

S1 Advection Analysis Methods

The advection of GPS through regions with different geometries and boundary conditions can cause changes in speed during the time series that were independent of variations in environmental forcing. In order to assess how advection potentially influenced our GPS-based speeds, supplemental remotely-sensed speeds were compared to our GPS derived surface speeds. Remotely-sensed speeds at a lower temporal resolution (1 week to 1 month) and spatial resolution (200x200m) were produced through a custom version of NASA's autoRIFT, CautoRIFT (Liu et al. 2024). This algorithm produces rasters- of glacier speeds through cross-correlation of distinct patterns in image brightness (i.e., feature-tracking) between satellite images. For this analysis, pairs of panchromatic Sentinel-2 and Landsat 8/9 images were used as inputs for CautoRIFT. Stations Ice12-2008, Ice14-2008, and Ice15-2106 traveled 722m, 1274m, and 211m, respectively, spanning multiple CautoRIFT grid cells. These three GPS' flow paths were sampled at regular 50m intervals which then functioned as survey transects from which CautoRIFT speeds were extracted. All the satellite images from the time period that spanned each of these three GPS records were run through CautoRIFT. For each CautoRIFT speed map, which reflects the average speeds between image acquisitions, speeds were extracted along the sample GPS transect. However, speed rasters often contained holes and if a speed raster covered less than 50% of a given GPS transect it was removed for further analysis. Additionally, poor image coregistration was a common issue and if a CautoRIFT speed profile had a difference greater than 10 m/d between two subsequent values, that speed profile was removed. Next, all of the CautoRIFT speed transects were averaged to create a characteristic speed transect that is less sensitive to short-term variations in speed than the GPS records. Variations in speed along the characteristic speed transect were assumed to represent variations in speed due to advection, i.e.,

changes in speed in space that are caused by constrictions or widening of the glacial channel
25 along flow. The magnitude of the spatial variation in speed caused by advection was compared to
the magnitude of variation in speed of the GPS records to assess the relative importance of
advection- and forcing-driven variations in speed. As described below, advection has minimal
influence on speed variation of our GPS records and therefore was not accounted for during our
speed analysis.

30 **S2 EBFM Methods**

Alongside comparing our GPS speed time series to rain estimates, we also analyzed our speed
records alongside various weather parameters from an energy balance firn model (EBFM) (van
Pelt et al. 2012). This model was chosen because it had been used previously for Sít' Kusá to
model subglacial melt and because it is able to produce time series of surface runoff components
35 that may impact glacier speeds (Terleth et al. 2024). Surface air temperature, rain, and the
estimated amount of water from melt and rain that penetrates through the firn layer into the
glacial system (i.e., meltwater equivalent or MWE), were all considered as potential drivers of
speed change in our analysis.

40 As climatic input to the model we used the $0.25^\circ \times 0.25^\circ$ ERA5 grid cell covering Sít' Kusá's
terminus (Figure 1). ERA5 reanalysis timeseries were downscaled to the surface using
ArcticDEM elevations from the Polar Geospatial Center (Porter et al. 2022) downsampled to
100x100m. The DEM was used to calculate terrain parameters for radiative fluxes across the
glacier and the ERA5 inputs were distributed across the glacier based on elevation. The EBFM

uses a snow model and a surface energy balance model to calculate the mass balance at each DEM grid cell on the glacier. Lastly, we set the model timestep to 3 hours.

S3 Characterization of Speed-up Events Methods

To assess whether a variety of climatological factors drove glacier acceleration, the timestamps of the identified STA/LTA speed anomalies were used to extract various independent and dependent variables for each speed anomaly. Independent variables were chosen on the basis that they may influence Sít' Kusá's surface speeds while the dependent variables were chosen on the basis of capturing metrics that would quantify Sít' Kusá's speed response (Table S1). The sampling rates of all independent and dependent variables corresponded to the datasets they were extracted from, every 3 hours for EBFM variables and every 15 seconds for speed variables. The independent variables include weather parameters from the EBFM and speeds prior to the anomaly. Most independent variables were identified from a window that spanned from the peak of a speed anomaly to four days prior. This search window needed to be large enough to account for the possible lag times between speed anomalies and the timings of their forcings but not so large that irrelevant weather variations were taken into consideration. The average time between speed anomalies and their preceding rain event peaks was 44.5 hours such that a four-day window was sufficient for capturing independent variables leading up to the speed anomalies. Previous studies exploring the relationship between rain and GPS derived surface speeds have also used a four day search window around speed anomalies to identify relevant weather forcings (Horgan et al. 2015). Once all variables were extracted, the strength of the relationship between all independent and dependent variables was explored to determine which variables scaled with one another.

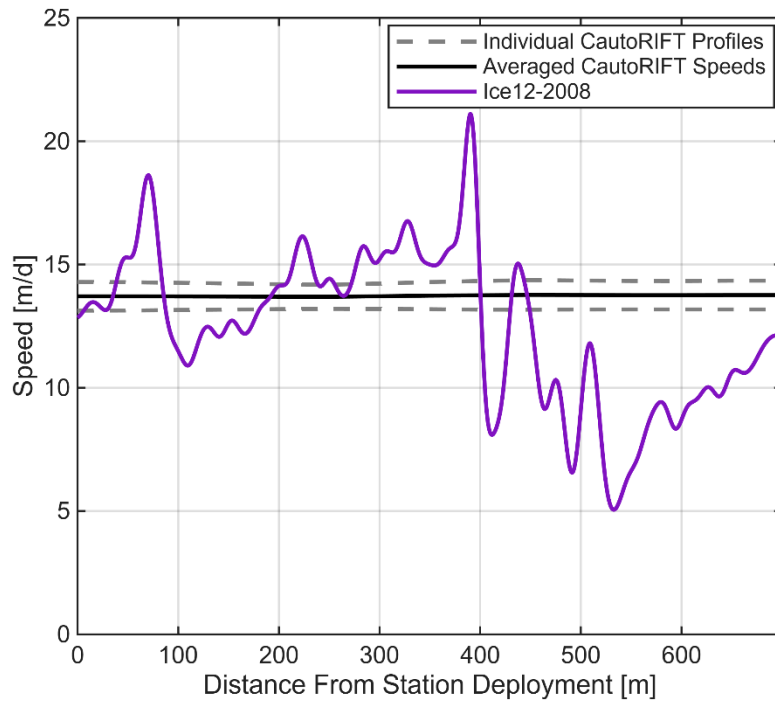
Table (S1): Independent and dependent variables explored in this study and the definition for each variable.

Independent Variables	<u>Variable Description</u>
Max Rate of Rain	[mm/h] Peak rate of rain observed 4 days prior to the peak of a speed anomaly
Duration of Rain Event	[hours] Time between when the rain rate >0.67 mm/h and <0.67 mm/h
Volume of Rain Event	[mm] Rain summed over the duration of a rain event
Max Temperature	[c] Max temperature observed within 4 days leading to the peak of a speed anomaly
Max MWE	[mm/h] Max MWE observed within 4 days leading to the peak of a speed anomaly
Time Between Speed Up Events	[hours] Hours elapsed from the max speed of a speed anomaly to another
Prior Speed Trend	[m/d ²] Slope of a linear polynomial applied to the non-detrended speeds over the two days leading up to the start of a speed anomaly
Dependent Variables	<u>Variable Description</u>
Max Speed	Peak speed of a given speed-up event calculated from the detrended speeds
Duration of Speed Up Event	[hours] Time between the start and end of a speed anomaly based on 1-hour average speed time series for the 4 days prior to and following a speed peak. The start was identified as the first hour before the peak that exceeded the prescribed threshold and the end was identified as the last hour after the peak that exceeded the prescribed threshold
Lag Time Between Max Rate of Rain and Max Speed	[hours] Time elapsed between the timing of the max rate of rain to the timing of the max speed of a speed-up event
Percent Increase in Speeds	<i>During the surge:</i> $\frac{(\text{non - detrended peak in speed}) - (\text{spline value})}{\text{spline value}} \times 100$ <i>During quiescence:</i> $\frac{(\text{detrended peak in speed}) - (\text{average of GPS record})}{\text{average of GPS record}} \times 100$
Lag Time Between Max MWE and Max Speed	[hours] Time elapsed between the timing of the max rate of MWE to the timing of the max speed of a speed-up event

S4 Advection Analysis Results

70 The remotely-sensed speeds for Ice15-2106 were inconsistent and therefore we were not
confident in drawing conclusions about advection from this station. In general, Ice12-2008 and
Ice14-2008 both had similar average speeds when compared to their averaged CautoRIFT speed
transect counterpart (Figure S1). The averaged CautoRIFT speed transect counterpart for Ice12-
2008 and Ice14-2008 both had minimal speed variability when compared to their corresponding
75 GPS record (Figure S1). Based on this, in addition to the following reasons, we chose to ignore
advection effects hereafter. First, seven of the ten GPS stations exhibited minimal displacement
over their recording periods, making it unlikely that they advected into different flow regimes.
Second, as shown in Figure 8, periods of temporal overlap between independent GPS records
indicate that speed-up events occur synchronously at multiple locations along the glacier. This
80 spatial coherence suggests that the observed accelerations are not purely local phenomena but
instead reflect glacier-wide responses to changes in forcing over time.

**Figure (S1) All of the sampled CautoRIFT speed rasters at GPS positions of Ice12-2008 in 50m intervals
plotted with a grey dashed line, GPS derived speed record of Ice12-2008 in purple, and the average of all the
CautoRIFT speed raster transects in black. The x-axis is the distance traveled, in meters, from where Ice12-
85 2008 was deployed.**



S5 Characterization of Speed-up Events Results

Out of all the combinations of independent and dependent variables that we extracted for every speed-up event, the strongest linear relationship found was between max temperature 4 days

90 prior to the speed-up and speed-up duration ($r = 0.64$) and between the prior speed trend over the 2 days leading up to the speed-up and the max speed of a speed-up ($r = -0.67$). The strength of all of the linear relationships can be seen in Figure S2.

Two variable pairings, peak rate of rain and percent increase in speed and peak rain rates and

95 peak speeds, although not having strong relationships, were explored further due to varying levels of correlation if the data was separated by year (Figure S1). A moderately-strong ($r = 0.39$) linear relationship exists between peak rate of rain and percent increase in speed (Figure S1a).

Although splitting the data between surge and quiescence does not reveal a significant difference

between the two, two groups emerge: one with moderate sensitivity and one with increased sensitivity to rain rates. Group one consists of surge and quiescent data from 2021 and quiescent data from 2024 (10 total speed-ups) and displays increased sensitivity to rain rates ($r = 0.94$). Group two consists of surge data from 2020 and quiescent data from 2022 and 2023 (27 total speed-ups) and shows moderate sensitivity to rain rates ($r = 0.52$). Evidence of differing sensitivities to rain rates between the surge and quiescence does arise in the relationship between peak rain rates and peak speeds (Figure S1b). When separated by surge phase, a relatively strong linear relationship exists between peak rain rates and peak speeds during the surge ($r = 0.60$), while a relatively weak relationship exists during quiescence ($r = 0.23$). The strength of the relationships should be interpreted with caution, however, because they are based on only 10 surge data points and 27 quiescent points.

Figure (S2): Relationship between (a) peak rate of rain and percent increase in speed and (b) peak rate of rain.

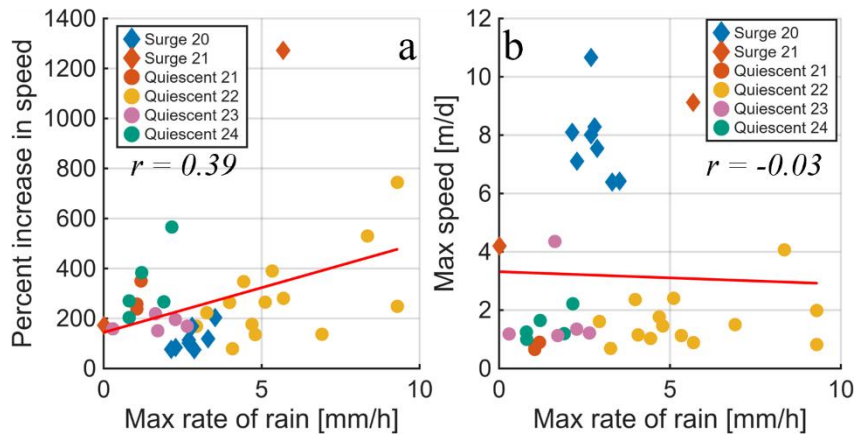
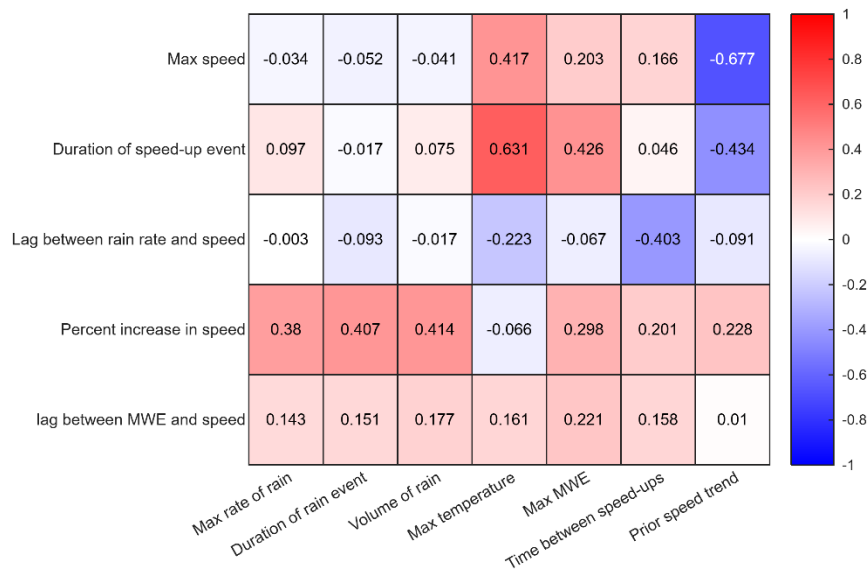


Figure (S3): Correlation heatmap between all independent and dependent variables. Independent variables are on the x-axis while dependent variables are on the y-axis. Red cells correspond to positive correlations while blue colors correspond to negative relationships. The darker the variant of color the stronger the relationship.



References

- 120 Horgan, Huw J., Brian Anderson, Richard B. Alley, et al. 2015. “Glacier Velocity Variability Due to Rain-Induced Sliding and Cavity Formation.” *Earth and Planetary Science Letters* 432 (December): 273–82. <https://doi.org/10.1016/j.epsl.2015.10.016>.
- 125 Liu, Jukes, Madeline Gendreau, Ellyn Mary Enderlin, and Rainey Aberle. 2024. “Improved Records of Glacier Flow Instabilities Using Customized NASA autoRIFT Applied to PlanetScope Imagery.” Preprint, February 22. <https://doi.org/10.5194/egusphere-2024-374>.
- Pelt, W. J. J. van, J. Oerlemans, C. H. Reijmer, V. A. Pohjola, R. Pettersson, and J. H. van Angelen. 2012. “Simulating Melt, Runoff and Refreezing on Nordenskiöldbreen, Svalbard, Using a Coupled Snow and Energy Balance Model.” *The Cryosphere* 6 (3): 641–59. <https://doi.org/10.5194/tc-6-641-2012>.
- 130 Porter, Claire, Ian Howat, Myoung-Jon Noh, et al. 2022. “ArcticDEM - Strips, Version 4.1.” Version 1.4. Harvard Dataverse, October 11. <https://doi.org/10.7910/DVN/C98DVS>.
- 135 Terleth, Yoram, Timothy C. Bartholomaeus, Jukes Liu, Flavien Beaud, Thomas Dylan Mikesell, and Ellyn Mary Enderlin. 2024. “Transient Subglacial Water Routing Efficiency Modulates Ice Velocities Prior to Surge Termination on Sít’ Kusá, Alaska.” *Journal of Glaciology*, April 18, 1–17. <https://doi.org/10.1017/jog.2024.38>.