speed and direction, temperature and humidity as input data, generally measured at weather stations. For the incoming solar and longwave radiation, and surface pressure, *MicroMet* can either compute these fields from other meteorological variables, or create them from observations through a data assimilation procedure (Liston and Elder, 2006a). *MicroMet* includes a preprocessor component that first analyzes meteorological data to identify and correct potential deficiencies (e.g. values out of the ranges given in the subroutine). It then fills in any missing data segments with realistic values. The atmospheric fields are distributed using a combination of lapse rates and spatial interpolation using the Barnes objective analysis scheme (Barnes, 1964).

EnBal performs standard surface energy balance calculations (Liston, 1995; Liston et al., 1999). This component simulates surface temperatures and energy fluxes in response to observed or modeled near-surface atmospheric conditions provided by *MicroMet*. Surface latent and sensible heat flux and snowmelt calculations are made using a surface energy balance model.

SnowPack is a single or multi-layer (max. six layers), snowpack evolution and runoff or retention model that describes snowpack changes in response to precipitation and melt fluxes defined by *MicroMet* and *EnBal* (Liston and Hall, 1995; Liston and Elder, 2006b).

SnowTrans-3D (Liston and Sturm, 1998; Liston et al., 2007) is a three-dimensional model that simulates snow depth evolution (deposition and erosion) resulting from windblown snow based on a mass-balance equation that describes the temporal variation of snow depth at each grid cell within the simulation domain.

3.2 Model set up

3.2.1 Spatialized meteorological forcing

Spatial interpolation using the Barnes scheme was used to distribute the nine AWS measurements of T, RH, LWi, SWi and pressure over the model domain. As relative humidity is a non-linear function of elevation, the relatively linear dewpoint temperature is used for the elevation adjustment. For more details refer to Liston and Elder (2006). In this study the *MicroMet* subroutine has been run with the default setting for the Southern Hemisphere, for air temperature and dewpoint temperature monthly lapse rates (Liston and Elder, 2006b). Monthly lapse rates computed from the available measurements are dependent on the year considered. As the mean is close to the default settings, it has been chosen to conserve these values. Radiation values for LWi and SWi are assimilated and specified using the default parameterization (Liston and Elder 2006a). The model has been run on the SRTM DEM and as a result, hourly meteorological data over a 100m-grid resolution are available for entire study period. Precipitation was interpolated similarly but without considering a lapse rate, as the comparison between the available measurements did not reveal consistent elevation gradients. Wind data and direction were first interpolated using linear lapse rates and then each gridded value was corrected considering topographic slope and curvature relationships (Liston and Elder, 2006b).

The 3km WRF outputs (section 2.2.1) were used as inputs for *MicroMet* which considers that each WRF cell corresponds to a virtual weather station located in the center of the WRF cell, following Mernild et al. (2017) and Baba et al. (2018a). *MicroMet* adjusts the elevation bias to the DEM at the corresponding coordinate and downscales the data to a 100 m grid.

3.2.2 Albedo calibration

The snow albedo evolution is computed as a function of the snow density and air temperature (more details in Liston and Hall, 1995; Liston and Elder 2006b). Minimum and maximum values have been adjusted based on measurements. The minimum snow albedo (*i.e.* the soil) is fixed at 0.2 and is quite homogeneous in this basin, as there is almost no vegetation. The minimum and maximum snow albedo (corresponding to old and fresh snow, respectively) are respectively fixed to 0.6 and 0.9 in agreements with all the measurements performed at the AWSs (Figure 2).

3.2.3 Turbulent fluxes calibration

As the model is using a bulk approach to simulate the turbulent fluxes, the turbulent latent and sensible heat fluxes (respectively *LE* and *H)* are parameterized using an effective surface roughness length z_0 (Liston, 1995; Liston et al., 1999). Note that this roughness length z_0 is considered as an effective value used in the model to represent the aerodynamic (z_m), temperature (z_t) and humidity (z_q) roughness values. As no measurements from the study period are available to calibrate and validate this value, it was initially fixed at 1 mm (Gromke et al., 2011; MacDonell et al., 2013), and a subsequent sensitivity test was undertaken. Note that the surface temperature is solved iteratively by closing the energy balance (Liston and Elder 2006). In addition, under stable atmospheric conditions, turbulent fluxes are modified based on a Richardson number correction (Liston and Hall, 1995).

3.2.4 Wind transport parameterization

The model considers the wind transport (saltation, turbulent suspension) after snow deposition, sublimation of blowing and drifting snow and erosion and deposition after snowfall, depending on the topography (Liston and Sturm, 1998). The topographic influence on wind transport has been set, following Gascoin et al. (2013). The curvature allows considering the typical redistribution length scale. Based on the DEM, it was estimated to be 500 m, *i.e.* approximately one-half the wavelength of the topographic features within the domain (Liston et al., 2007). The model considers different weights for slope and curvature and values. We have chosen 0.58 and 0.42, respectively, following Gascoin et al. (2013).

3.3 Simulations

Two types of simulations have been performed over the entire catchment for the period 1 January 2014 – 1 January 2016 on a 100-m resolution DEM. The first simulation was forced with input from the nine automatic weather station measurements (referred to as AWS-forcing), whereas the second simulation was forced with the WRF data (referred to as WRF-forcing).

After indicating the differences observed for these two forcing sets, the model is primarily validated at local points. Results for the two simulations were first compared to local snow depth measurements at each AWS (described in Section 2.2.1). The performance was evaluated using a Kappa statistic coefficient (Cohen, 1960) denoted *k,* to measure the agreement between the simulation and the observation, considering the percentage of time with and without snow. The calculation of k is here performed according to the following formula:

$$k = \frac{\Pr(a)-\Pr(e)}{1-\Pr(e)} \qquad (1)$$

where: *Pr(a)* represents the actual observed agreement (i.e. snow or no snow for both simulation and observation); and *Pr(e)* represents the hypothetical probability of chance agreement. Complete agreement is defined when k=1. The Root Mean Square Error (*RMSE*) was also calculated.

Second, the model performance was evaluated over the entire catchment, by comparing the simulated snow cover extent and duration to that observed by the satellite images (described in Section 2.2.2). The model performance was evaluated by computing the Nash-Sutcliffe efficiency coefficient (*NSE*, Nash and Sutcliffe, 1970) between simulations and observations, and the *RMSE*.

After validating the model, the sublimation ratio and sublimation and melt rates were computed over the catchment for the two years. The sublimation rate corresponds to the mass sublimated per unit of time and does not include evaporation from meltwater. The sublimation ratio is defined as a percentage, and equal to the sublimation divided by the total ablation (i.e. sublimation plus melt rates). The melt rate corresponds to meltwater that runs off from the snowpack. Whilst the model calculates refreezing, the final melt rate described here does not include snow melt that refreezes in the snowpack. Note that ablation and energy balance terms are only computed over snow surfaces. This means that annual and monthly means are only computed at grid-cells with snow.

3.4 Comparison with MODIS

The snow cover area (SCA) and the snow cover duration (SCD) over the entire catchment were compared to the MODIS product. A threshold of 0.003 m w.e. was used to convert the simulated SWE into snow presence or absence for each grid cell (within the same range as Gascoin et al., 2015). Since the MODIS SCA product corresponds to the maximum visible extent over a period of 8 days, we also computed the maximum SCA over the same 8 day period from the simulated SCA for comparison.

4. RESULTS

4.1 Meteorological forcing comparison

4.1.1 AWS 2014 *vs* 2015

According to the AWS measurements, Jan-Jul 2015 was warmer than Jan-Jul 2014. Conversely, observations indicate lower temperatures for Aug-Dec 2015 than for Aug-Dec 2014 (daily mean difference of -2.6°C). Relative humidity was higher for 2015 compared to 2014 (daily mean difference of 11%) whereas SWi was lower (mean difference of -18 W m^{-2}, i.e. 6% of the mean SWi), with larger differences in Jul-Dec (daily mean difference of -32 W m^{-2}, i.e. 12% of the daily mean SWi), and LWi was higher (daily mean difference of 20 W m^{-}

^{2}, i.e. 7% of the daily mean LWi). This decrease SWi and increase in LWi can be explained by higher degree of cloud cover in 2015.

4.1.2 *MicroMet* output comparison: AWS *vs* WRF

Figure 4 shows *Micromet* outputs forced by WRF and AWS. Colder air temperatures are observed for the WRF-forcing (4.5 to 7.5°C depending on the year and the elevation), as well as lower RH (between 13 and 24%), and higher precipitation (annual cumulative difference larger than 1 m w.e. and a difference ranging between a factor of 1.6 to 3.4 depending on the elevation (Figure 4d)). The SWi and LWi remain very similar. The wind speed outputs differ (Figure 4e), especially above 4500 m a.s.l. where differences reach a maximum of 4 m s^{-1}. Details and statistical information about the comparison at each AWS locations are available in Table S1 (in the supplementary material). Note that here the comparison between the AWS measurements and the closest WRF grid point is not presented due to the significant vertical offset between the two points (Table S1 in the supplementary material). Despite these differences between AWS and WRF, both forcings were used as inputs in order to quantify the impact of the forcing choice on the sublimation estimation in this study.

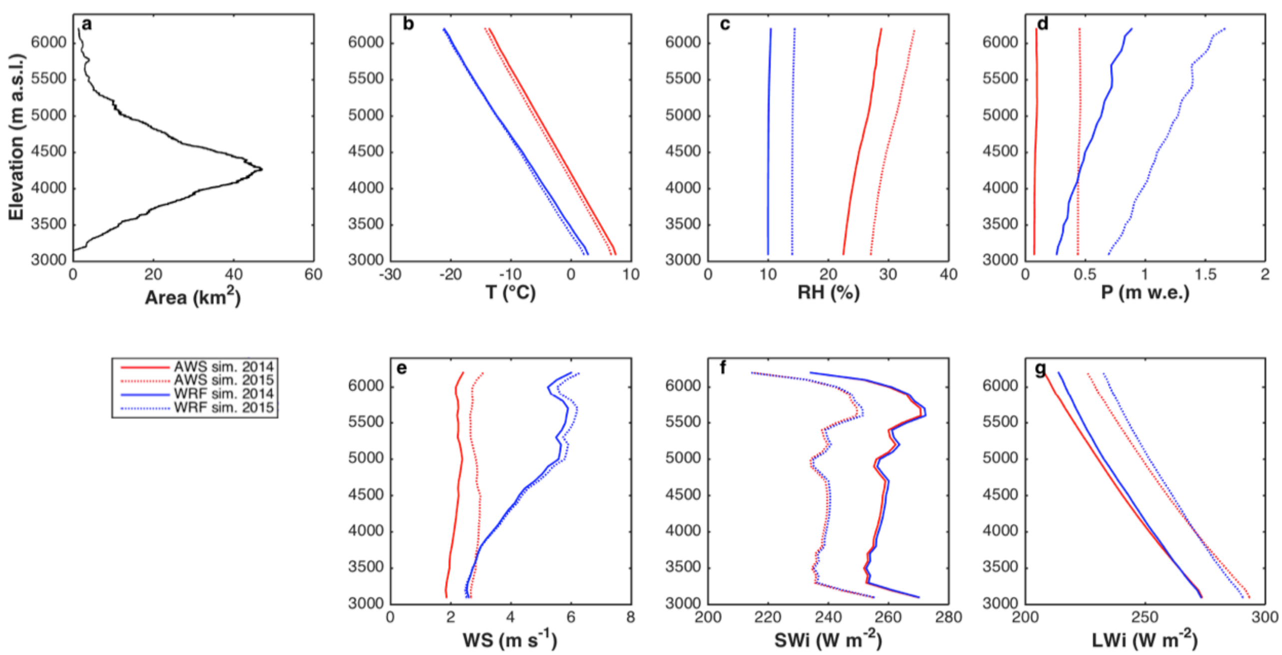

Figure 4: (a) Area-elevation distribution of the La Laguna catchment. (b to g) MicroMet outputs at the catchment scale forced by the AWS (red) and the WRF (blue) for 2014 (lines) and 2015 (dashed lines).

4.2 Snow depth and snow cover comparison

4.2.1 Comparison with local snow depth measurements

Simulated snow depths using the AWS-forcing (Figures 5 a-f) are in good agreement with measured snow depth values (mean *k*=0.14 and mean *RMSE*=0.15 m, corresponding to 36% of the maximum mean snow depth). Note that the largest RMSE corresponds to 63% of the maximum snow depth. Comparisons have been performed at individual stations for 2014 and 2015, and we observe across all stations, better performances (i.e. higher *k* and lower *RMSE*) for 2015 (Figures 5 d-f) than for 2014 (Figures 5 a-c).For 2014 the highest *k* and lower *RMSEs* are observed at Tapado AWS, as precipitation measurements were available at this site, but performances are much lower at the two other sites where precipitation was interpolated. Interpolation results in overestimation of the simulated snow depth during 2015, probably due to an over-estimation of the precipitation for the large event on June 21st 2015 (Figure 3) caused by large differences in measured precipitation at the La Laguna and Tapado AWSs especially. Nevertheless, the start and the end date of the snow season are in good agreement with observations (maximum difference of 3 days observed at La Gloria site). Note that this comparison probably over-estimates the accuracy as snow depths are compared at the exact location of meteorological forcing. Larger uncertainties are expected at the interpolated locations.

Simulations performed with the WRF-forcing indicate lower performances in simulating snow depth evolution at the AWS (Figure 5 g-m; mean *k*=0.12, and mean *RMSE*=0.20 m, corresponding to 39% of the maximum mean snow depth, and the largest RMSE corresponds to 76 % of the maximum snow depth). The results indicate an over-estimation of the simulated snow depth compared to the observations. In addition, for 2014, the timing of the start and the end of the snow season does not fit well with observations (and explain the low *k* values). In 2015, the first day of snow is generally in good agreement with observations (maximum difference of 5 days observed at La Laguna).

While AWS-forcing yields a better performance overall, in both cases, better correspondence is obtained for 2015. This could possibly be explained by the dry conditions in 2014 which would have resulted in precipitation having a higher spatial variability. The low snow amounts in 2014 created localized snow patches, which are complex to represent in models.

These results underline the complexity of modeling the spatial variability of SD, even when snow transport is implemented. Results show an overall similarity of the simulated SD between some stations (e.g. Vega Tapado, Colorado Alto and La Gloria), while measurements indicate that SD are much more variable in reality. Note that the windy conditions on the local depression at Vega Tapado is very local (i.e. few meters) and make complicated the simulation at this site where the measured SD is larger than the surrounded area and not representative of the 100 m grid cell.

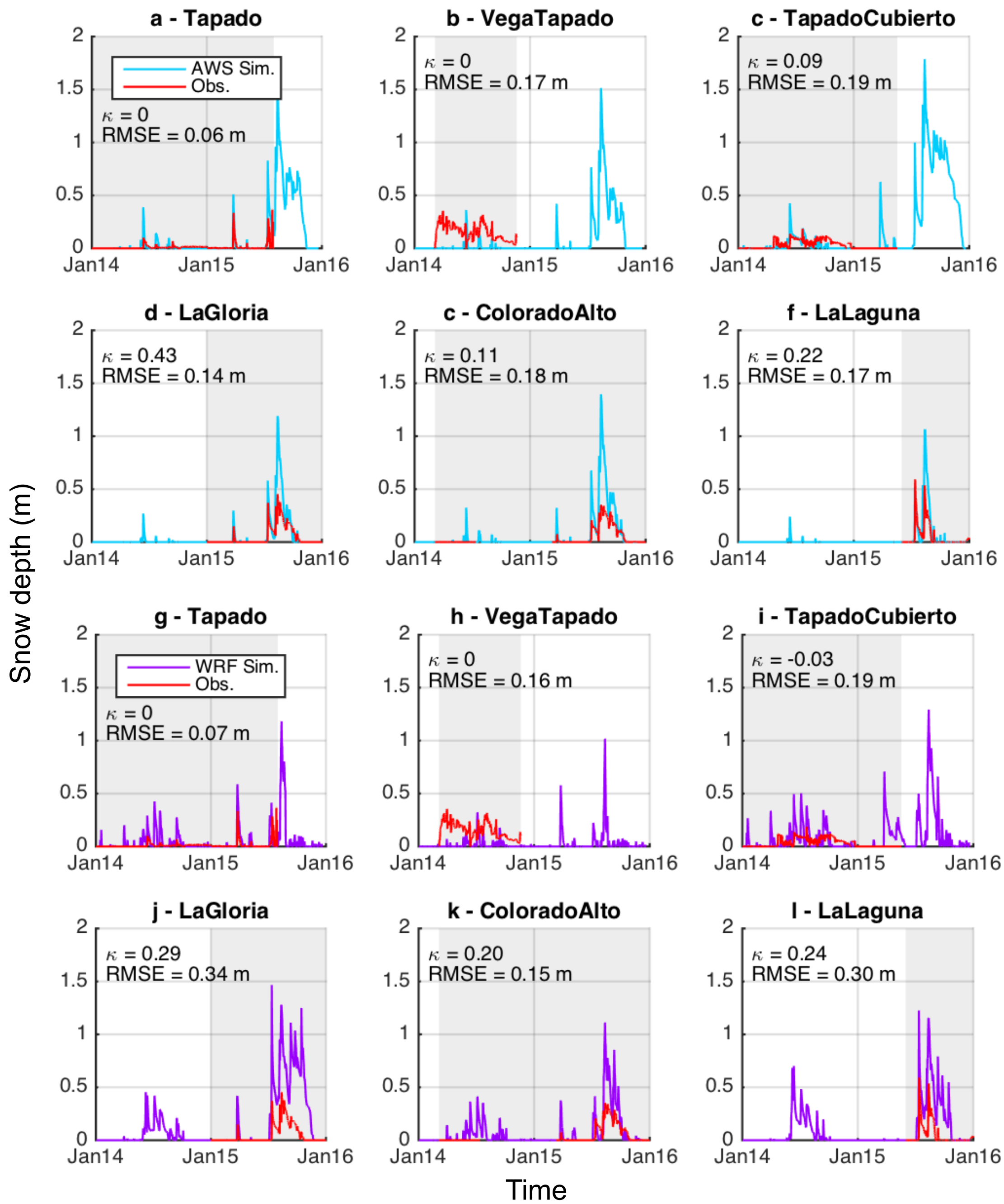

Figure 5: Simulated (cyan/purple) vs. observed (red) snow depth at 6 automatic weather stations. Cyan lines (a-f) represent simulations performed using AWS meteorological forcing. Purple lines (g-m) correspond to

simulations performed using WRF meteorological forcing. Grey shaded areas indicate the period of available measurements.

4.2.2 Snow cover comparison with satellite images

a/ Snow cover area

The simulated snow cover area (SCA), forced by the AWS-forcing is in good agreement with observations from MODIS products (Figure 6a) with, in particular, a good simulation of the timing of precipitation events. Best fits are observed for the winter and spring 2015 (*i.e.* from July to December), with higher calculated correlations (NSE_{SCA}=0.94, $RMSE_{SCA}$=41.6 km^2 (i.e. 8.3%)). Regarding the ablation, in June 2014 and April - May 2015, the simulated SCA decreases faster that the observed SCA, which can be due to an over-estimation of melt or/and sublimation or an underestimation of accumulation.

When using the WRF-forcing, the agreement between SCA and MODIS is lower than with the AWS forcing (Figure 6b). The timing of snowfall events is not always in good agreement with the observations due to missing events (e.g. March 2015), a timing bias of a few days (e.g. March 2014) and/or additional events (during both 2014 and 2015 winter season). The simulated SCA evolution over winter and spring of 2015 shows strong variation over the entire catchment, which is not observed in the MODIS record. Here again, for both forcing datasets, better performances are observed for 2015 (NSE_{AWS} = 0.79, $RMSE_{AWS}$ = 93.2 km^2 (i.e. 19% of the total area); NSE_{WRF} = 0.61, $RMSE_{WRF}$ = 125 km^2 (25%)) than for 2014 (NSE_{AWS}=0.41, $RMSE_{AWS}$=117 km^2 (23%) ; NSE_{WRF} = 0.23, $RMSE_{WRF}$ = 133 km^2 (27%)).

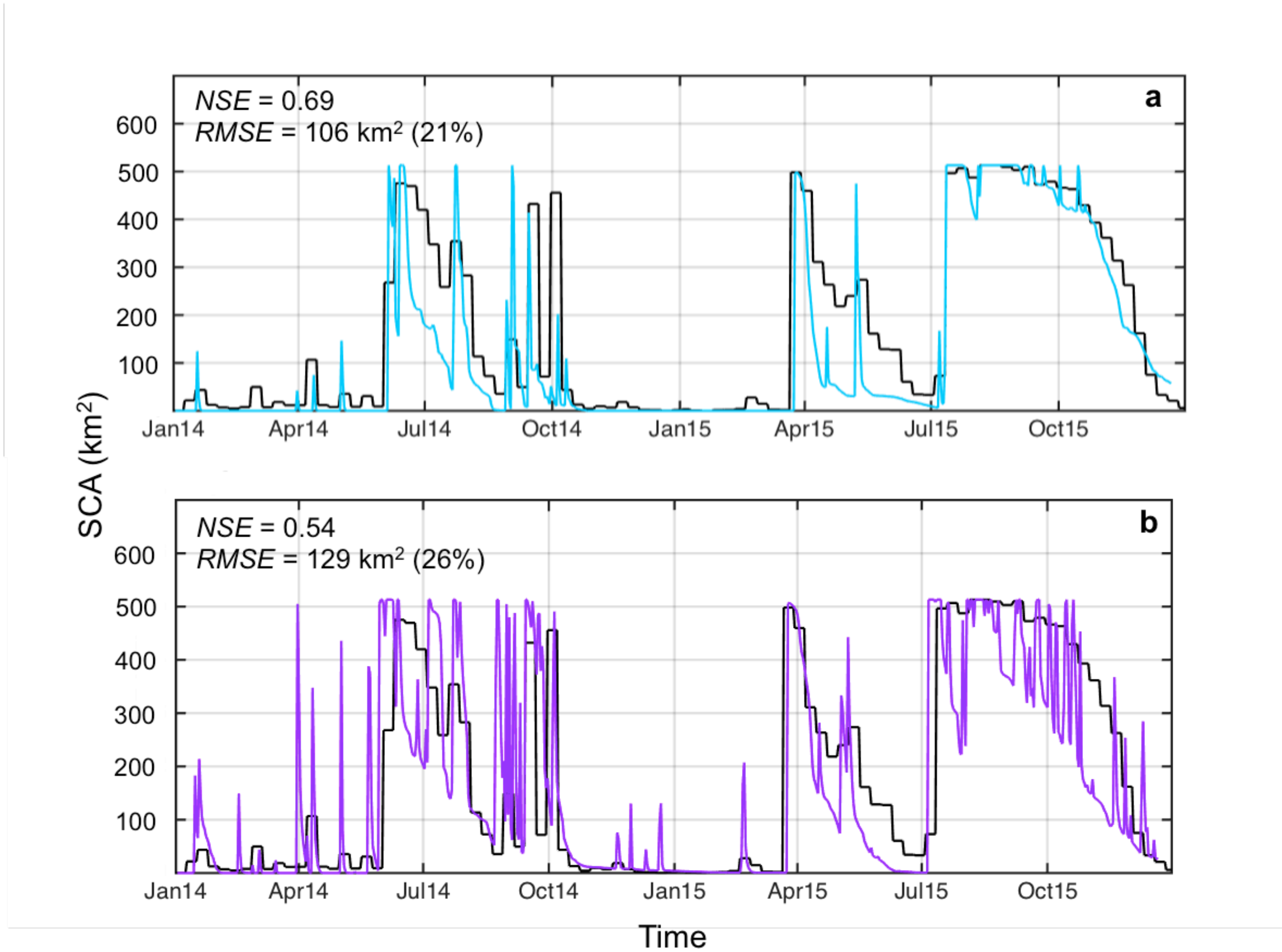

Figure 6: Snow cover area evolutions over the 2014-2015 period, from MODIS images (black lines), and simulations using (a) AWS-forcing (blue line) and (b) WRF-forcing (purple line).

b/ Snow cover duration over the catchment

The simulated snow cover duration (SCD) was also compared to the observed duration (from MODIS) by elevation band (Figure 7, Figure S2 in the Supplementary Information). For all each 200 m elevation band, the total number of snow-covered days for each grid cell was computed and then averaged for each band. For 2014, better performances were obtained for the AWS-forcing than for the WRF-forcing (Figure 7). For 2015, while better performances were also obtained for the AWS-forcing, the improvement using this forcing was minor.

Results based on AWS-forcing are in good agreement with observations at low elevations (i.e. below 4600 m a.s.l.; Figure 7), but show an over-estimation of the SCD at high elevation (absolute mean difference of 30 and 27 days for 2014 and 2015 respectively).

When using WRF forcing, SCD is over-estimated for the entire catchment in 2014 (absolute mean difference of 67 days). In 2015, simulations indicate an over-estimation of the SCD at low elevations (i.e. below 4500 m a.s.l.), and a small under-estimation at higher elevations (absolute mean error of 34 days for 2015).

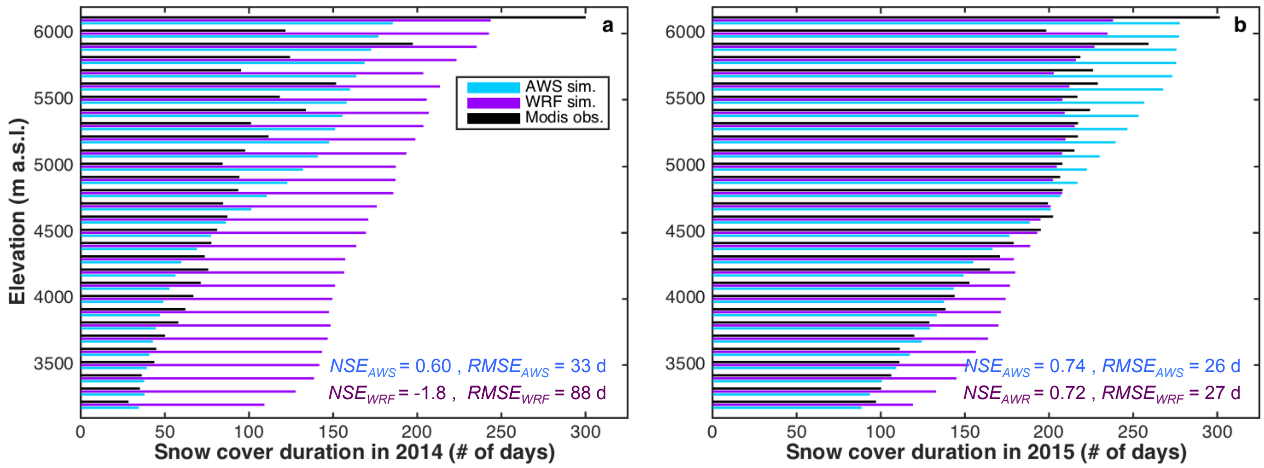

Figure 7: Snow cover duration per each 200m elevation band, from MODIS images (black), AWS-forcing (blue) and WRF-forcing (purple) for (a) 2014 and (b) 2015.

4.3 Ablation and energy balance fluxes

The forcing strongly impacts the simulated sublimation ratio. The annual means computed over the entire catchment (only considering snow grid-cells) for the AWS-forcing were 42/49% for 2014/2015, respectively, whereas 86/80% was obtained for WRF-forcing. The mean daily rate is 0.6 mm w.e. d^{-1} and 3.6 w.e. d^{-1} for 2014 and 2015, respectively, when the model is forced with the AWS-forcing. Values are larger and reach 3.1 mm w.e. d^{-1} and 4.1 mm w.e. d^{-1} for 2014 and 2015 when simulations are performed with the WRF-forcing.

4.3.1 Mean annual elevation gradients

a/ Ablation

The annual sublimation ratio is variable in space and increases with elevation for both years and both forcings (Figure 8 a,b). Comparison between the two forcings shows larger discrepancies below 5300 m a.s.l. (50% of differences for 2014 and 30% for 2015). Note that larger differences were observed for 2014 related to larger differences in snow cover and snow duration between forcings.

Melt predominates at all elevations when using the AWS-forcing (Figure 8 c,d), except above 6000 m a.s.l. in 2015. Melt and sublimation rates increase with elevation until 5300 m a.s.l.. Above this elevation the melt rate first stagnates and subsequently decreases. This increase in sublimation rate and decrease in melt at high elevations explains the increase in sublimation ratio with elevation observed in Figure 8 a,b.

For the WRF-forcing, sublimation rates are larger than the melt rates at all elevations. Melt is relatively constant above 3800 m a.s.l. whereas the sublimation ratio increases, explaining the larger values of the sublimation ratio at high elevations.

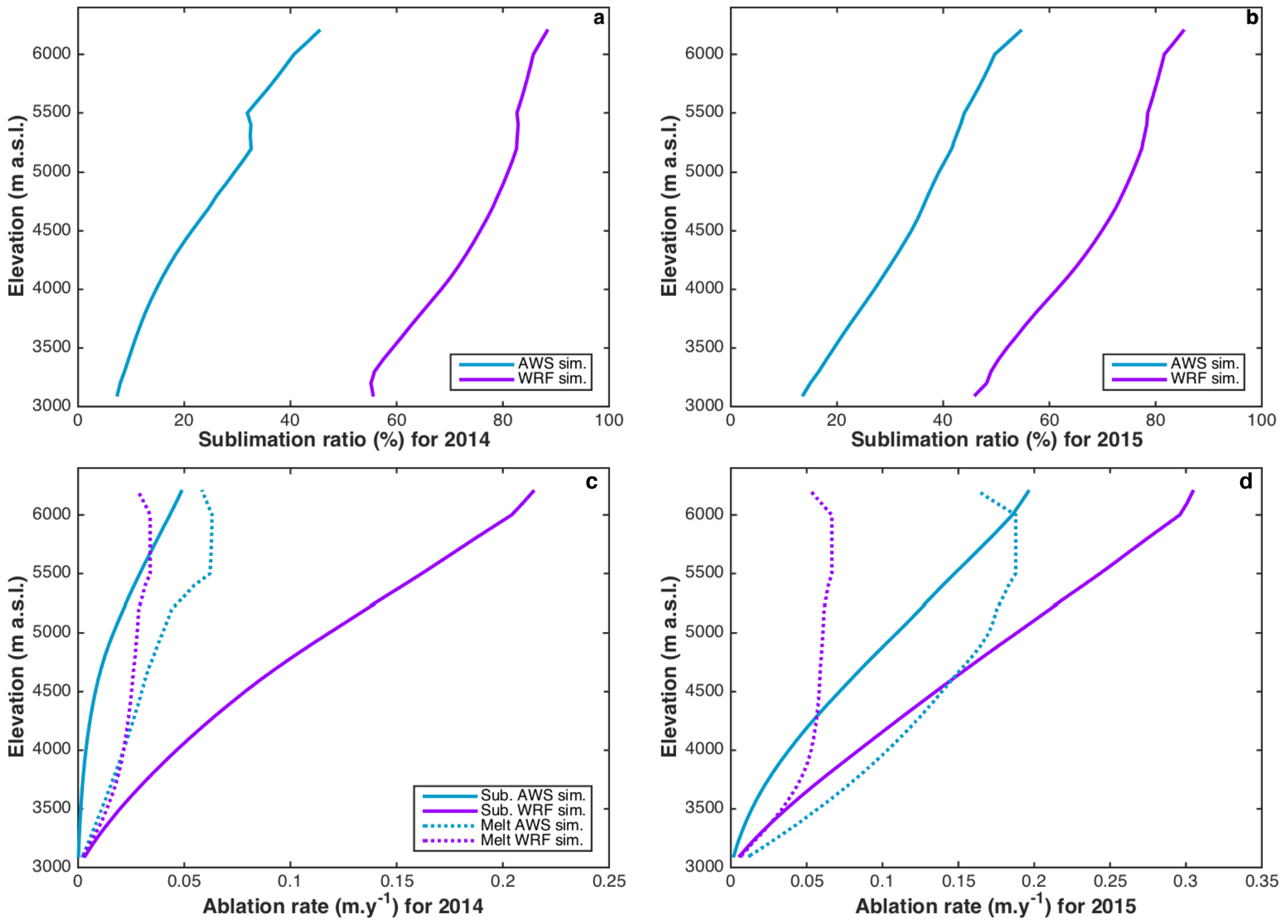

Figure 8: Simulated annual sublimation ratio against elevation band using AWS (blue) and WRF (purple) forcing for 2014 (a) and 2015 (b). Simulated annual average total ablation (sublimation and melt) against the elevation using AWS and WRF-forcing for 2014 (c) and 2015 (d).

b/ Energy fluxes.

Figure 9 shows the distribution of energy fluxes with elevation to aid the interpretation of the relationship between elevation and sublimation for both forcings. Both LW and SW show little variability between elevations bands for the AWS forcing. LW also does not change strongly between years. The SW and turbulent fluxes, however, show a strong variability between 2014/2015. For 2015 the modeled turbulent fluxes (mainly QE) are higher, especially at lower elevations, resulting in higher sublimation ratios (Figure 8 a,b., Section 4.3.1a). The WRF simulations, on the other hand, don't show this interannual difference in energy fluxes. Comparison of the AWS and WRF simulations, however, show higher turbulent fluxes for WRF-forcing, which in agreement with higher sublimation rate and ratio mentioned above.

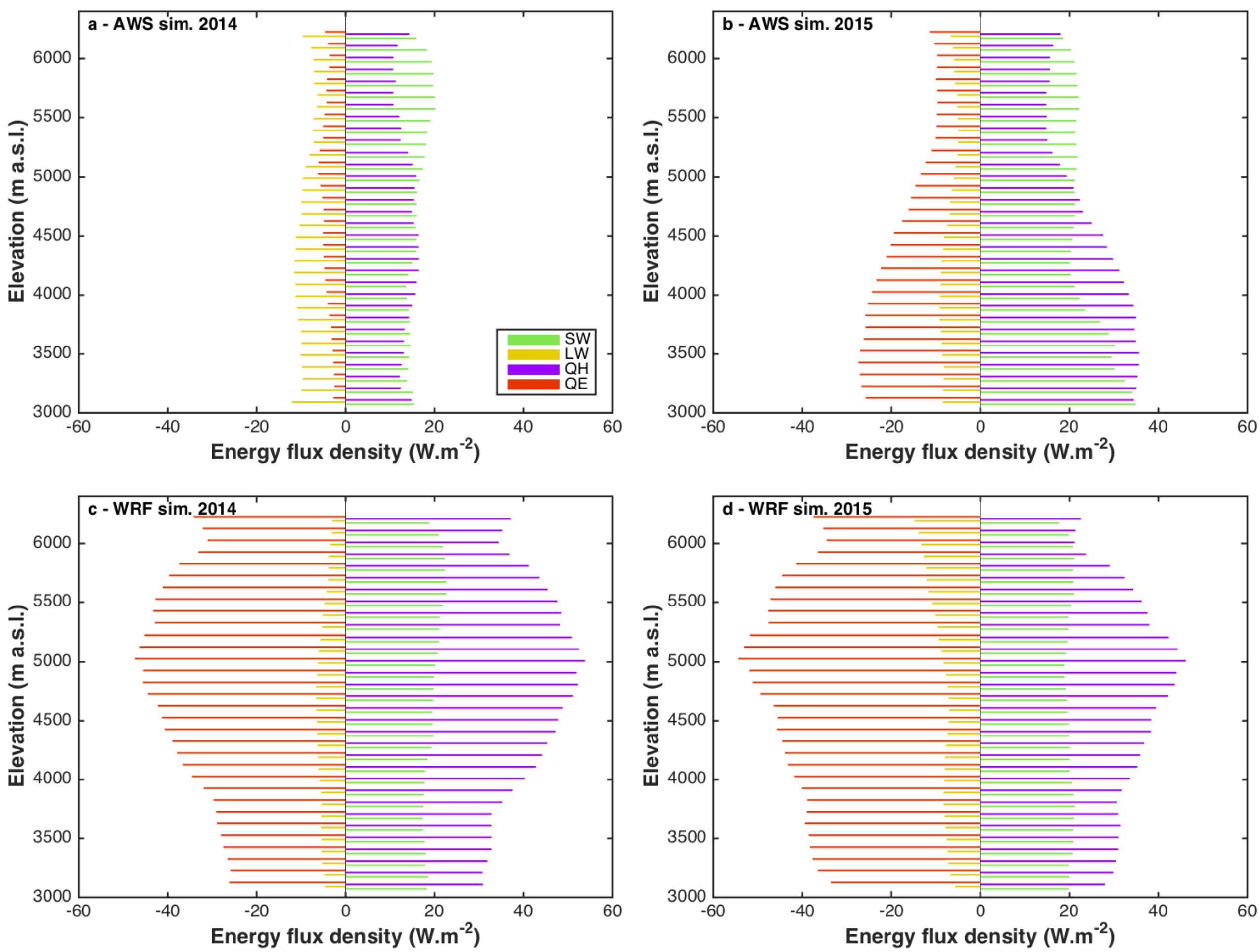

Figure 9: Annual mean of main modeled energy fluxes (computed over snow surfaces only) for each 200 m elevation band using AWS (a,b) and WRF (c,d) forcing for 2014 (a,c) and 2015 (b,d). SW is net shortwave radiation, LW is net longwave radiation, QE is the latent heat flux and QH is the sensible heat flux.

4.3.2 Monthly evolution

Analysis of the monthly sublimation ratios and rate show a strong seasonal variability in sublimation (Figure 10). Independently of the forcing chosen, larger sublimation rates are found in June and September for 2014, and in August, September and October for 2015, corresponding to the warm parts of the snow season.

Figure 11 indicates that turbulent fluxes (*QE* and *QH*) have the greatest impact on sublimation in all cases, except for the 2014 AWS-simulation. Net SW is also an important factor, and relatively similar for all the simulations. For the annual mean net SW is 18/22 W m^{-2} for 2014/2015 for the AWS forcing and 24/23 W m^{-2} for the WRF forcing, respectively. The contribution of net LW on the other hand is low for all simulations (annual mean of -7/-6 W m^{-2} for AWS/WRF-simulations respectively). Note that these losses are small in comparison to mid-latitude sites (e.g. -25 to -20 W m^{-2} according to the study by Giesen et al, (2009)), because of the very dry conditions of the atmosphere and to the cold surface temperature of the snow surfaces.

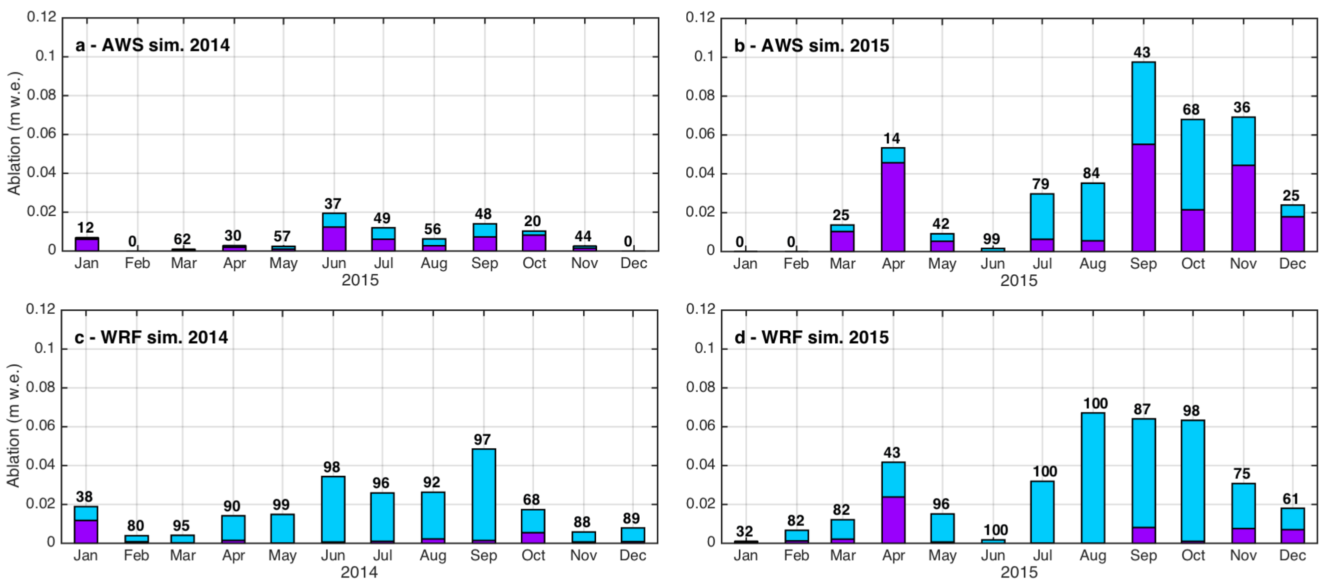

Figure 10: Stacked simulated melt (purple) and sublimation (blue) per month using AWS-forcing (a,b) and WRF-forcing (c,d). Black numbers indicate the monthly sublimation ratio in %.

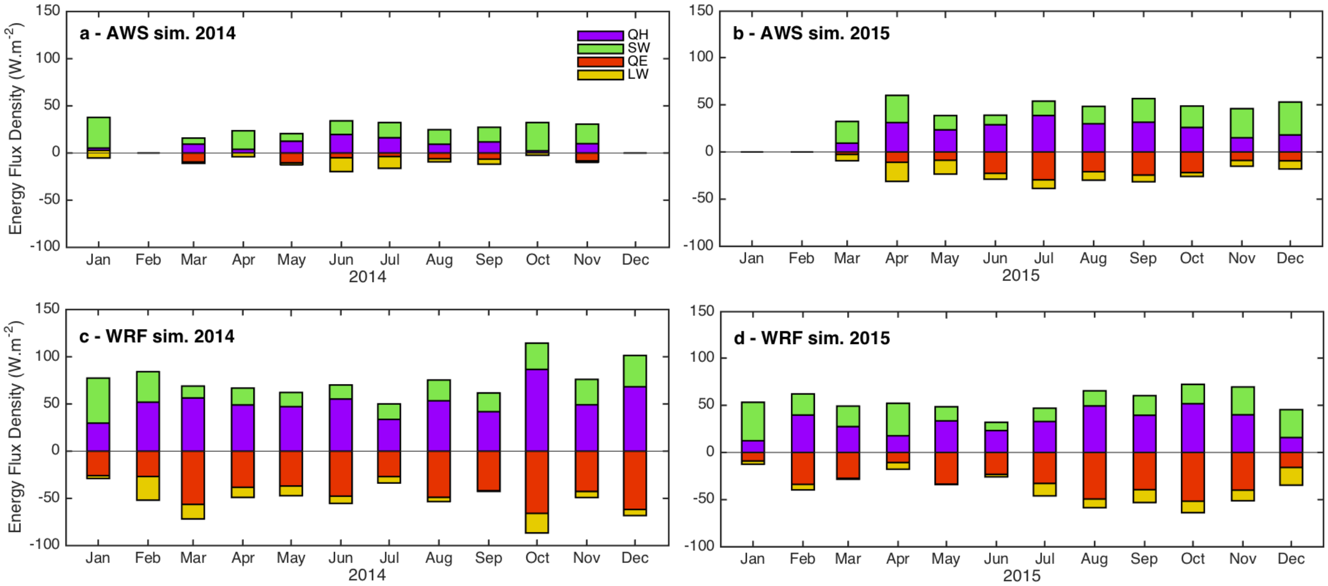

Figure 11: Monthly average of the main modeled energy fluxes for the entire catchment, over snow surfaces only. SW is net shortwave radiation, LW is net longwave radiation, QE is the latent heat flux and QH is the sensible heat flux.

5. DISCUSSION

5.1 AWS *vs.* WRF forcing.

Results presented in this study highlight the importance of forcing when modeling snow depth, snow cover and sublimation. Differences in model outputs are largely due to differences in temperature and precipitation inputs.

5.1.1 Air temperature and precipitation

The cold bias in air temperature from WRF simulations, using the combination NCEP-WRF, is often observed and well documented (e.g. Ruiz et al., 2010). It can be explained by the model parameterization complexity such as: *(i)* the initial or lateral conditions especially for the land surface surface temperature (Cheng and Steenburgh, 2005) or soil thermal conductivity (Massey et al., 2014), *(ii)* the parameterization of the planetary boundary layer scheme (Reeves et al., 2011), or *(iii)* the radiation parameterization scheme as it has been observed for other models (e.g. Müller and Scherer, 2005). However, the exact source of this bias remains difficult to identify (e.g. Reeve *et al.,* 2005). In this study, the default parameterization has been used, but works are in progress regarding the evaluation of the most appropriate calibration over this area, using direct observations.

Otherwise, precipitation is known to be over-estimated using the WRF model, particularly in the Andes (e.g. Mourre et al., 2016). One possible explanation is that biases can exist in the reanalysis data, in particular at high elevations, where observations are often scarce. Precipitation over-estimation might also be related to the parameterization used for the model which may not be the most appropriate for the Andes; further work is needed to determine the most appropriate ones. Outputs may also be inaccurate due to the relatively low-resolution DEM used (100 m).

Precipitation measurements using rain gauges can be biased towards an underestimation due to an undercatch, especially for snowfall because of the influence of wind (e.g. MacDonald and Pomeroy, 2007; Wolff et al., 2015). This gauge undercatch uncertainty (see Section 5.4.1) could increase the difference between the precipitation simulated by WRF and that measured at the AWSs. In addition, questions arise regarding the representativity of point measurements compared to the grid cell considered in the model.

The spatio-temporal variability observed in the difference between AWS and WRF precipitation data, highlight that it would be inappropriate to use a constant correction factor to adjust WRF data with measurements. More studies comparing WRF output to AWS among other data sets are required to determine a realistic correction method.

5.1.2 Consequences of the forcing used

Biases between the two forcing datasets cause significant differences in the energy and associated mass balances during both study years. In 2014 there are lower RH and P biases (Figure 4c,d), but larger air T differences, especially at high elevations (Figure 4b). Wind speed is on average higher in the WRF-forcing, whereas biases in incoming LW and SWi and air pressure are low for both years (results not shown).

The larger RH bias in 2015 indicates an over-estimation of the dryness for this year (compared to 2014), and would lead to larger differences in sublimation rate for 2015 than for 2014, which is the opposite of the results observed. Likewise, the larger over-estimation of precipitation amount observed in 2015 (Figure 4d) does not explain the larger difference in sublimation, as a deeper snow depth should result in more persistent snow cover during the warm period and hence a lower sublimation ratio related to larger melt rate. Therefore, although the relationship between temperature and sublimation rate is complex and not necessarily direct, in this case, the colder temperature is the most probable explanation for at least part of the larger difference in sublimation rate observed at high elevation.

Lower temperature and relative humidity values from WRF outputs compared to AWS measurements can explain, in part, the larger simulated sublimation ratio found with this forcing (Figures 8 a,b and 10). The relatively high amounts of precipitation simulated by the WRF outputs, and resulting snow cover overestimation, may also play a role. Differences in the sublimation ratio when using the AWS and WRF-forcing are quite similar for the two years (mean annual difference of 42% and 36% for 2014 and 2015 respectively), although the difference between the melt rate and sublimation rate depends on the year (Figures 8 c,d) and corresponding energy balance.

In 2014 the turbulent fluxes are dominant for the WRF forcing but not for the AWS forcing (Figure 9 a,c). This can be partially explained by the larger SCA simulated by WRF-forcing with snow cover in the entire catchment while the AWS-forcing only results in snow at higher elevations. Additionally, WRF-forcing indicates colder, drier and windier condition than the AWS-forcing (Figure 4). Lower RH and higher wind speed will directly increase the latent heat flux, and potentially sublimation ratio, depending on surface temperature (see Figure S3 in Supplementary Material for surface temperature comparison).

The large variation of the SCA resulting from the WRF driven model results (Figure 5) is likely related to the higher frequency of relatively small precipitation events modeled by WRF than are recorded by the AWS. These small events cover the catchment with a relatively thin layer of fresh snow, which sublimates relatively quickly causing the SWE to decrease to < 3 mm w.e. at lower elevations, causing high variability in modeled SCA.

The SCD also has a significant influence on sublimation. For 2014, the differences in SCD between the two forcings were 100 days below 4500m, and close to 50 days above this elevation (Figure 7a). Snow that persists until later in the year (austral Spring and Summer) results in an increased total melt rate and can influence the sublimation ratio (especially in 2015, Figure 10). This is the only explanation for the larger melt fraction observed with AWS-forcing compared to WRF-forcing at low elevations, given the cold bias in WRF-forcing (Figures 8c and 4b). Since a larger SCD can be related to larger precipitation amount, precipitation uncertainties likely play a significant role and the sublimation estimation.

5.2 Comparison between dry and wet conditions

5.2.1 Comparison between 2014 and 2015

Differences in sublimation ratio and rates between 2014 and 2015 are related to both meteorological conditions related to energy fluxes, and snow cover duration. First, the similar annual mean sublimation ratio found for both years is likely due to a compensation between the dry 2014 year (low precipitation) associated with cold conditions in spring and summer, *vs.* the wet 2015 year with longer snow duration and warmer spring and summer (according to meteorological measurements made in the region). Both sublimation and melt rates were larger overall during the wet 2015 year compared to the dry 2014 year. Thus the higher melting rates in 2015 compensated the enhanced sublimation rates and resulted in sublimation ratios comparable with 2014. The larger sublimation rates observed in 2015 are related to higher RH and wind speed, but also higher precipitation, snow accumulation and snow duration in 2015 compared to 2014. Results show particularly large sublimation rates over the long melt period in 2015. This may be explained by the warmer conditions which induce a warmer snow pack, increasing the saturated vapor pressure at the snow surface and providing energy to increase the sublimation rates (Herrero and Polo, 2016). According to these results, the snow duration seems to modulate the annual average ablation ratio, such that a longer-lasting snow cover extending further into the warm spring climate is subjected to both enhanced sublimation and melt in response to an increase in incoming energy fluxes. Nevertheless, it remains difficult to disentangle the respective effects of meteorological conditions and snow duration on sublimation. To better evaluate these effects, the influence of the meteorological forcing related to energy fluxes and the snow cover duration must be evaluated separately. For that purpose, we performed simulation experiments in which a common precipitation input was used for both years. In the first experiment the 2014 precipitation inputs ('dry input' with shorter snow cover duration) were applied to both years, then the 2015 precipitation was applied to both years ('wet input' with longer snow cover duration). All other meteorological forcings were left unchanged.

5.2.2 Impact of the precipitation amount

Forcing the 2014 year with the 'wet precipitation input' reduces the mean annual sublimation ratio by 12% (Figure 12 a,d), while forcing the 2015 year with the 'dry precipitation input' increases the mean annual sublimation ratio by 3% (Figure 12 b,d). In summary, a decreased annual mean sublimation ratio is observed when the precipitation is increased (which likely increases the SD and SCD), and other factors are held constant. However the amplitude of the response differs between the two years. This is mainly due to differences in the ablation rates (Figure 12). For 2014, increasing the precipitation amount leads to a sublimation rate increase of 0.8 mm w.e. d^{-1} while for 2015, decreasing the precipitation amount decreases the rate by 2.8 mm w.e. d^{-1}. Despite these annual differences, the maximum monthly sublimation rates are still observed for the same months, independent of the precipitation forcing used, with the exception of June and August (Figure 12). In June, snow covered the entire catchment in 2014 but not in 2015 (Figure 6), related to a strong snow event in June 2014 and no precipitation in June 2015. The opposite was observed for August. Changing the precipitation forcing strongly impacts the SCA and therefore the snow amount available for ablation and sublimation.

Comparisons made for months with a maximum SCA (i.e. when the entire catchment is covered by snow and it persists over the entire month), allow the influence of SCD to be independently analyzed since the SCA remains constant. In July, a month where maximum SCA was observed in both years, sublimation differences of 27 mm w.e. m^{-1} and 57 mm w.e. m^{-1} were found between dry vs wet precipitation inputs for 2014 and 2015, respectively. In 2015 the SD was thicker than in 2014 for both dry and wet inputs, thus the results indicate an increased sublimation rate with thicker SD. The thicker SD also implies larger melt rates, such that the sublimation ratio decreases when increasing the precipitation in 2014 but increases with increased precipitation in 2015, highlighting the complexity of the influence of SD on the sublimation ratio.

Otherwise, differences in mean sublimation rates are much higher when changing the precipitation amount for the 2015 meteorological forcing than for the 2014 meteorological forcing 2014 (i.e. 0.8 mm w.e. d^{-1} for 2014 vs. 2.8 mm w.e. d^{-1} for 2015 as mentioned above). Sublimation rates are also higher in 2015 compared to 2014, especially at the end of the snow season (i.e. from September to November; Figures 12 a,d). This holds true when considering wet conditions (Figures 12 b,c). This highlights the significant influence of meteorological conditions on sublimation. As mentioned in section 5.2.1, 2015 experienced higher wind speeds and RH and colder air temperatures. The contribution of turbulent fluxes is higher in 2015 than 2014 (Figures S4 a,d in the supplementary information), suggesting that wind speed has a greater influence on sublimation than RH.

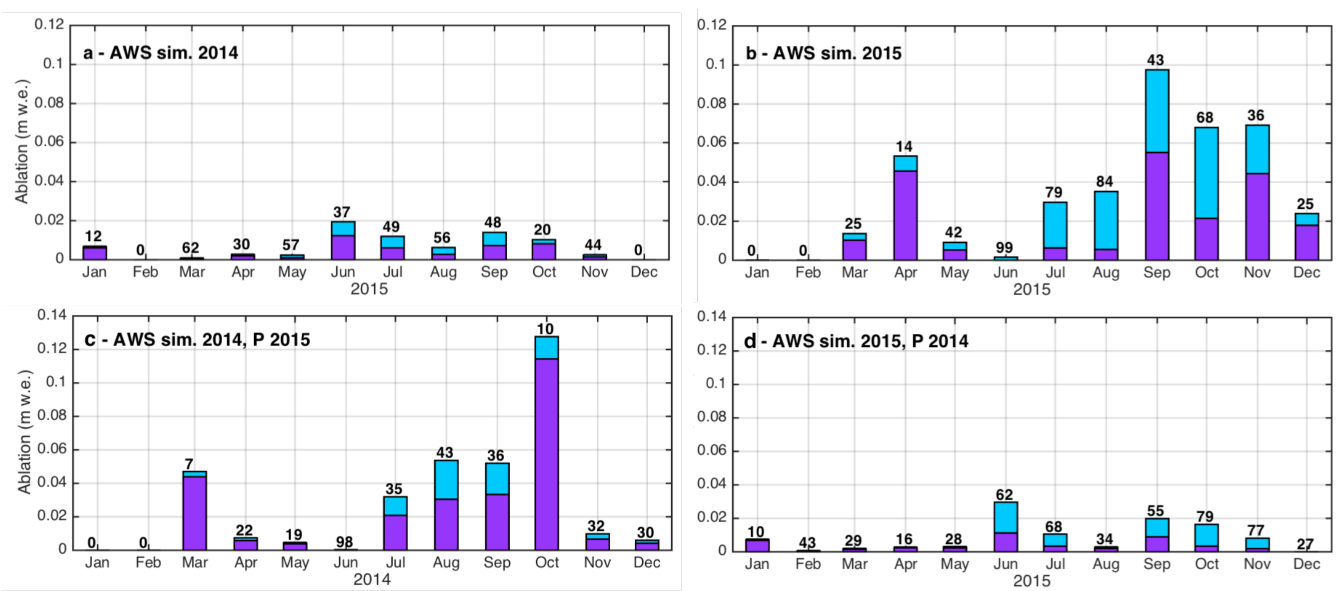

Figure 12: Monthly simulated melt (purple) and sublimation (blue) using AWS-forcing (a,b) and AWS-forcing with (c) 2015 precipitation ('wet forcing') and (d) 2014 precipitation ('dry forcing'). Back numbers indicate the monthly sublimation ratio in %.

5.3 Limits of the study

The main objective of this study was to investigate the impact of forcing data on modeled mass and energy balance to explain sublimation ratios. Nevertheless, we recognize that uncertainties also exist depending on model calibration choices. To discuss this point, four different parameters were tested to evaluate the uncertainties related to the calibration of modeled parameters: roughness value, precipitation amounts (due to measurement uncertainties), topographic curvature length and slope versus curvature length (Figure S5; Supplementary Information F). The results showed that the sublimation ratio was most sensitive to roughness values, and that differences due to the other three variables were an order of magnitude lower (For more details, please refer to the Supplementary Information). The strong sensitivity to the roughness value and the absence of measurements to validate the turbulent fluxes calibration limits precise sublimation quantification for this area.

6. CONCLUSION

In this study, the snow energy and mass balance have been simulated over La Laguna catchment located in the semi-arid Andes of Chile. Using the snow pack model SnowModel, simulations were performed over two contrasting years (2014 considered as a dry year and 2015 considered as a wet year), using two distinct forcings (nine AWS located in the catchment and 3km resolution WRF model outputs).

Results indicate strong differences in simulated snow depth depending on the forcing chosen, mainly due to a cold bias in air temperature in WRF as well as an over-estimation of precipitation. As a result, performances in simulating the snow cover using the AWS-forcing are more realistic, both at the local scale (comparison with AWS snow depth measurements), and over the entire catchment (comparison with SCA and SCD from MODIS images). In addition, independently of the forcing choice, the simulation of snow cover is better for 2015 compared to 2014, mainly due a larger sensitivity to the precipitation uncertainties during dry conditions. This highlights the complexity in properly modeling the snow cover evolution for years with low precipitation.

There are also large differences in modeled sublimation ratio depending on the forcing chosen. When using WRF-forcing the sublimation ratio is approximately twice that modeled with the AWS-forcing. This is partially due to the differences in temperature and relative humidity between the two forcings, but mostly due to precipitation differences. For example, when holding all model inputs constant except for precipitation, there are significant differences in the modeled sublimation, especially for 2014 which was a dry year. Otherwise, the annual mean of the sublimation ratio over a catchment is similar during the two years and but it increases with elevation. This partly explains the larger sublimation values reported in previous studies performed at high elevations in the semi-arid Andes of Chile (e.g. Gascoin et al., 2013; Ginot et al., 2001; MacDonell et al., 2013). Sublimation simulated in this study is associated with several sources of uncertainty related to the forcing chosen and the model calibration. Regarding the calibration, the roughness value is the key concern to properly simulate the turbulent fluxes and result showed strong sensitivity to this value. Nevertheless, without measurements to properly calibrate this value, it appears to be the main source of model calibration uncertainty. Results presented here highlight precipitation as the main forcing uncertainty, due to measurement errors and lack of spatial representation as precipitation data was only available for two stations. Precipitation uncertainties directly impact snow on the ground, and therefore indirectly sublimation rates. Uncertainties in wind speed were likely the second source of error in sublimation results, which needs to be better constrained in future studies. Therefore, this study highlights that this uncertainty has a strong impact on sublimation and further work is suggested to *(i)* improve measurements uncertainties, *(ii)* increase the number of sensors over the catchment, and *(iii)* incorporate AWS measurements into the WRF model and use data assimilation to improve model outputs. CEAZA is currently working on point *(iii)* to provide improved WRF outputs for the semi-arid Andes of Chile. This study has highlighted the current difficulties in using standard WRF model outputs in a semiarid, Andean catchment. Moving forward, it would be highly advantageous to improve WRF model performance in mountainous areas where high relief and difficult access often limits AWS distribution to valley floors, therein limiting the accuracy of interpolation techniques for terrain sensitive variables, such as precipitation and wind speed and direction.

Acknowledgment

The authors thank G.E. Liston for providing SnowModel code and for the interesting and useful discussions and suggestions. We are also grateful to P. Salinas and A. Hammann for providing the WRF simulation outputs and for providing useful assistance related to these data. MR and SM were supported by CONICYT-Programa Regional R16A10003, and the Coquimbo Regional Government FIC-R(2015) BIP 30403127-0. CK was supported by a *Coopération bilatérale – Québec-Chili Ministère des Relations Internationales et Francophonie.* Finally we acknowledge Jono Conway and the anonymous reviewer for their detailed comments and the helpful suggestions which significantly improved the quality of the manuscript.

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SUPPLEMENTARY MATERIAL

A – Climatology at La Laguna

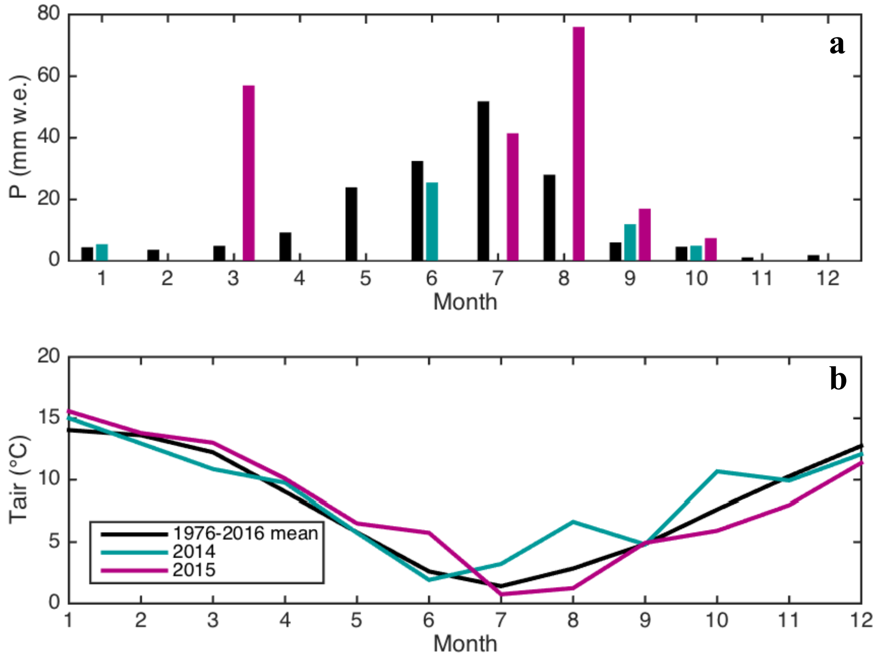

Figure S1: (a) Monthly precipitation and (b) air temperature recorded at La Laguna AWS. The monthly mean (black) is computed over the 1976-2016 period.

B – Comparison AWS vs. WRF grid point

Table S1: Statistics (R2, RMSE and AME (Absolute Mean Error)) between micromet outputs forced by the AWS measurements and the WRF outputs.

	Vertical offset with the WRF grid point	T (°C)			RH			SWi			LWi			WS (m s^{-1})			P (mm d^{-1})		
		R^2	RMSE	AME	R^2	RMSE	AME	R^2	RMSE	AME	R^2	RMSE	AME	R^2	RMSE	AME	R^2	RMSE	AME
Colorado Bajo	278m	0.94	5.02	5.32	0.04	15.7	15.7	1	1.29	0.65	0.96	5.53	4.10	0.01	1.61	1.29	0.35	2.96	3.42
La Laguna	144m	0.91	5.01	4.60	0.04	19.4	14.8	1	1.65	0.72	0.94	6.66	5.00	0.15	1.71	1.15	0.51	5.72	3.52
Llanos de las Liebres	305m	0.91	6.39	6.06	0.04	20.6	15.8	1	1.34	0.51	0.98	5.57	4.48	0.37	2.08	1.46	0.51	7.17	4.31
La Gloria	56m	0.89	5.33	4.81	0.08	19.7	15.2	0.99	2.95	1.09	0.93	6.61	5.12	0.17	1.34	1.01	0.58	5.05	3.05
Colorado Alto	196m	0.89	6.61	6.27	0.04	21.6	16.6	1	1.54	0.53	0.99	4.46	3.69	0.52	2.31	1.70	0.51	8.35	4.16
Vega Tapado	-145m	0.88	7.01	6.73	0.03	22.8	17.6	0.99	3.43	1.40	0.99	4.24	3.67	0.53	4.28	3.48	0.53	8.95	4.73
Tapado	462m	0.88	6.83	6.54	0..01	22.9	17.8	0.99	2.98	1.33	0.99	1.48	1.11	0.52	3.45	2.78	0.51	9.48	4.92
Paso Aguas Negras	-121m	0.83	7.29	6.99	0.00	24.6	19.0	1	1.96	0.75	0.98	2.96	2.39	0.54	5.19	4.27	0.56	7.89	4.25

C- Spatial variability of the annual SCD.

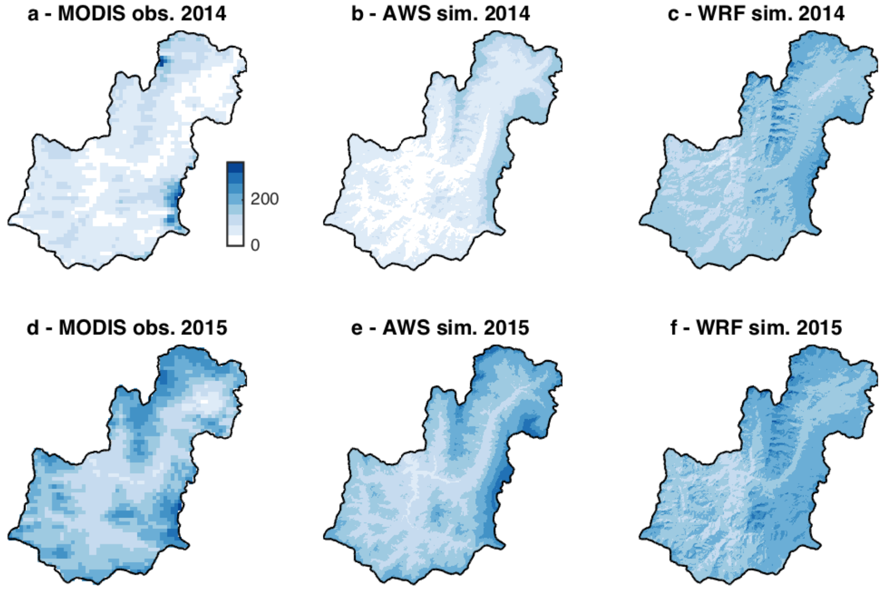

Figure S2: Snow cover duration from MODIS images for (a) 2014 and (d) 2015. Simulated snow cover duration using AWS-forcing for (b) 2014 and (e) 2015. Simulated snow cover duration using WRF-forcing (c) 2014 and (f) 2015.

D – Surface temperature

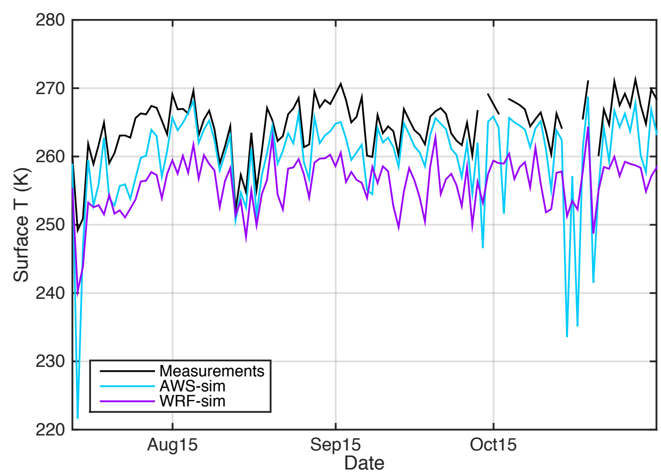

Figure S3: Observed and modeled surface temperature at Tapado AWS. Measurements correspond to the surface temperature computed from the outgoing long wave measured by the station. Cyan line correspond to the simulated surface temperature using the AWS-forcing and the purple one the WRF-forcing.

E- Influence of the precipitation amount on the energy fluxes contribution

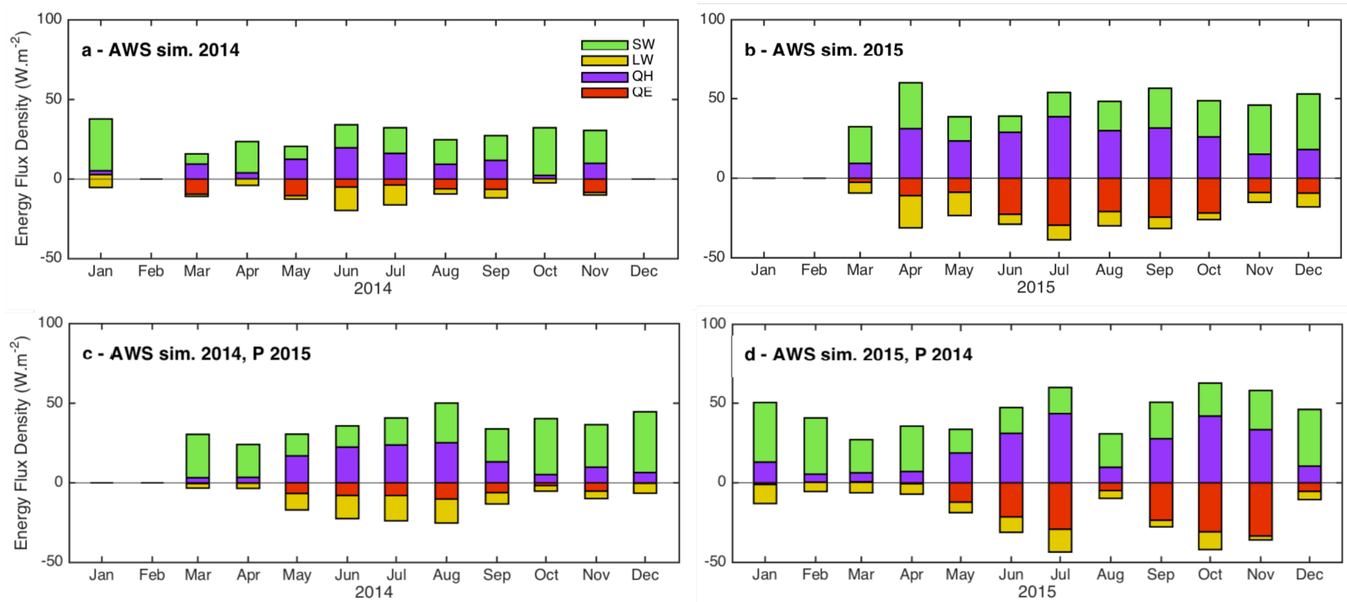

Figure S4: Monthly average (for the entire catchment, over snow surfaces only) of the main modeled heat fluxes for (a) 2014 and (b) 2015 AWS-forcings, (c) a simulation using the 2015 precipitation and the 2014 AWS-forcings, and (d) a simulation using the 2014 precipitation and 2015 AWS-forcings. SW is net shortwave radiation, LW is net longwave radiation, QE is the latent heat flux and QH is the sensible heat flux.

Figure S2: Monthly simulated melt (purple) and sublimation (blue) using AWS-forcing (a,b) and AWS-forcing with (c) 2014 precipitation and (d) 2015 precipitation. Forcing. Back numbers indicate the monthly sublimation ratio in %.

F. Model uncertainties

The main forcing uncertainties were estimated to be the precipitation (related to P measurements and the P spatialization as there are only 2 recording stations); and the wind speed spatialization (Gascoin *et al.,* 2013). Regarding the other variables T, RH, SW, and LW, a similar study performed in a nearby catchment indicated a very good performance of MicroMet to spatialize these variables, with high correlations and low biases (for more details please refer to Gascoin *et al.,* 2013).

The principal calibration uncertainties are the topographic length scale used for the wind distribution and *z0* due to the absence of measurements to properly calibrate the model. Note that the albedo measurements have been used to calibrate the model, that is why this calibration is not considered as a main calibration uncertainty in this study. Indeed, if we compare the model output albedo with the measurements, the mean *R* is 0.74 with mean *RMSE* of 0.22 and errors are considered related to the simple approach of the albedo computation of the model.

Table S2: Mean annual melt and sublimation ratio of each simulation. Bold values indicate when results are different than the reference study (i.e. results present in section 4 with the AWS-forcings) indicated in the first line.

	2014		2015	
	Melt (m.w.e.)	Sub. (m w.e.) (Sub. Ratio)	Melt (m.w.e.)	Sub. (m w.e.) (Sub. Ratio)
Reference sim.	0.047	0.030 (42%)	0.21	0.19 (48%)
Precipitation +10%	**0.048**	**0.029 (41%)**	**0.23**	0.19 **(47%)**
Curvature 100m	0.047	0.030 (42%)	0.21	0.19 (48%)
Curvature 1000m	0.047	0.030 (42%)	0.21	0.19 (48%)
Slope 0.25 - Curv. 0.75	0.047	0.030 (42%)	0.21	0.19 (48%)
Slope 0.75 - Curv. 0.25	0.047	0.030 (42%)	0.21	0.19 (48%)
Z0 = 10 mm	**0.033**	**0.049 (66%)**	**0.12**	**0.29 (72%)**

F1. Precipitation uncertainties

a) Precipitation measurements

As mentioned in section 5.1.2 snowfall measurements in windy conditions can suffer from an undercatch bias, and corrections are generally performed using empirical relationship (e.g. MacDonald and Pomeroy, 2007; Wolff *et al.,* 2015). The strong wind gusts in this region, and especially at high elevations (Figure 3) increase measurement uncertainties. Nevertheless, in this study it was chosen not to apply any correction. First, given the lack of continuous SWE measurements, it is not straightforward to establish an empirical correction. Also, precipitation data from two rain gauges (one shielded and the second one unshielded) located in Tapado have been averaged, to reduce the random error. Note that the data from the two rain gauges is surprisingly similar (see section 2.2.1), while we would expect a larger amount of precipitation catched by the shielded Geonor sensor, in this area of strong wind speed. This suggest that either the under catch is not si important or that the shield is not that efficient.

b) Spatialization

The main uncertainty for the precipitation data is due to the data spatialization at catchment scale. As only two stations have been used to force the model, the uncertainty is expect to be significant due to the orographic complexity of the catchment, but cannot be evaluated based on the current available measurements.

The interpolation of precipitation in MicroMet subroutine has been done without the use of an altitudinal gradient (called precipitation adjustment factor, Liston and Elder, 2006a) as no consistent altitudinal gradients were found in the observations (results not shown). Each event is very specific (e.g. Sinclair and MacDonell, 2016) and as a result, the altitudinal lapse rate can be either positive or negative. In addition, due to low precipitation rate and the few number of events, mainly in 2014, most of the time precipitations are recorded at one station but not at the other, or there is a delay between the events recorded at both stations, which are 14 km from one another. Different altitudinal gradients (monthly *vs* event scale) were tried but the best comparisons between simulated and observed snow depths were found without considering any gradient. Considering an altitudinal lapse rate systematically leads to an over-estimation, especially at high elevations, where the snow persists until the next season.

In addition, the model simulates the wind transport only after deposition and does not consider the preferential deposition. Again, the available measurements make it difficult to estimate this uncertainty.

c) Sensitivity test

A sensitivity test was performed by increasing the precipitation by 10%. Results indicate that the mean annual sublimation ratio over the catchment is very similar to that of the initial simulation (Figure 2). Indeed, it decreases by 1% for 2014 and for 2015. Regarding the spatial variability (Figure 11) the difference varies between +1 and -3 %, and larger differences are observed for 2014 between 5000 and 5500 m a.s.l. and around 4600 m a.s.l. for 2015. This maximum difference can be related to changes in spatial distribution of snow when some events occur only at high elevations.

d) Impact on model performances

The precipitation uncertainties explain also the better performances of the model for 2015 than 2014. Indeed, the model is sensitive to patchy snow, mainly observed at low elevation. As mentioned in section 4.2.1, modeling the spatial variability of the SD is complex and results show an overall similarity of the simulated SD between some stations. When dealing with low amount of snow, patches over the catchment are more present an increase the error.

F2. Wind uncertainties

a) Wind data spatialization uncertainty

As mentioned by Gascoin *et al.,* (2013), the wind speed simulated by MicroMet model tend to be under-estimated especially at low elevation. With the exception of Paso del Agua Negra, similar results are found in this study, with largest bias found at low elevations. Indeed, the results of the cross validation test indicate an *RMSE* of at

4.1 m.s^{-1} at La Laguna and a larger bias (RMSE = 7.8 m.s^{-1} at Paso del Agua Negra. Differences are related to the MicroMet interpolation and can be explained by different reasons. First, The main shortcoming of the wind interpolation module is the lack of thermal winds (e.g. katabatic winds). In addition MicroMet does not take any topography into account that determines the dynamic wind direction, implying bias in the wind interpolation. Nevertheless, the absence of general trends of the under-estimation (both low and high values are under-estimated and the bias strongly depend on the location and the wind speed) makes difficult to establish a relationship to correct the bias and also to evaluate the uncertainty at catchment scale.

Therefore, the number of stations used is important as increasing the number will decrease the uncertainty. The wind uncertainty has an impact on the sublimation ratio. Indeed, for instance, increasing the wind speed by 10% can induces sublimation ratio changes of 40% at high elevation (i.e. where there is no melt). The wind speed is, in fact, known to directly affect the turbulent fluxes (e.g. Litt et al., 2017)

In addition, the wind speed also impacts the snow density, which directly affects the thermal conductivity of the upper snow layers (Yen, 1981). As a consequence it impacts the surface temperatures thus the turbulent fluxes.

b) Topographic influence on wind transport

In the model, the curvature length and the influence of the slope *vs.* curvature can be calibrated to consider the topographic influence of the wind transport. While the curvature length can be approximately constrained from the DEM, the relative influence of slope and curvature is more difficult to quantify a priori. As such, sensitivity tests have been performed to evaluate the impact of these parameters on the simulation.

First, the curvature length value has been varied from 100m to 1000m, and does not impact the annual mean sublimation ratio at the catchment scale (Figure 2). Nevertheless the spatial variability of the differences depends on the elevation (Figure 11). Considering a larger curvature length leads to larger sublimation ratio at low elevation (in the valley) and lower one at high elevation. When choosing a larger curvature value, the simulated snow depth is larger in the valley as the snow transport is from a larger area, and increasing the snow depth decreases the sublimation ratio. Indeed, in that case the snow persists longer in spring, and warmer temperature allow increasing the melt rate.

The annual mean of the sublimation ratio at the catchment scale is not sensitive to the influence of the slope *vs.* curvature either (Figure 2) when values are ranging between 0.25 and 0.75. Nevertheless, varying this influence changes the spatial distribution of snow depth. Larger snow depths (between 18 and 26%) are observed on the ridges when the influence of the slope is larger than the curvature (results not shown). As a consequence, the sublimation ratio decreases by about 10 to 20% in areas with thicker snow, and can also be explained by a the persistence of the snow cover during the spring, increasing the melt rate. On the contrary the sublimation ratio is larger on steep slopes, when the influence of the slope is set to be larger than the curvature, as this calibration allows for more snow redistribution, decreasing the mean snow depth.

The change in snow distribution is more important when changing the influence of slope vs. curvature from 0.25 to 0.75 than when changing the curvature length from 100 to 1000 m. The calibration of these parameters remains important when the sublimation is evaluated in the valley for instance but according to our results, it does not affect the sublimation ratio when evaluated at the catchment scale

F3. Roughness value

Increasing the roughness value by a factor 10 increases the annual mean of the sublimation ratio by 24% for 2014 and by 20% for 2015 (Table S1). Larger changes are observed around 4600 m a.s.l. for 2014 and 2015 where the difference can reach 30% (Figure 11) .

This sensitivity test highlights the strong sensitivity and the importance of choosing an accurate value to properly quantify sublimation over the catchment. Further studies are therefore recommended to calibrate this value using turbulent flux measurements such as with an Eddy Covariance System (e.g. Litt *et al.,* 2017). Nevertheless even with measurements, significant uncertainty remains due to the strong spatio-temporal variability of the snow surface roughness. While the roughness value is used as a calibrated parameter and is not an absolute physical value, it depends on the surface roughness. The roughness is expected to increase with elevation, as penitentes are commonly observed on the lower Tapado glacier (e.g. Lhermitte et al., 2014; Nicholson et al., 2016) and surrounding areas. There is therefore a strong spatial variability of the roughness value, as penitentes are not observed over the entire catchment, but mainly in the upper part. In addition, penitentes grow in size over the season (Lliboutry, 1954) leading to a strong temporal variability of the roughness.

Due to the strong sensitivity to z_0 and the potential for significant spatio-temporal variability of the snow surface roughness, to reduce uncertainties, a spatio-temporal evolution of z_0 could be envisaged. At this stage, without more measurement it is a complicated task. Further studies based on two EC measurements over the season could help to evaluate the variability.

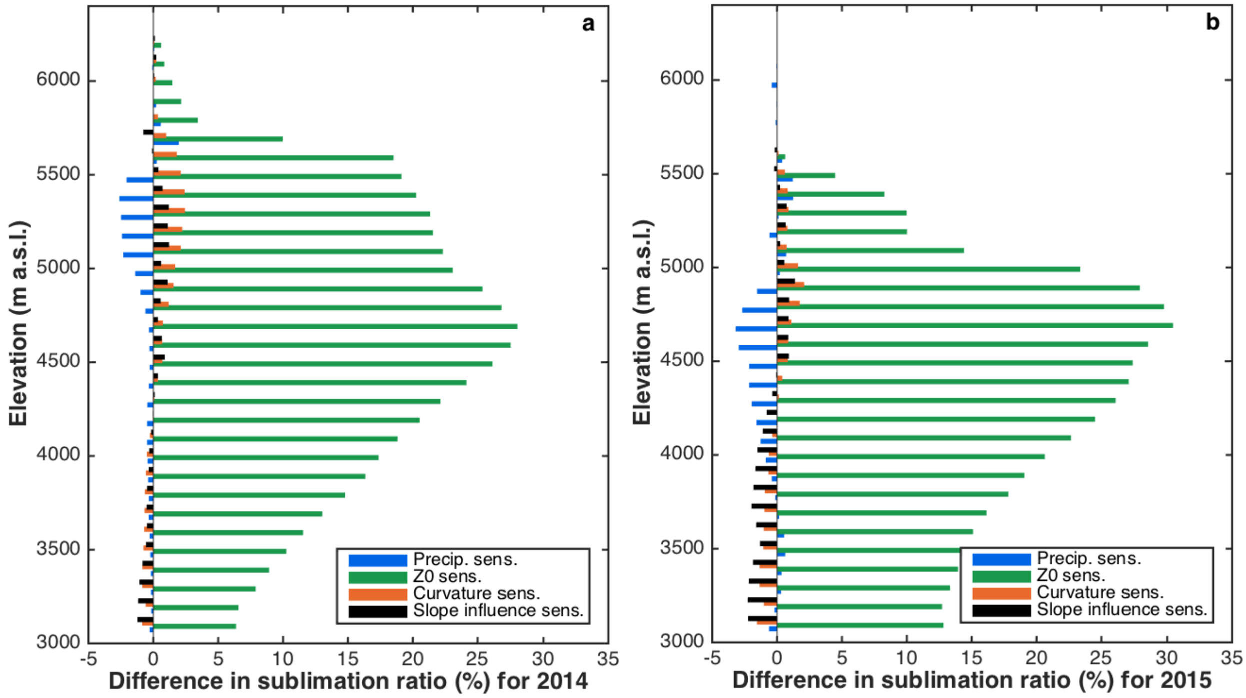

Figure S5: Differences in sublimation ratio per elevation range for (a) 2014 and (b) 2015, between: reference simulation and the simulation performed with a precipitation increase at the two AWS by 10% (blue); reference simulation (z_0=1mm) and with an increase of z_0 to 10mm (green); 100 and 1000m curvature length simulations (orange) and slope vs. curvature weight of 0.25 – 0.75 and 0.75 – 0.25 (black).