



1 **Brief communication: Nonlinear sensitivity of glacier-mass balance attested**
2 **by temperature-index models**

3 *Christian Vincent and Emmanuel Thibert*

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5 *Université Grenoble Alpes, CNRS, IRD, Grenoble-INP, INRAE, Institut des Géosciences de*
6 *l'Environnement (IGE, UMR 5001), F-38000 Grenoble, France.*

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8 Correspondence : *Christian Vincent* (christian.vincent@univ-grenoble-alpes.fr) and *Emmanuel Thibert*
9 (emmanuel.thibert@inrae.fr)

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11 **Abstract**

12 Temperature-index models have been widely used for glacier-mass projections over the 21st century.
13 The ability of temperature-index models to capture nonlinear responses of glacier mass balance (MB)
14 to high deviations in air temperature and solid precipitation has recently been questioned by mass-
15 balance simulations employing advanced machine-learning techniques. Here, we performed numerical
16 experiments with a classic and simple temperature-index model and confirmed that such models are
17 capable of detecting nonlinear responses of glacier MB to temperature and precipitation changes.
18 Nonlinearities derive from the change of the degree-day factor over the ablation season and from the
19 lengthening of the ablation season.

20

21 **Introduction**

22 Glacier surface MB projections in response to climate change over the 21st century can be analysed via
23 physical approaches using energy-balance calculations and empirical approaches linking simple
24 meteorological variables to MB such as temperature-index models. Most glacier-mass projections in
25 response to climate change in large-scale studies over the 21st century have been based on temperature-
26 index models (Huss and Hock, 2015; Fox-Kemper *et al.*, 2021), given the lack of available or reliable
27 information on detailed future meteorological variables (Réveillet *et al.*, 2018). The deep artificial neural



28 network (ANN) approach is a promising new empirical approach to simulate surface MB in the future
29 (Bolibar *et al.*, 2020).

30 Recently, Bolibar *et al.* (2022) analysed the sensitivity of glacier MB to future climate change using a
31 deep ANN. They write that, unlike linear statistical and temperature-index models, their deep-learning
32 approach captures nonlinear responses of glacier MB to high deviations in air temperature and solid
33 precipitation, improving the representation of extreme MBs. Bolibar *et al.* (2022) argue that
34 temperature-index models, widely used to simulate the large-scale evolution of glaciers, provide only
35 linear relationships between positive degree-days (PDDs), solid precipitation and MB. Their paper
36 questions the use of temperature-index models for projections of glacier-mass changes in response to
37 global warming. Here, we performed numerical experiments with a classic and simple temperature-
38 index model to show nonlinear responses of glacier MB to temperature and precipitation changes.

39

40 **Data**

41 For our numerical experiments, we selected two very different glaciers in the French Alps. The
42 Argentière Glacier is located in the Mont-Blanc range (45°55' N, 6°57'E). Its surface area was about
43 10.9 km² in 2018. The glacier extends from an altitude of about 3,400 m a.s.l. at the upper bergschrund
44 down to 1,600 m a.s.l. at the snout. It faces north-west, except for a large part of the accumulation area
45 (south-west facing tributaries). Sarennes is a small south-facing glacier (0.51 km²) with a limited altitude
46 range between 2,820 and 3,160 m (mean values over the period used for the present study), located in
47 the Grande Rousses range (45°07'N; 6°07'E). The field MB observations of the Argentière and Sarennes
48 glaciers come from the French glacier monitoring program called GLACIOCLIM (Les GLACIers, un
49 Observatoire du CLIMat; <https://glacioclim.osug.fr/>).

50

51 **Method**

52 We ran numerical experiments with a classic simple temperature-index model (Hock, 1999; Reveillet *et al.*,
53 2017). For this purpose, we used the daily temperature and precipitation dataset from the SAFRAN
54 (System d'Analyse Fournissant des Renseignements Adaptés à la Nivologie) reanalyses (Durand *et al.*,
55 2009; Verfaillie *et al.*, 2018). These numerical experiments were run on the two very different French



56 glaciers, Argentière and Sarennes, observed over several decades (Thibert *et al.*, 2013; Vincent *et al.*,
57 2009). The surface MB model is expressed as:

$$58 \text{ MB} = \text{DDF}_{\text{snow/ice}} \cdot T + k \cdot P,$$

59 Where:

- 60 - T is the difference between the mean daily air temperature and the melting point,
- 61 - $\text{DDF}_{\text{snow/ice}}$ is the degree-day factor for snow and ice (0.0035 and 0.0055 m w.e. $\text{K}^{-1}\text{d}^{-1}$
62 respectively) and $\text{DDF}=0$ if $T < 0^\circ\text{C}$,
- 63 - P is the precipitation (m w.e.),
- 64 - k is a ratio between snow accumulation and precipitation and $k=0$ if $T > 0^\circ\text{C}$.

65 Other enhanced temperature-index models including potential direct solar radiation could be used for
66 our study, but here the purpose is to show that responses in MB are not linear to temperature or
67 precipitation changes even using a simple degree-day model.

68

69 Results

70 The reconstruction of the glacier-wide MBs of these glaciers from our simple temperature-index model
71 shows good agreement with data (Fig. 1). Using these data, we calculated the MB sensitivities to
72 temperature and winter precipitation at 2,750 metres and 3,100 metres on the Argentière and Sarennes
73 glaciers respectively. These altitudes were selected because they correspond to the approximate center
74 of the glaciers. For each day of each series, we calculated an annual MB anomaly by adding a
75 temperature anomaly or a precipitation anomaly. We report the results in Figure 2 to mirror Figure 3 of
76 Bolibar *et al.* (2022) and make the comparison easier. We also ran these numerical experiments at
77 different altitudes and over the entire glacier surface (Fig. 3).

78 From our experiments, we found first that the response of MB to temperature, using a temperature-index
79 model, is not linear, contrary to the conclusions of Bolibar *et al.* (2022) relative to temperature-index
80 models. As expected, the sensitivity of annual MB (i.e. the slope of the green curves in the graphs of
81 Figure 2) increases with the PDD anomaly. To explain the physical processes involved in nonlinearity,
82 we again used our PDD model, but using synthetic data for atmospheric temperature changes over a
83 year (Fig. 4a). As shown in Figure 4, this nonlinearity (the spread between MB plots in Fig.4c) comes



84 from (i) the lengthening of the ablation season (Fig.4a) and (ii) the earlier disappearance of the winter
85 snow cover which increases the ablation rate due to the change in the degree-day factor from snow to
86 ice (Fig. 4b).

87 Concerning the winter balance, we found a nonlinear response of MBs to winter precipitation with our
88 PDD model and this is also inconsistent with the conclusions of Bolibar *et al.* (2022) relative to the
89 sensitivity of temperature-index models. Runs of our PDD model on synthetic data under different
90 conditions of winter balance (Fig. 5) used a reference scenario of 1,700 mm of winter balance changed
91 by increments of ± 300 mm in precipitation. Results show that the increase in sensitivity can be
92 physically explained by the earlier disappearance of the winter snow cover. The earlier and abrupt
93 increase in the ablation rate under lower conditions of winter balance (Fig.5a) results in nonlinearity
94 attested by the spread between MB plots in Figure 5b. Surprisingly, we detect sensitivity to winter
95 accumulation, contrary to the Bolibar *et al.* (2022) findings using their ANN (Fig. 2 and 3). Indeed, MB
96 sensitivity increases with low winter-accumulation anomalies using our model, but decreases in the
97 deep-learning model of Bolibar *et al.* (2022). The opposite results obtained from the deep-learning
98 model are paradoxical and may be due to an issue in the calibration of the model.

99 Summing up, the ability of PDD models to provide nonlinear sensitivity to air temperature and solid
100 precipitation is due to the different ablation rates and the associated change in the degree-day factor that
101 can be involved depending on snow or ice conditions at the glacier surface. An additional nonlinearity
102 to temperature forcing is caused by changes in the ablation duration.

103 Another question arises in the Discussion section of Bolibar *et al.* (2022), concerning the comparison
104 between their results and those from other studies. The authors claim that all glacier models in the
105 Glacier Model Intercomparison Project (GlacierMIP) (Hock *et al.*, 2019) rely on MB models with linear
106 relationships between PDDs, melt and precipitation. The authors argue that these PDD models present
107 behaviour very similar to the linear-build statistical LASSO model. This is erroneous given that, except
108 for one model (that of Marzeion *et al.*, 2014), all temperature-index models used in GlacierMIP include
109 two degree-day factors. Consequently, they cannot provide a linear response to climate forcing as shown
110 above. In the Bolibar *et al.* (2022) paper, the MB anomalies in response to climate forcing were obtained
111 using a linear LASSO MB model. The choice of the LASSO model is even more surprising given that



112 the authors also used the GloGEMflow model in their paper (see their Discussion section), which is a
113 temperature-index model widely used for glacier projections (Huss and Hock, 2015).

114

115 **Conclusions**

116 From our numerical experiments with a classic and simple temperature-index model, we found nonlinear
117 responses of glacier MB to temperature and precipitation changes. These results refute those of Bolibar
118 *et al.* (2022), which argue that temperature-index models provide only linear relationships between
119 positive degree-days (PDDs), solid precipitation and MB.

120 We tried to understand the cause of this discrepancy. Bolibar *et al.* (2022) compare the response of MB
121 to climate forcing (air temperature, winter and summer snow falls) using a deep-learning approach and
122 a LASSO model. From this comparison, the authors conclude that deep learning provides a nonlinear
123 response, contrary to the LASSO model. The conclusions of Bolibar *et al.* (2022) may be due to the use
124 of a linear LASSO MB model instead of a temperature-index model. We would suggest testing the
125 capability of an ANN to capture nonlinearity by comparing its results with that of the GloGEM Positive
126 Degree-Day (PDD) model that they used in their paper.

127 Regarding specifically MB changes due to solid precipitations, the deep-learning model used by Bolibar
128 *et al.* (2022) foresees decreasing sensitivity under low winter-accumulation conditions. We point out
129 that this result directly contradicts PDD model outcomes. We explain in physical terms why a PDD
130 model expects higher sensitivity to low winter accumulation, but do not yet understand why the approach
131 of Bolibar *et al.* (2022) does not.

132 Given that detailed meteorological variables are highly unpredictable in the future, most glacier-mass
133 projections in response to climate change in large-scale studies over the 21st century are still today based
134 on temperature-index models with simple temperature and precipitation variables. It follows that the
135 questions raised here relative to the nonlinear responses of surface MB to meteorological variables are
136 crucial.

137

138 **Data availability**



139 This commentary does not include original data. All data referred to in the text have been published
140 elsewhere. Data are accessible through the project website at <https://glacioclim.osug.fr>

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142 **Author contributions:** ET and CV ran the numerical modelling calculations and produced the analysis.
143 CV supervised the study and wrote the paper. Both authors contributed to discussion of the results.

144

145 **Competing interests:** The authors declare that they have no conflicts of interest.

146

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152

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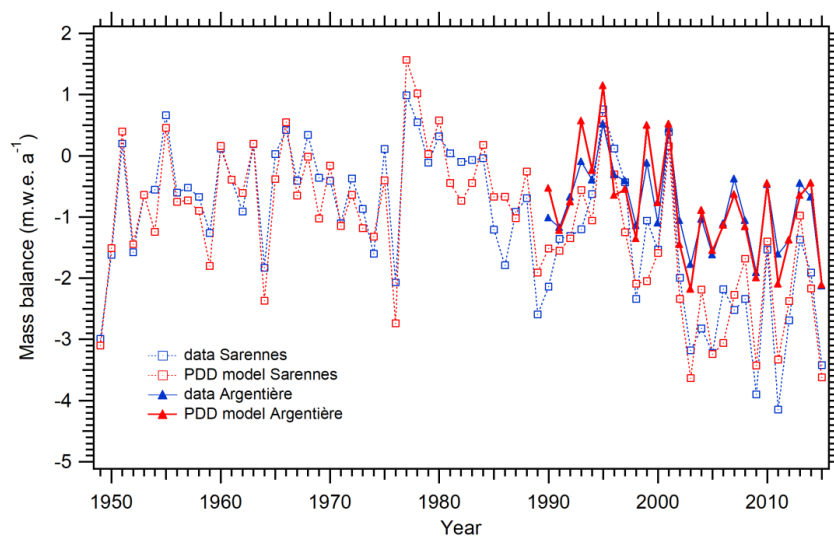
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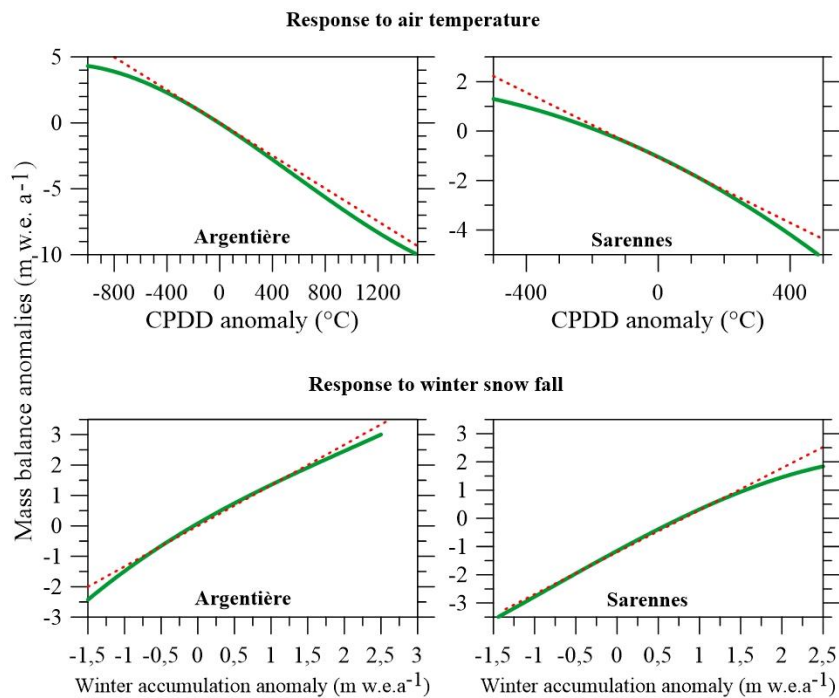
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217 Figure 1. Glacier-wide mass balance of the Argentière glacier (1990-2015) and the Sarennes glacier
218 (1949-2015). Observations and simulations from the simple degree-day model used in our experiments.

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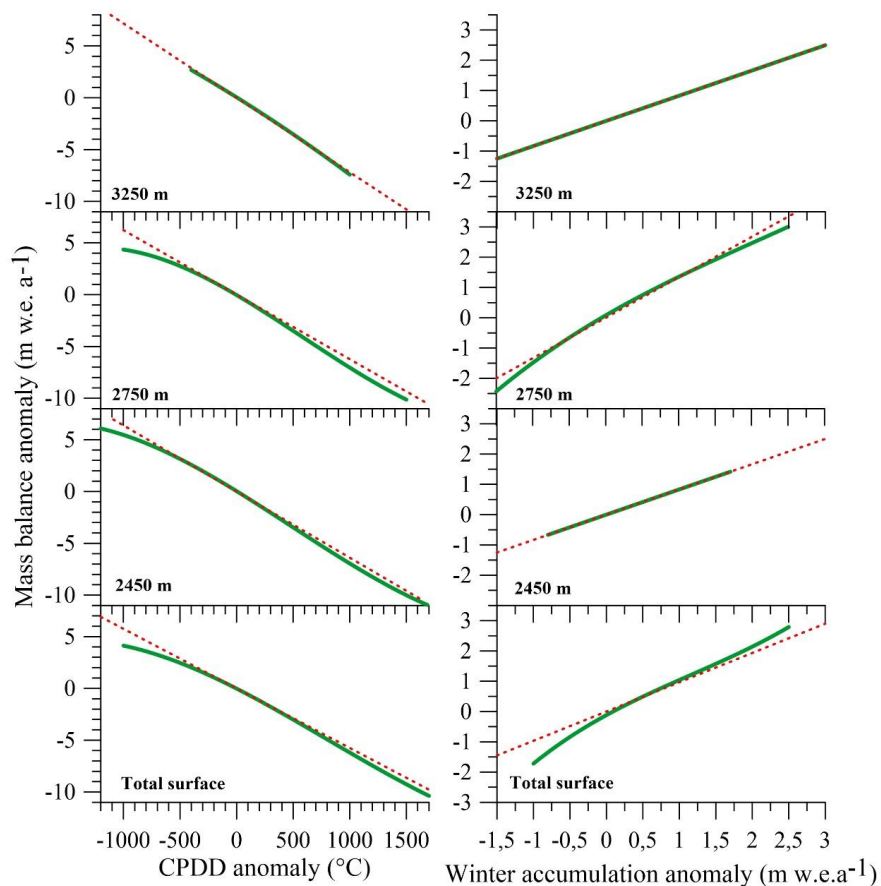


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223 Figure 2. Response of mass balance to climate forcing using a temperature-index model (green line) at
224 2 750 m and 3 100 m on the Argentière (left panel) and Sarennes (right panel) glaciers, respectively.
225 The red dashed lines are the best linear fit. Note that in such graphs, the sensitivity of the mass balance
226 to temperature and winter accumulation changes is the slope of the curves.



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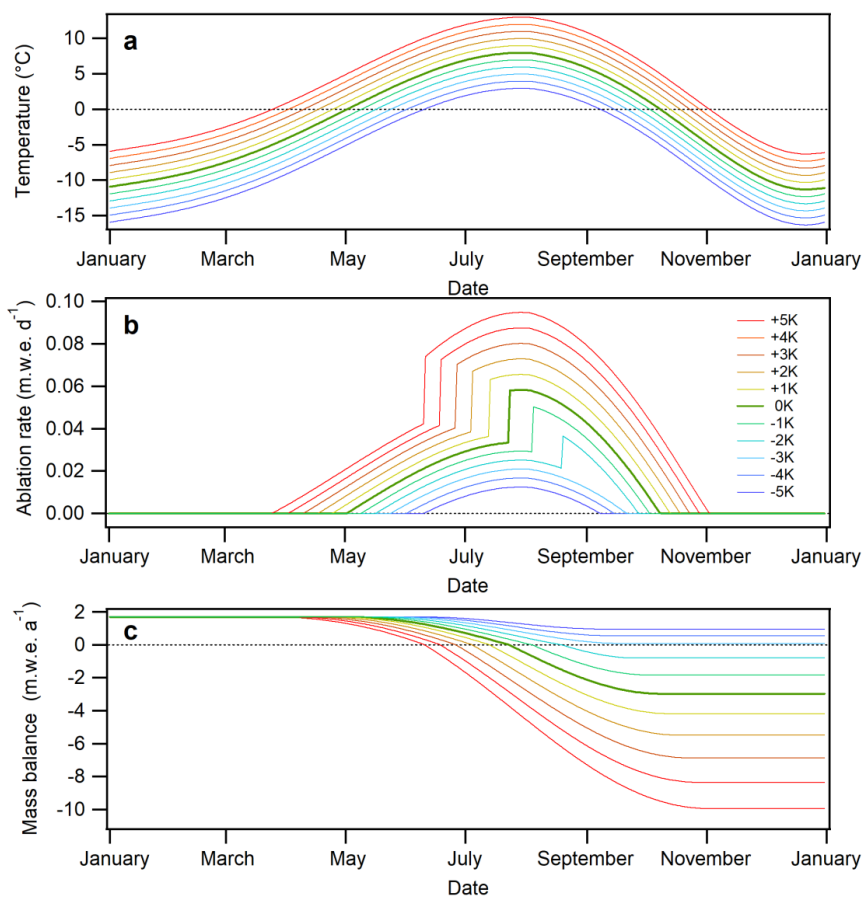
230 Figure 3. Response of annual mass balance to air temperature (left panel) and to winter accumulation
231 (right panel) using a temperature-index model (green line) on the Argentiere glacier. The red dashed
232 lines are the best fit forced through the origin.

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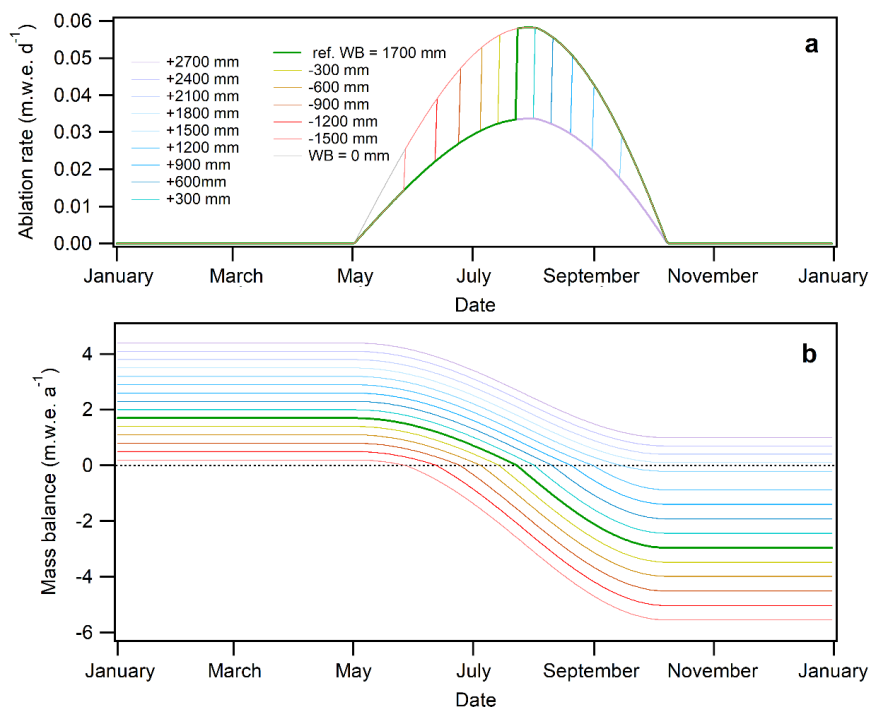
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238 Figure 4. Positive degree-day model running on synthetic data (response to air temperature). Evolution
239 of air temperatures (a), ablation rates (b) and mass balance (c) over the year, according to different
240 temperature scenarios, calculated at 2 800 m. Note the jump in ablation rates when ablation shifts from
241 snow to ice. This occurs earlier with temperature forcing. Note also the lengthening of the ablation
242 season with rise in temperature.

243



244

245 Figure 5. Positive degree-day model running on synthetic data (response to winter balance). Change in
246 ablation rates (a) and mass balance (b) over the year, according to different winter-balance scenarios
247 calculated at 2 800 m. Note the jump in ablation rates when ablation shifts from snow to ice. This occurs
248 earlier under lower winter-balance conditions. Note that the ablation season duration is unchanged under
249 variable winter-balance conditions.

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