Supplementary material for the article

Fusing geostationary satellite cloud properties with signal attenuation from microwave links for rain detection

S1 Supplementary figures and analysis

This supplement provides additional analyses supporting the main manuscript. Section S1.1 evaluates whether the model ranking is stable between daytime and nighttime conditions. Section S1.2 presents the extended comparison across all training setups. Section S1.3 evaluates the added value of CML total loss for satellite based CNN rain detection under mixed-domain training. Section S1.4 provides a diagnostic comparison between temporal and spatial test conditions to support the interpretation of link specific dry signal behaviour.

S1.1 Day–night stability of ROC performance

Figure S1 shows ROC curves for the mixed setup using all observations, daytime observations, and nighttime observations. The satellite enhanced models keep higher AUC values than the CML only CNN in all three cases. This indicates that the improved wet–dry discrimination is not only driven by daytime CPP microphysical variables. The result supports the main manuscript finding that SEVIRI information improves the separation between dry and wet periods under both daytime and nighttime conditions.

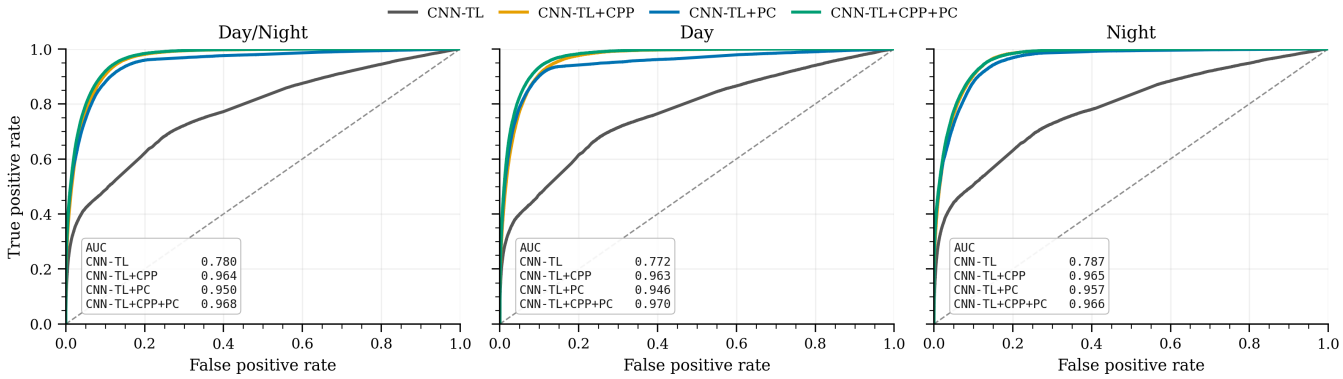

Figure S1. ROC curves for the mixed setup using all observations, daytime observations, and nighttime observations. The satellite enhanced CNN models keep higher AUC values than the CML only CNN in all cases, supporting the day–night stability of the model ranking.

S1.2 Extended training setup comparison

Figure S2 shows the extended MCC distributions for the same domain, cross domain, single source all link, and mixed training setups. The setup labels follow the notation used in Table 3 of the Method section, where the first term indicates the training domain and the second term indicates the test domain. Thus, `DE/DE` and `CZ/CZ` are same-domain setups, `CZ/DE` and `DE/CZ` are cross-domain transfer setups, `CZ-all/DE` and `DE-all/CZ` are single-source all-link transfer setups, and `Mixed/DE` and `Mixed/CZ` are mixed-domain training setups.

The results show that the satellite enhanced models are generally more stable than the CML only CNN and the benchmark methods across the tested test domains. The additional single source all link setups also show that using more links from one source dataset does not automatically remove the transfer gap to the other test domain. This supports the interpretation

that transfer depends not only on the number of training links, but also on the diversity and representativeness of the training domain.

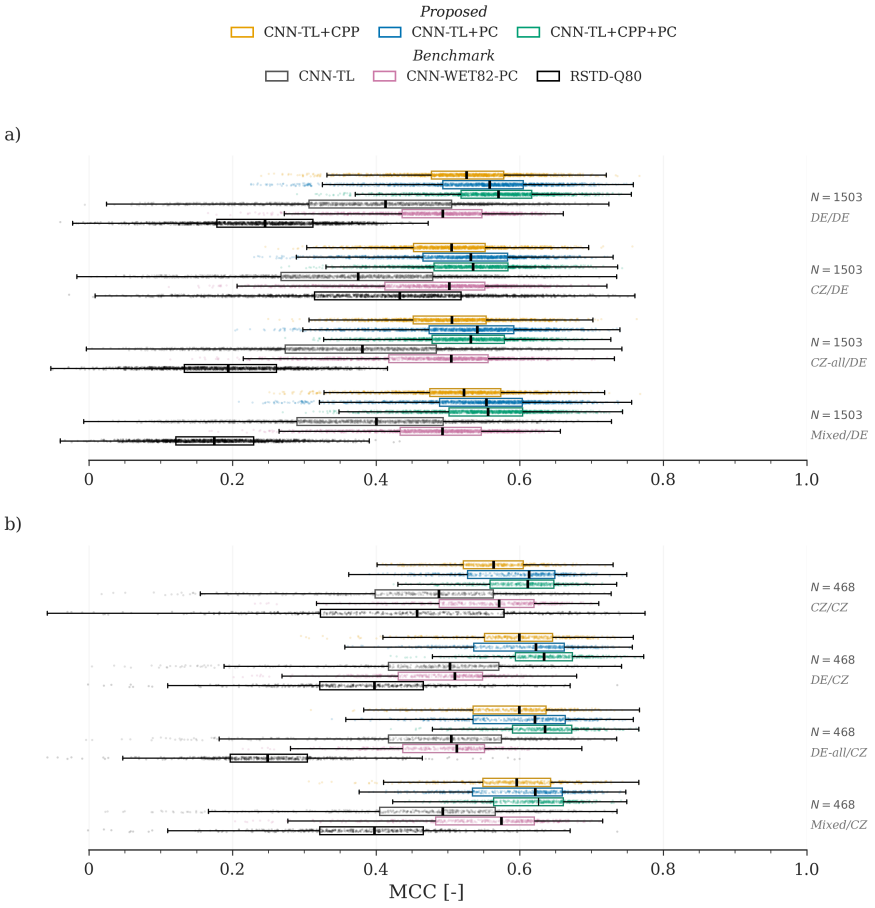

Figure S2. Extended MCC comparison across training setups for the German and Czech test domains. Setup labels follow the notation training domain/test domain. `DE/DE` and `CZ/CZ` represent same-domain testing, `CZ/DE` and `DE/CZ` represent cross-domain transfer, `CZ-all/DE` and `DE-all/CZ` test whether using all links from one source domain improves transfer, and `Mixed/DE` and `Mixed/CZ` show mixed-domain training. The figure highlights that satellite enhanced CNNs remain more stable than the CML only CNN across the transfer setups, while the single-source all-link tests do not remove the cross-domain performance gap.

S1.3 Added value of CML total loss for satellite based CNN rain detection

Figure S3 evaluates the added value of CML total loss from the perspective of satellite based CNN rain detection. The comparison is restricted to the mixed-domain training setup and combines the German and Czech test domains into one analysis. This setup is used here because it represents the most general training configuration and avoids separating the comparison into several transfer cases.

The satellite only CNNs using PC, CPP, or both products already provide useful rain detection skill, confirming that SEVIRI contains relevant atmospheric information. However, the corresponding models that also include CML total loss generally achieve higher MCC values. The same tendency is visible across the broader set of tested training setups, where adding CML total loss to PC, CPP, or CPP+PC generally increases MCC relative to the corresponding satellite only input. This indicates that

CML total loss provides link scale, path integrated near-surface information that is not fully captured by the satellite products alone. The result supports a two-way interpretation of the CML–SEVIRI fusion: SEVIRI information improves CML based wet–dry classification, while CML total loss can also add value to satellite based CNN rain detection.

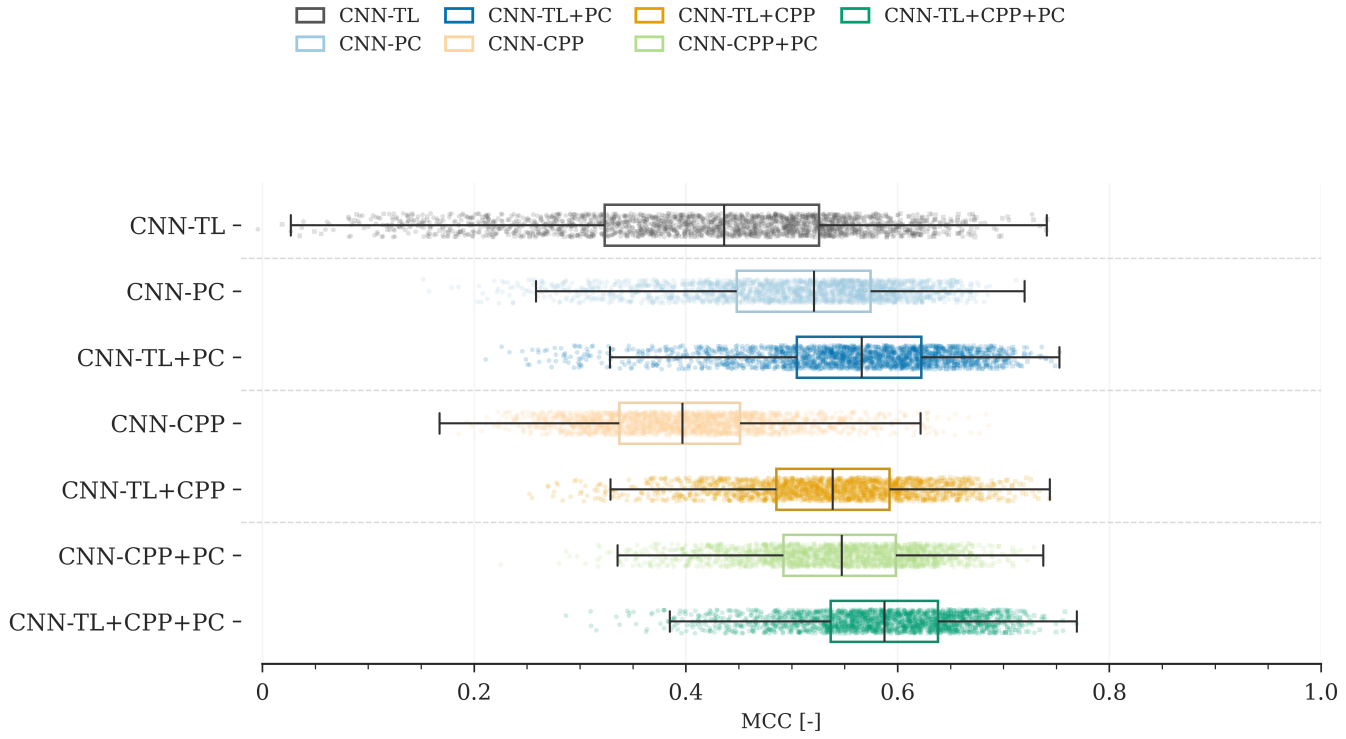

Figure S3. Mixed-domain comparison of satellite only CNNs and CML–satellite fusion CNNs. German and Czech test links are combined into one setup. The comparison shows that adding CML total loss generally improves the corresponding satellite based CNN configurations, indicating that CMLs provide complementary link scale information to SEVIRI PC and CPP products.

S1.4 Temporal and spatial test diagnostics

A supplementary diagnostic analysis was performed to compare model probabilities under temporal and spatial test conditions. The purpose of this analysis is to test whether the model behaviour changes when the evaluation data come from the same CML links used during training or from spatially separated CML links.

In the temporal test setup, the training and test samples come from the same CML links but from different time periods. This setup tests whether the model can generalize in time for links whose signal behaviour has already been seen during training. In the spatial test setup, the test samples come from CML links that were not used during training. This setup is more demanding because the model must generalize to links with different local signal properties, including different dry period variability.

To make the comparison fair, the temporal and spatial inference outputs were intersected before plotting. This means that both test setups were evaluated on the same CML IDs and the same time steps. Therefore, differences between the two columns in Figure S4 mainly reflect the test strategy rather than differences in the evaluated samples.

The probability distributions were analysed for three subsets. Dry periods are samples where the reference rain rate is below or equal to 0.1 mm h^{-1}. Wet periods are samples where the reference rain rate is above 0.1 mm h^{-1}. High RSTD dry periods are a subset of dry samples for which the rolling standard deviation of the CML total loss is in the upper 10 % of dry period values. These high RSTD dry periods are important because they represent dry conditions with strong CML signal variability.

They are therefore a difficult case for a CML only classifier, since non-rain signal fluctuations can resemble rainfall induced attenuation.

For clarity, Figure S4 shows the Czech test domain only. The German test domain showed the same qualitative behaviour and is therefore not repeated. The rows in the figure correspond to dry periods, high RSTD dry periods, and wet periods. The columns compare temporal and spatial test. Within each panel, the distributions show the CNN wet probabilities assigned by the different models. Low probabilities are expected for dry and high RSTD dry periods, while high probabilities are expected for wet periods.

The comparison shows that the CML only model assigns higher rain probabilities during dry periods, especially during high RSTD dry periods. This behaviour is more pronounced under spatial test, where the test links were not seen during training. In contrast, the models using satellite information shift the dry period probabilities toward lower values while maintaining high probabilities during wet periods. This indicates that the satellite based models are less sensitive to link specific dry signal variability.

This diagnostic supports the interpretation in the main manuscript. When the same links are used in training and test, the CML only model can partly adapt to link specific dry signal behaviour. When the model is evaluated on unseen links, this adaptation is weaker and dry signal variability more easily leads to elevated rain probabilities. The satellite enhanced models are less affected by this change, suggesting that SEVIRI information provides an additional atmospheric constraint and reduces dependence on link specific dry signal variability.

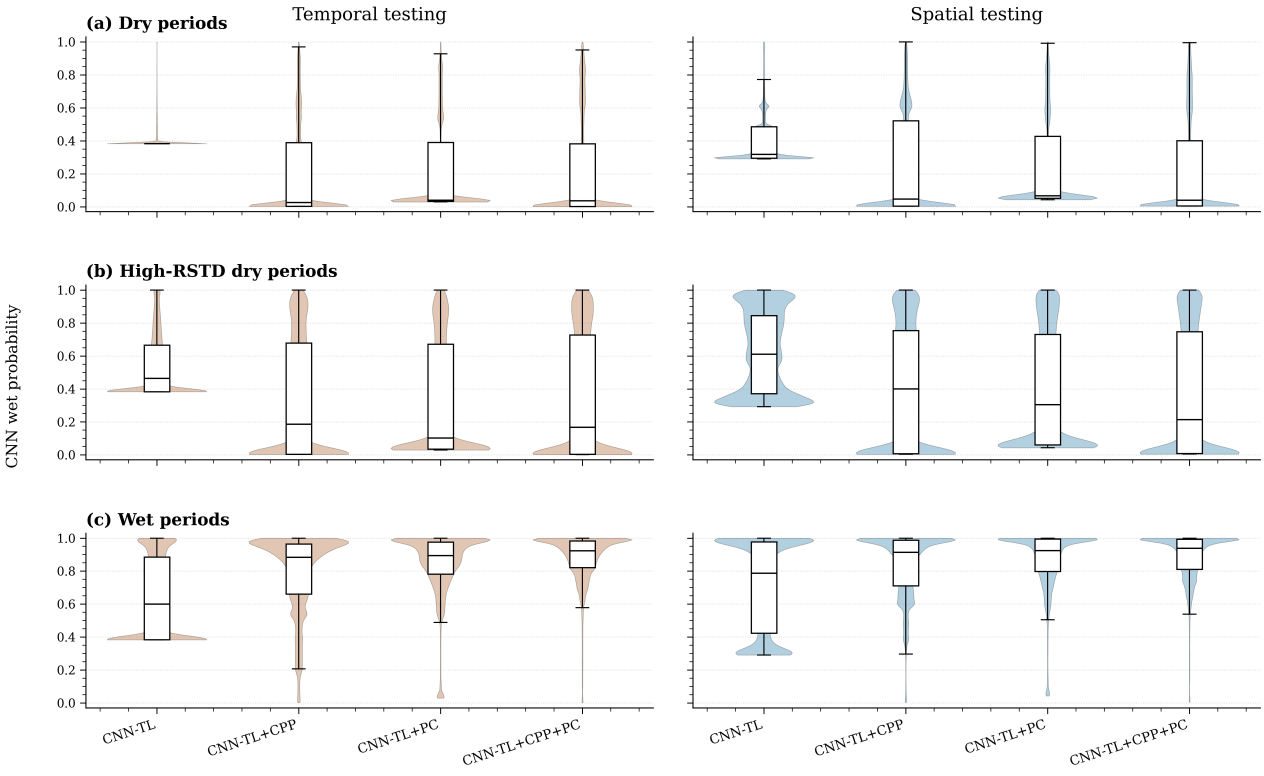

Figure S4. Temporal and spatial test diagnostic for the Czech test domain using common CML IDs and time steps. Rows show dry, high RSTD dry, and wet periods; columns compare temporal and spatial test. Lower probabilities are expected for dry periods and higher probabilities for wet periods. The CML only model assigns higher probabilities during high RSTD dry periods, especially under spatial test, while the satellite based models shift dry probabilities lower.