Assessment of intense rainfall detection using PWV and SNR variations

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Abstract

The central objective of this study is to analyze the behaviour of GNSS products, namely Precipitable Water Vapor (PWV) and Signal-to-Noise Ratio (SNR), before, during, and after various intense rainfall periods to assess their precision and response time in detecting heavy rainfall. To achieve this goal, several GNSS stations are examined, covering Austria's entire territory within the EPOSA (Echtzeit Positioning Austria) area during the experimental period in July 2021. Subsequently, two different analyses are conducted, including (1) PWV time series (sample rate 10 minutes) and (2) SNR time series (sample rate 30 seconds), considering both lower and higher elevation angle ranges. These analyses are performed over multiple time windows to determine the response time of these parameters to heavy rainfall. As a result of this study, a new methodology based on PWV and SNR is investigated, demonstrating its potential for characterizing intense rainfall.

Data Preparation

PWV (Temporal resolution: 10 minutes)

- Estimation ZTD using Bernese GNSS software in baseline mode.
- Using the Saastamoinen model by applying surface pressure derived from the GeoSphere meteorological stations to calculate ZHD.
- Estimating ZWD using ($ZWD[mm] = ZTD[mm] - ZHD[mm]$).
- Applying the Random Forest to Calculate the weighted mean temperature (T_m).
- Finally, PWV is calculated using:

$$PWV[mm] = \Pi \times ZWD[mm] \quad (1)$$

$$\Pi = \frac{10^6}{(k_2' + k_3/T_m) \times (\rho_w R_v)} \quad (2)$$

SNR (Temporal resolution: 30 seconds)

- Using the GNSS-IR software (rnx2snr) to extract GPS L2 (1.2276 GHz) SNR data ($SNR2$) from Rinex observation files.
- Adjust the SNR data by shifting it 4 minutes forward each day to compensate for the satellite's geometry changes.
- Using data for the visible satellite at the intended GNSS station with $25 < el \leq 85$.
- Detrend data by:

Fitting a 2-order polynomial to the $SNR2$ $[dB - Hz]$ data:

$$SNR_{linear}[volt/volt] = (10^{(SNR/20)}, \sin(el)) \quad (3)$$

and then subtracting this polynomial model from the $SNR2$ data.

- Event detection in the range of $\pm 2.5\ \sigma_{res}$.
- Calculating the temporal variation of $SNR2$ ($DSNR$) in the following epochs:

Epoch#1: Difference of $SNR2$ during the hour of rainfall to $SNR2$ one hour before rainfall.

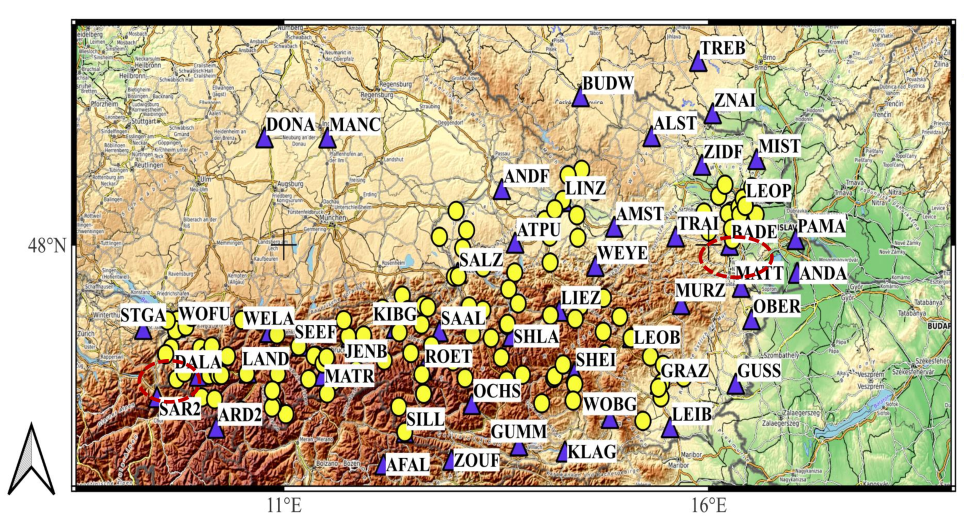
Epoch#2: Difference of $SNR2$ during the hour of rainfall to $SNR2$ one hour after rainfall.

Rainfall (Temporal resolution: 10 minutes)

- Filtering the nearest weather stations to the desired GNSS station (<=20 km).
- Employing the IDW interpolation method to calculate rainfall in the GNSS location.

Case Study

The study area encompasses 49 permanent GNSS stations distributed across Austria. In addition, two stations marked with red circles (LEOP and WOFU) were used to investigate the impact of the intense rainfall during the experimental period on PWV and SNR data.

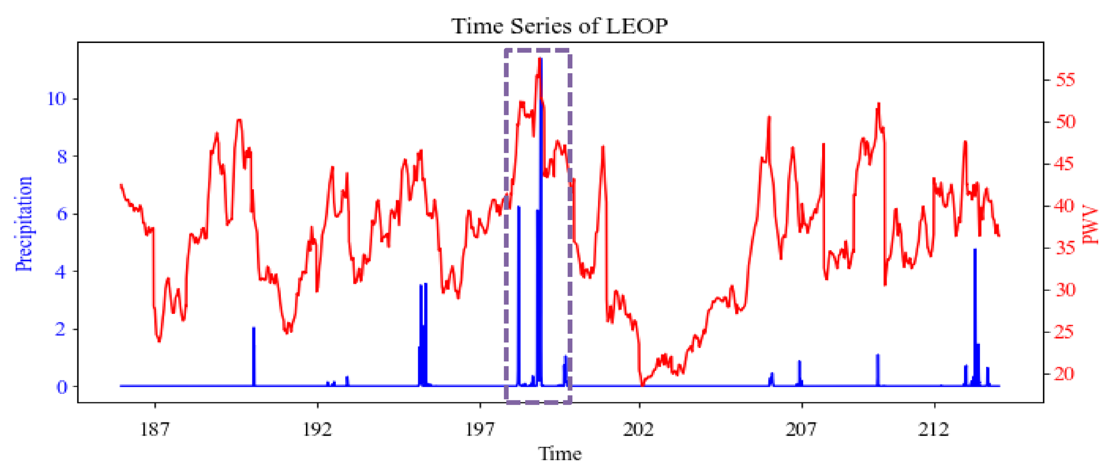


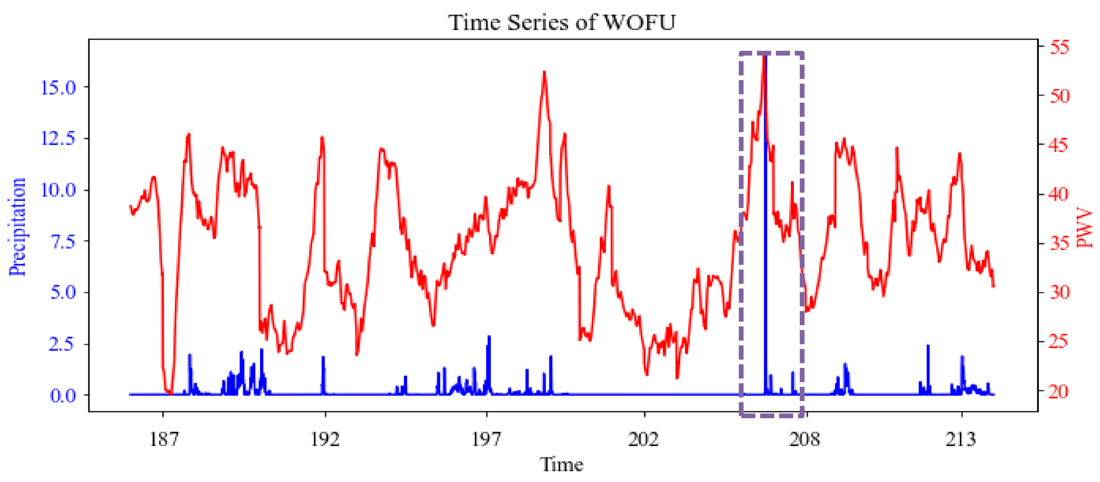
Distribution of GNSS and GeoSphere Stations in the Austria territory

GeoSphere data accessible at https://data.hub.geosphere.at/dataset/inca-v1-1h-1km

Weather Condition

The shown figures demonstrated that rainfall at stations LEOP and WOFU reaches approximately 10 mm on DoY 198 and 16 mm on DoY 205, falling within the category of heavy rainfall. These figures also show changes in PWV.

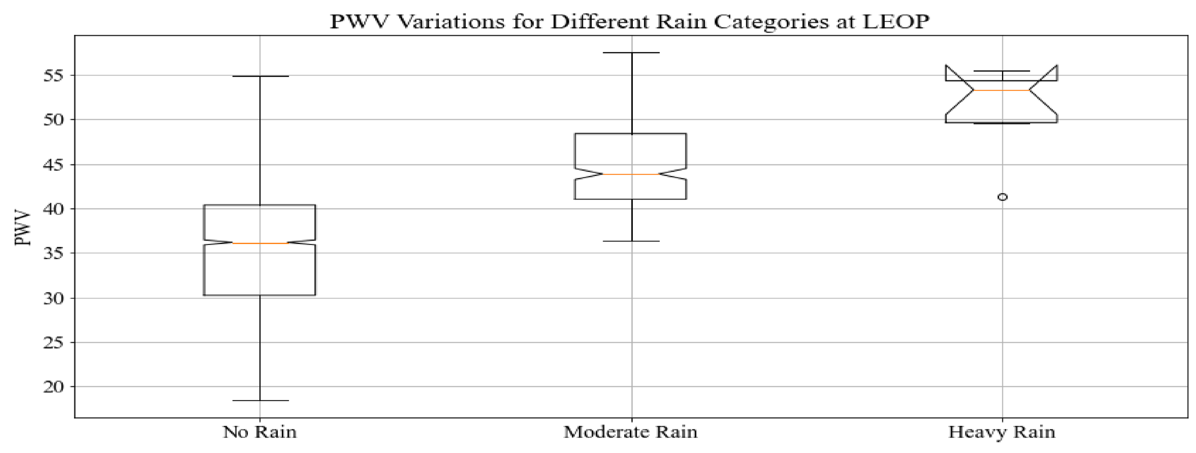




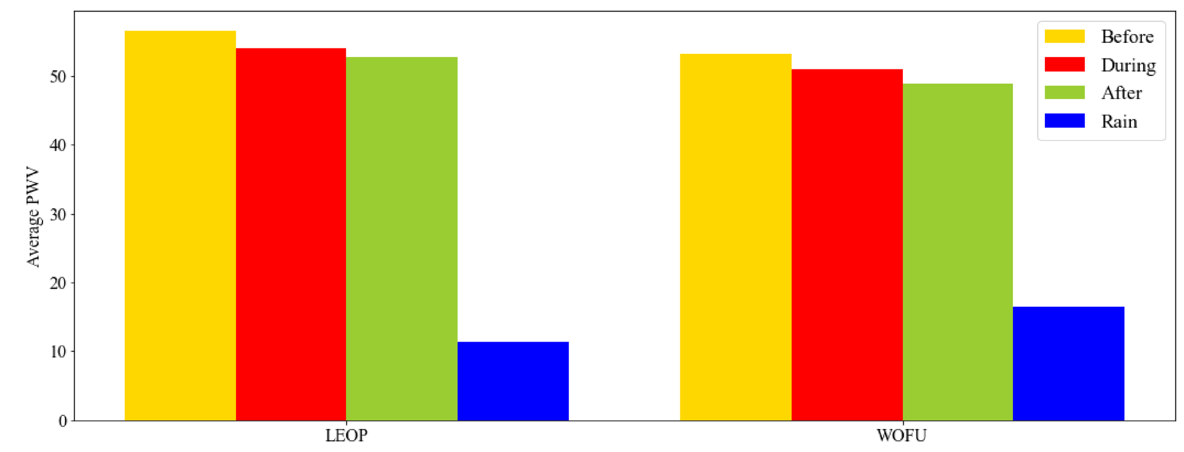
Additionally, heavy rain can cause slight attenuation of GNSS signals. Therefore, we analyzed this period to assess variations in PWV and SNR, as well as the potential response time of these parameters to such weather events.

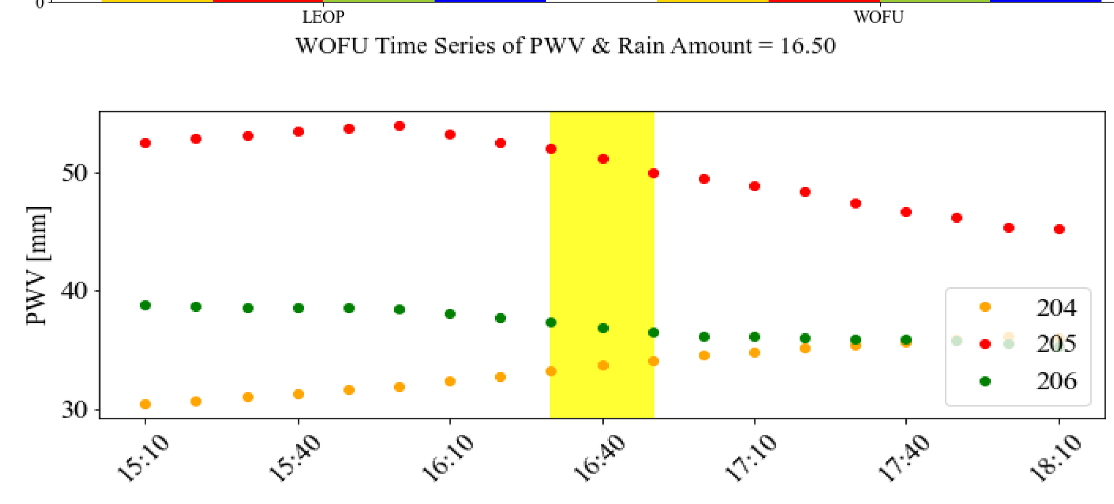
PWV Analysis

Ten-minute PWV data from two stations, LEOP and WOFU, were selected to investigate the impact of rainfall. In the first analysis, we categorized rainfall into three classes: No Rain, Moderate Rain, and Heavy Rain. We then used boxplots to summarize the distribution of PWV in these classes. As seen in the following figure, the distribution of PWV is close to normal when there is no rain. Interestingly, the PWV distribution is less disturbed during heavy rain compared to moderate rain. As expected, the PWV values are noticeably higher in both rain classes compared to the No Rain class.



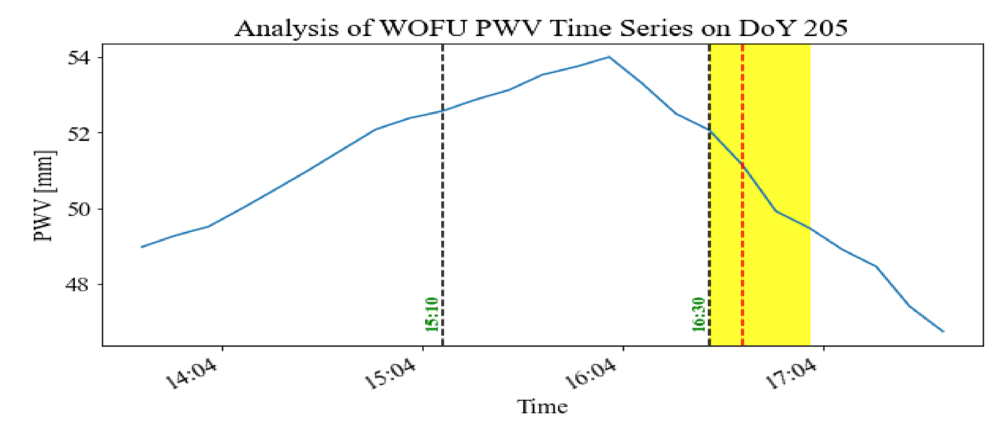
In the second step, we investigated the variation of PWV before, during, and after the rainfall event. As shown in the following figure, the PWV increases prior to the rainfall and then begins to decrease once the rainfall has occurred.





To investigate the possibility of defining a time interval for early warning of intense rainfall, we employed a change point detection algorithm to find significant shifts in PWV data prior to rainfall events. We utilized the PELT (Pruned Exact Linear Time) method from the Python Ruptures library for this purpose.

The shown figure reveals a notable change in PWV amount roughly one hour before the intense rainfall begins. This behaviour was also observed at the LEOP station. However, further analysis, including additional time periods and case studies, is necessary to verify this finding



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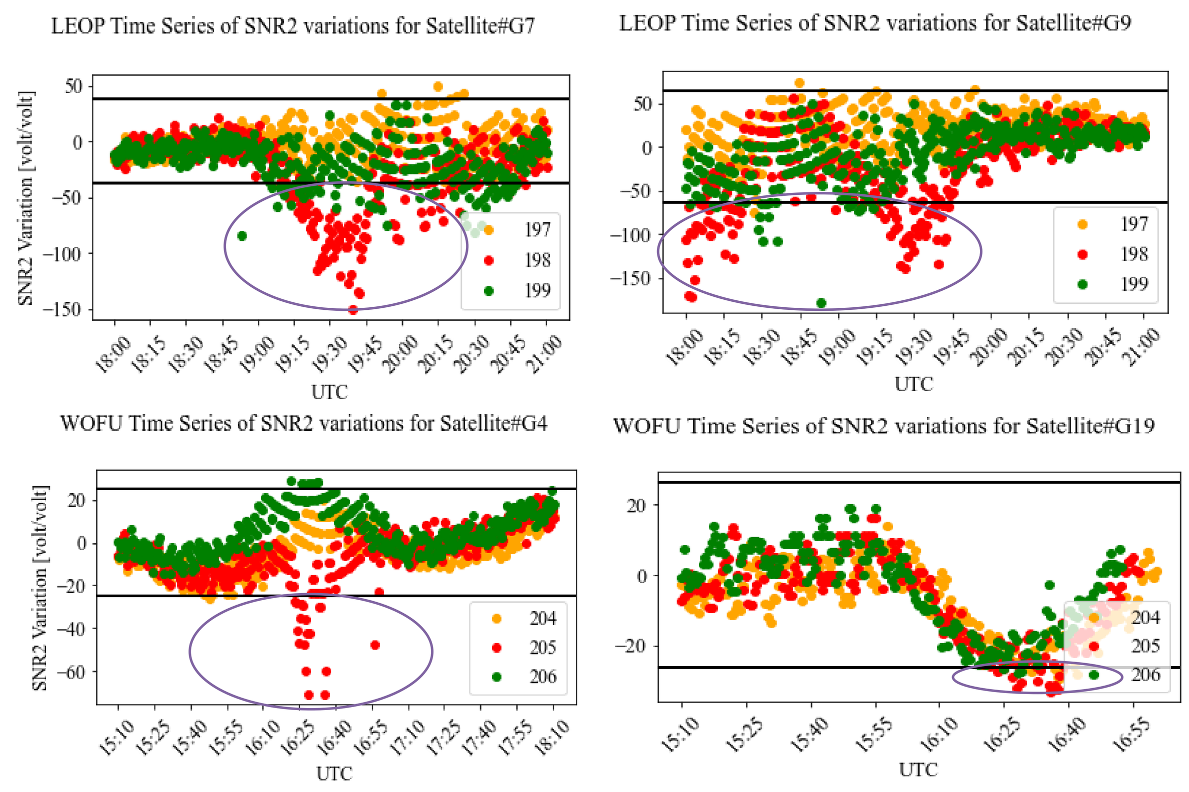
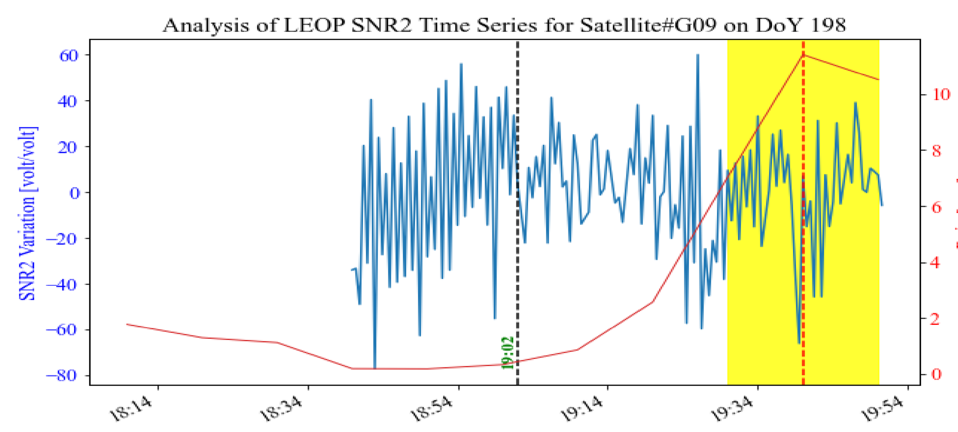
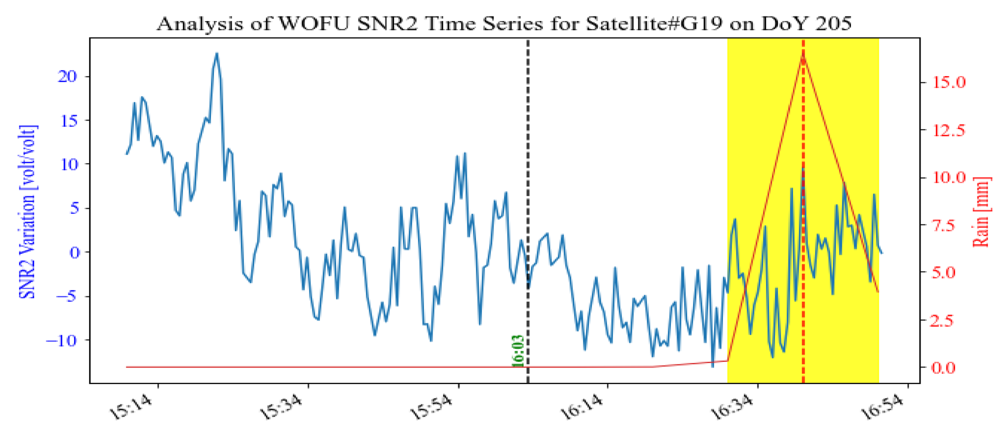
SNR Analysis

To analyze the impact of rainfall on SNR data, we first examined the $SNR2$ variations. We removed the direct signal derived from Eq. (3) to eliminate any dependence on the elevation angle, which could lead to misinterpreting the $SNR2$ behaviour. The following figures show the $SNR2$ variations for the event, as well as the day before and after. Interestingly, the results for both stations (LEOP and WOFU) and their corresponding satellites reveal a clear degradation in $SNR2$ several minutes before the rainfall event. LEOP's $SNR2$ also degraded on DoY 199, which is associated with the rain.

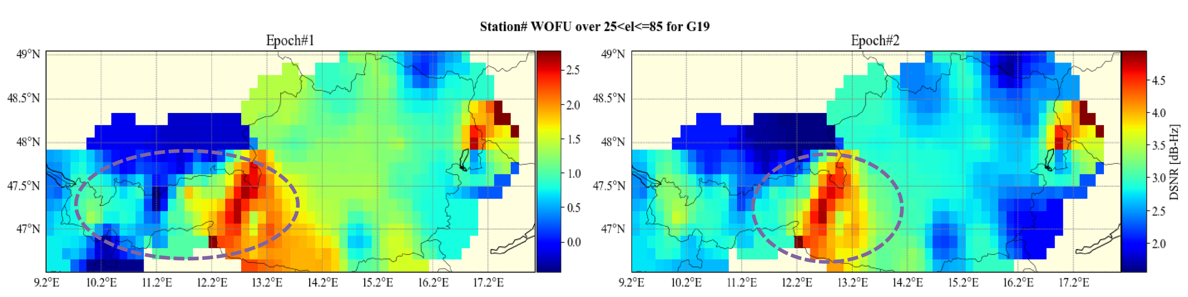


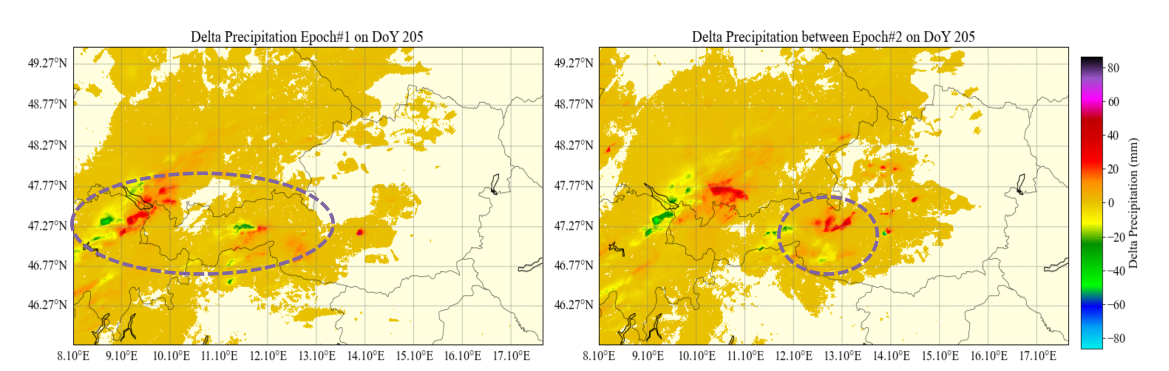
Similar to the PWV analysis, we applied the PELT method to the $SNR2$ data to identify potential time periods where $SNR2$ begins to decrease. The following figure shows the output of this analysis for the G09 and G19 satellites corresponding to the LEOP and WOFU stations. The results indicate that the first signs of change in $SNR2$ appear approximately thirty minutes before rainfall.





Finally, we calculated preliminary $DSNR$ maps for Epoch#1 and Epoch#2 for an exemplary satellite at the WOFU station and compared them to the corresponding precipitation variations within the same period. As the figure shows, a degree of similarity exists between the temporal variations of $SNR2$ and precipitation. In future studies, we intend to define an index that could help strengthen GNSS capability as an early warning system for rainfall events.





Conclusions and Outlook

This analysis represents a preliminary exploration of utilizing PWV and $SNR2$ for rainfall prediction, which revealed a noticeable degradation in both parameters prior to the rainfall event. The increase in water vapour is a known requirement for rainfall. However, other external parameters, such as cloud height and wind patterns, also play a significant role. These factors will be incorporated in future studies. To further refine the GNSS tool as an early warning system, we will conduct additional analyses including more case studies and time periods.