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Drivers of fog and low stratus - a satellite-based evaluation with machine learning

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1. Motivation and Idea

• Knowledge about drivers of fog and low stratus (FLS) development limited but crucial especially for climate models



- Relationship of spatial and temporal FLS patterns to land cover and meteorological conditions have not been studied explicitly, quantitatively and on a continental scale
- Approach: Link FLS to various meteorologial and land surface parameters using machine learning

2. Data and Methods

- FLS dataset from Egli et al. (2017), daily data from 2006-2015 on the basis of Meteosat SEVIRI
- Land surface data from LSA-SAF (Trigo et al. 2011), meteorological data from ERA5 (Copernicus Climate Change Service (C3S), 2017)
- Study area: continental Europe from 48°-53°N and 5°-15°E
- One Gradient Boosting Regression Trees (GBRT) model is trained and tested for each 10x10 or 15x15 SEVIRI pixel model unit spanning the study area

Predictand: FLS hours day⁻¹

- Predictors: Mean Surface Pressure (MSP), Wind Speed (WS), FLS on the previous day (FLS_{prev}), Fraction of Vegetation Cover (FVC), Land Surface Temperature (LST), Evapotranspiration (ET), Albedo (ALBEDO)
- Analysis of differences between all and high pressure situations and differences between model runs including and excluding seasonality

3. Results



Fig. 3: Mean 10x10 permutation importance over all model units for all features and all seasons. The darker, left bars display the feature importances of the model run with all pressure situations, the right, brighter bars display the feature importances of the model run with high pressure situations. The left plot shows the feature importances from the model run including the seasonality, the right plot shows the feature importances of the deseasonalized model run.



Fig. 4: Partial dependence plot showing the mean response in modeled FLS occurrence to changes in all input features over all seasons, for the model run using data with seasonality and all pressure situations. The top plot displays the partial dependency, the bottom plot shows a kernel density estimation of the data distribution. The shown features are: Fraction of Vegetation Cover (FVC) (A), Mean sea level pressure (MSP) (B), Land Surface Temperature (LST) (C), Wind Speed (WS) (D), Evapotranspiration (ET) (E), Albedo (ALB) (F) and FLS_{prev} (G). In the additional (H) plot, the mean response in modeled FLS occurrence to changes in MSP in high pressure situations is shown.

- Good model performance ($\mathbb{R}^2 > 0.9$) (Fig. 1) with performance results depending on modeling time frame, grid size, pressure exclusion and seasonality exclusion settings
- Units in the eastern part of the study area have a positive deviation from the mean R² over all model units, whereas model units in the western part of the study area and units in topographically higher areas show a negative deviation (Fig. 2)
- Main drivers of FLS occurrence are meteorological (MSP, WS) as well as FLS_{prev} and ET (especially during high pressure situations) (Fig. 3)
- High mean surface pressure, low wind speed and high FLS_{prev} lead to high modeled FLS values (Fig. 4)



4.Conclusions

Results show that FLS occurrence can be accurately modeled using machinelearning techniques based on meteorological and land surface predictors in large spatial domains such as central Europe

Fig. 1: R² of training and test sets over all grid sizes and seasons using either all pressure situations (left) or high pressure situations (right).



Fig. 2: Deviation of R^2 from the mean R^2 over all model units, using a 10x10 pixel modeling grid and all values from 2006-2015 (full-year run) in all pressure situations (left) and high pressure situations (right).

Further studies will integrate the GBRT model into a land surface-based model grid to further analyze regionally different sensitivities and performances and apply the model to fog and low cloud properties such as cloud top height and liquid water path

References

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