

## **RealPEP P2 QPN** Satellite observations of total column water vapor, clouds and convective intiation

Cintia Carbajal Henken, Jan El Kassar, Rene Preusker



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### Total column water vapor **TCWV** in clear-sky regions

- **OLCI** on polar-orbiting satellite Sentinel-3a/3b:
  - high precision 2d TCWV fields
  - high spatial resolution 300x300m<sup>2</sup>
  - morning time snapshots (9-10 UTC)
  - processed 2016-2022
- SEVIRI on geostationary satellite MSG:
  - lower accuracy timeseries 2d TCWV fields
  - spatial resolution ~3x6km<sup>2</sup>
  - every 15 min
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Exploit satellite-based TCWV to advance Convective Initiation (CI) detection → information on potential CI can be used as a proxy for future new (convective) cells in radar-based precipitation nowcasting

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TCWV  $\rightarrow$  clear-sky Cl  $\rightarrow$  clouds  $\rightarrow$  cloudy Cl  $\rightarrow$  thunderstorm  $\rightarrow$  heavy precipitation



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9-10 UTC/ 11-12 LT



#### 9-10 UTC/ 11-12 LT

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## **Convective cloud observations**

### Why the NWC-SAF RDT product?

- freely available software, well established and supported
- SEVIRI L1 + ERA5 reanalyses: processed 2016-2022
- detection of (small) convective clouds
- tracking/monitoring of all detected convective systems:
  - life cycle/phase, duration, severity etc.
  - gravity lat/lon since detected as convective cloud





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## **Match-up dataset**

### Constraints for non-convective/(pre-)convective environments

- clear-sky fraction through most of timeseries (CF > threshold)
- good quality TCWV pixels (outliers, buffer zone)
- no observed convection in hours before
- First observed convective cloud at least one hour after OLCI overpass
- no more than 3 hours after OLCI overpass
- short duration of RDT to avoid looking at advected convective system



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- > 1000 non-convective/no RDT
- ~ 100 (pre-) convective/RDT



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## **TCWV-based metrics**

### Characterizing non/pre-convective environments

Possible features/predictors for classification/prediction

### Amount of TCWV (OLCI+SEVIRI):

- TCWV mean, std, percentiles (10, 50, 90)
- TCWV anomaly: mean, std, percentiles (10, 50, 90)



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### **TCWV spatial information** (OLCI):

spatial auto-correlation and texture measures

- Grey Level Co-Occurrence Matrices
- Gradient
- Etc.



Measures of contrast, homogeneity/ correlation, orderliness:

- Varying pixel distances
  - perpendicular/parallel to average BL wind direction (assymetry factor)



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### **TCWV temporal information** (SEVIRI):

- Trends: SMA, CMA, relative, ...
- Jumps

### Model parameters (ERA5)

- T and T<sub>dew</sub>
- Difference OLCI TCWV & ERA TCWV<sub>corrected</sub>



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## Likelihood functions/ PDFs



**TCWV** amount





**TCWV** spatial information





### **TCWV** temporal information



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I have **conditional probabilities/likelihoods** (from relative frequencies):

**P(Data | RDT)** = what is the probability of seeing Data if RDT development later on

Using a small set of features/predictors I want to compute:

**P(RDT | Data)** = what is the probability of observing RDT development later on given Data



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Using a small set of features/predictors I want to compute:

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Use **Bayesian Theorem/Bayes'rule** to get from P(B|A) to P(A|B)

Powerful machine-learning classification tool, simple implementation, fast



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## **Naive Bayesian approach**

### Chain rule of conditional probabilities

Features are assumed to be conditionally independent **D: Data** 

- **D1**: Amount of TCWV
- D2: TCWV spatial information
- D3: TCWV temporal information

H: Hypothesis RDT occurrence within X hours

$$P(H|D_1 \cap D_2 \cap D_3) = rac{P(D_1|H) * P(D_2|H) * P(D_3|H) * P(H)}{P(D_1) * P(D_2) * P(D_3)}$$



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Posterior P at timestep t becomes prior P at timestep t+1

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### For ff in feature\_combinations:

select random feature set

## > 1000 x • 1 TCWV amount, 1 TCWV spatial info, 1 TCWV temporal info



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## K-fold cross-validation

- divide samples in k groups to estimate skill of model on new data
- here dataset (1000+100) into 10 parts

## For k in range(9):

• 9/10 for training  $\rightarrow$  read Likelihood Tables for each SEVIRI time step

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**10** x

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1/10 for testing

### ~ 4-12 x For tt in seviri\_timeseries: Bayesian framework

- read in prior and likelihood and apply Bayesian update
- store posterior probability timeseries



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## Compute and save skill scores for test data

Compute and save mean skill scores for feature set Assessment of best feature set performance



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## **Posterior probability timeseries**



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## **Evaluation example**





## **Evaluation example**









### **Reconsidering constraints for match-up dataset**

- Unbalanced dataset
- RDT vs. Cl, new NWCSAF software version
- independent a-priori information (ERA5 stability indices)

## **Extend feature set**

- Difference ERA5 TCWV forecast (height corrected) and OLCI TCWV
- Measure of (relative) water vapor amount in BL?
- Apply Kernel density estimator for PDFs

### **Evaluation performance**

- Classification vs. probabilities
- Skill scores

## Towards (Pred)RNN

- Match-up dataset of timeseries of TCWV fields + convective cloud information + metrics
- Python modules
- Merge satellite data with QPE data



# **Thank you!**



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