

SUPPLEMENTARY MATERIAL

A – Climatology at La Laguna

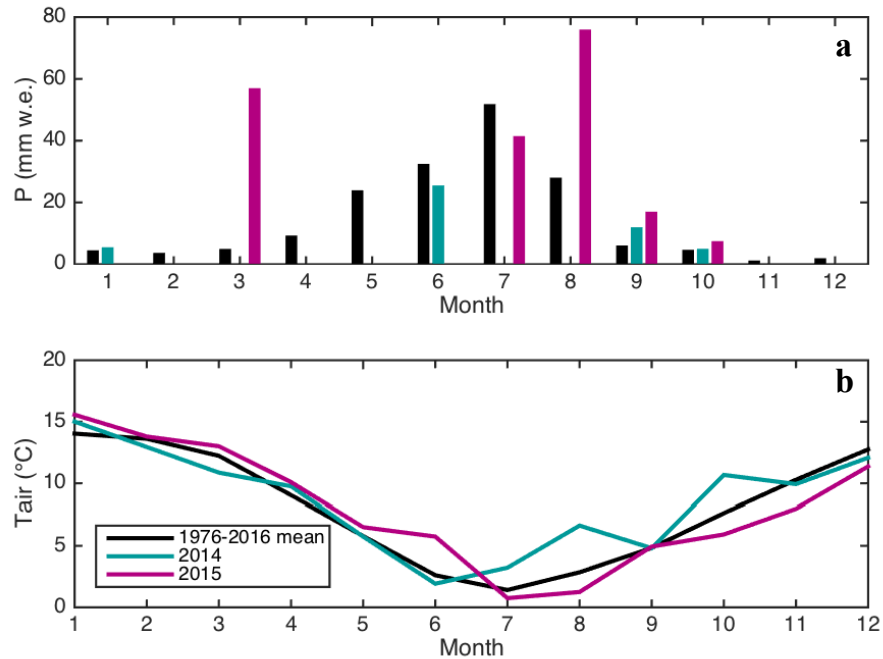


Figure S1: (a) Monthly precipitation and (b) air temperature recorded at La Laguna station. The monthly mean (black) is computed over the 1976-2016 period.

B – Comparison AWS vs. WRF grid point

Table S1: Statistics (R^2 , 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.

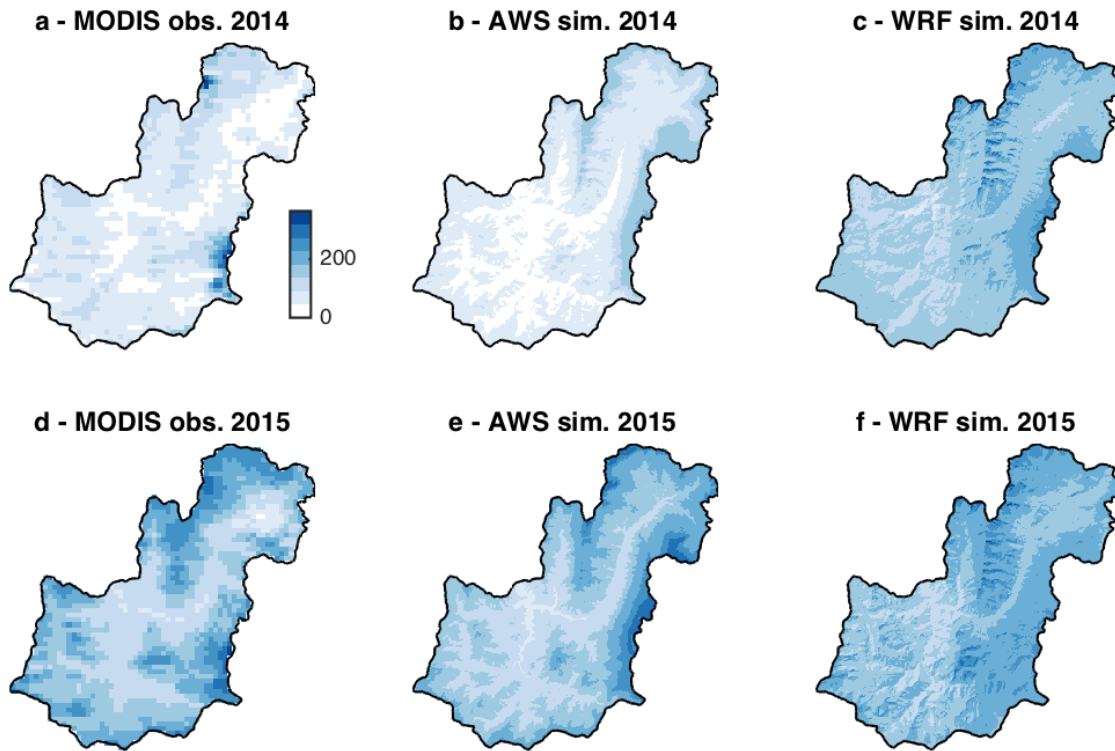


Figure S2: Snow cover duration from MODIS images for (a) 2014 and (d) 2015. Simulated snow cover duration using AWS-forcing for (b) 2014 and (e) 2015. Simulated snow cover duration using WRF-forcing (c) 2014 and (f) 2015.

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

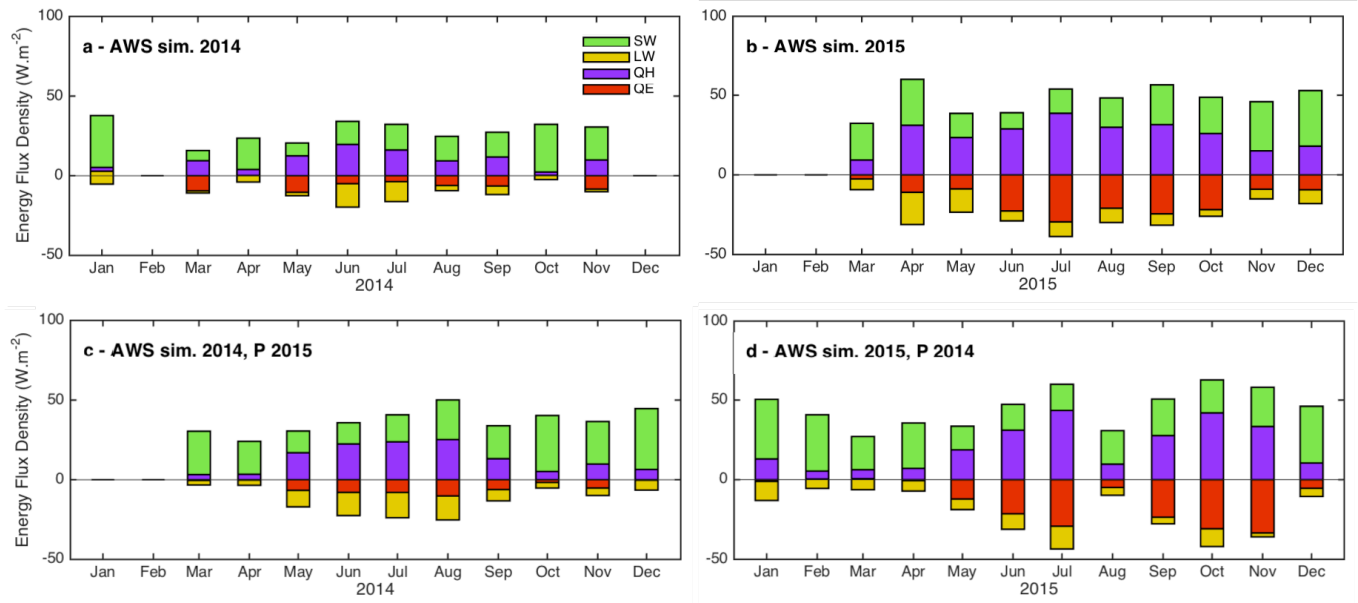


Figure S3: Monthly average (for the entire catchment, over snow surfaces only) of the main modeled heat fluxes for (a) 2014 and (b) 2015 AWS-forcings, (c) a simulation using the 2015 precipitation and the 2014 AWS-forcings, and (d) a simulation using the 2014 precipitation and 2015 AWS-forcings. SW is 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 %.

E. 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 z_0 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%)

E1. 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 caught 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.

E2. 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.

- 5 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%
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

- 15 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
20 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
25 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
30 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

E3. 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.

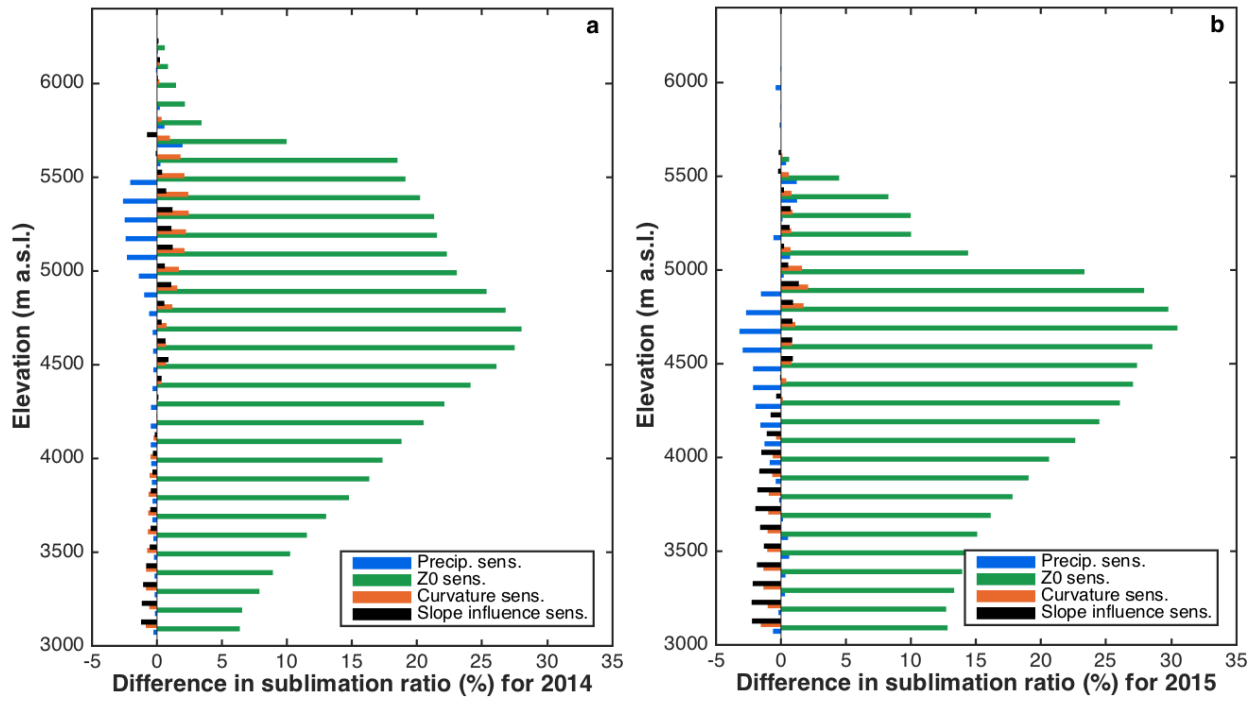


Figure S4: Differences in sublimation ratio per elevation range for (a) 2014 and (b) 2015, between: reference simulation and the simulation performed with a precipitation increase at the two AWS by 10% (blue); reference simulation ($z_0=1\text{mm}$) and with an increase of z_0 to 10mm (green); 100 and 1000m curvature length simulations (orange) and slope vs. curvature weight of 0.25 – 0.75 and 0.75 – 0.25 (black).