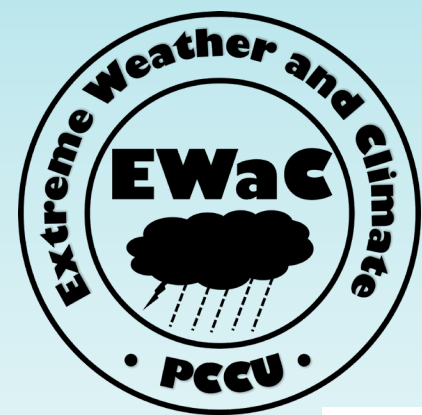


# The long-term variation of the frontal systems in Taiwan with machine-learning based classifier



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<sup>1</sup>Chinese Culture University

<sup>2</sup>National Taiwan University

<sup>3</sup>National Science and Technology Center for Disaster Reduction

@2020 Conference on Weather Analysis and Forecasting (CWB)

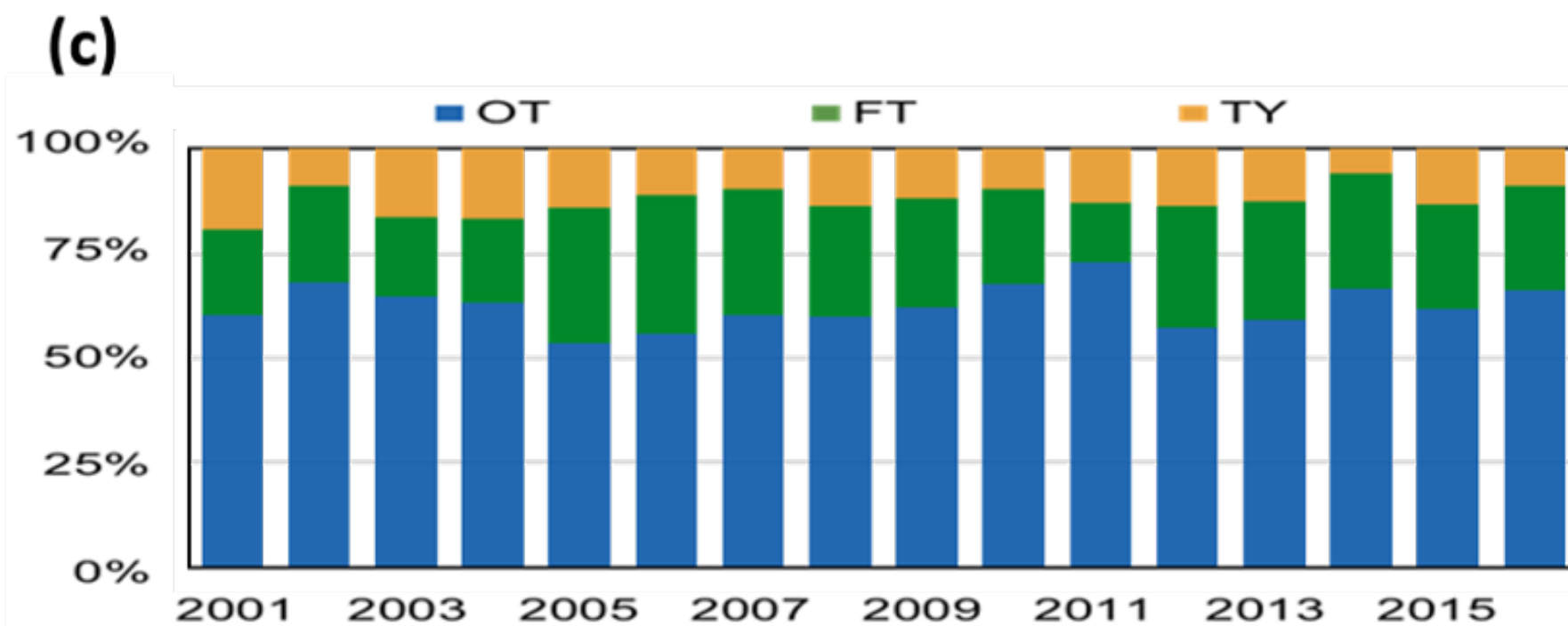
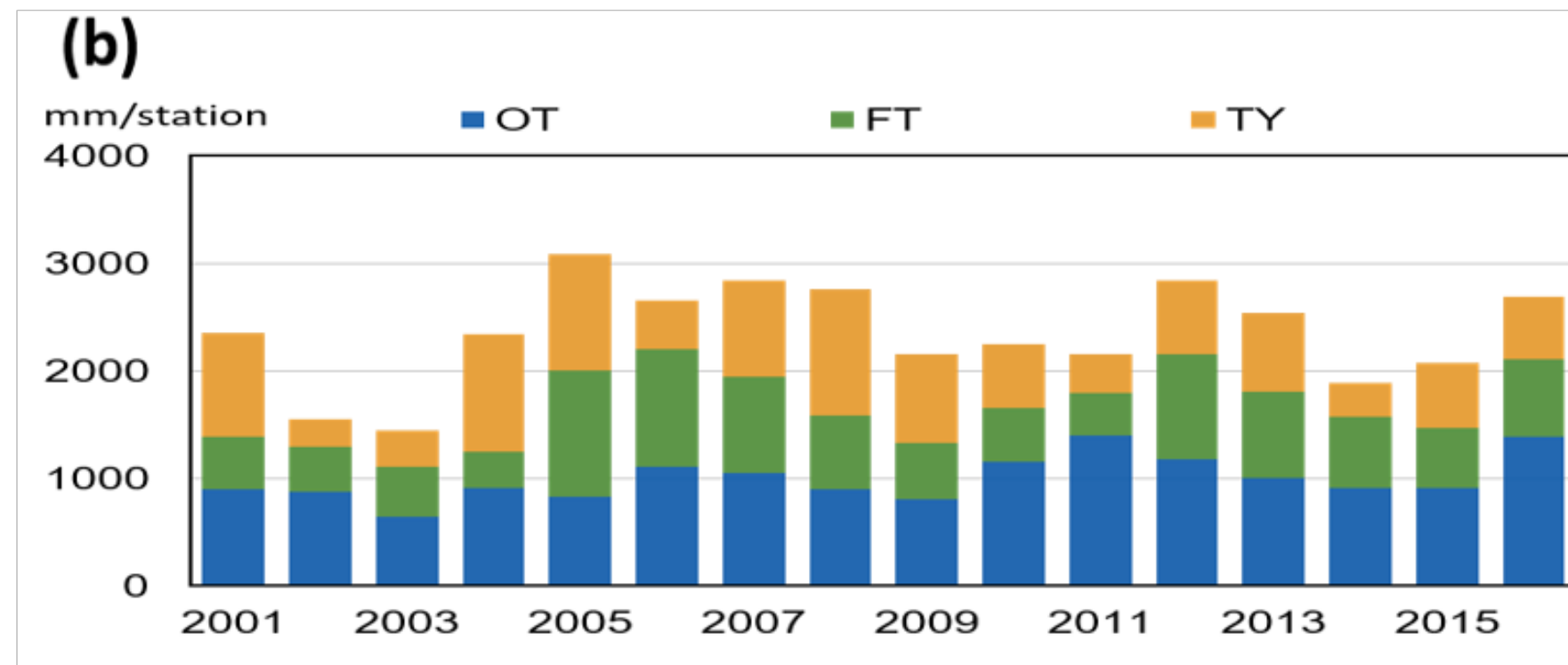
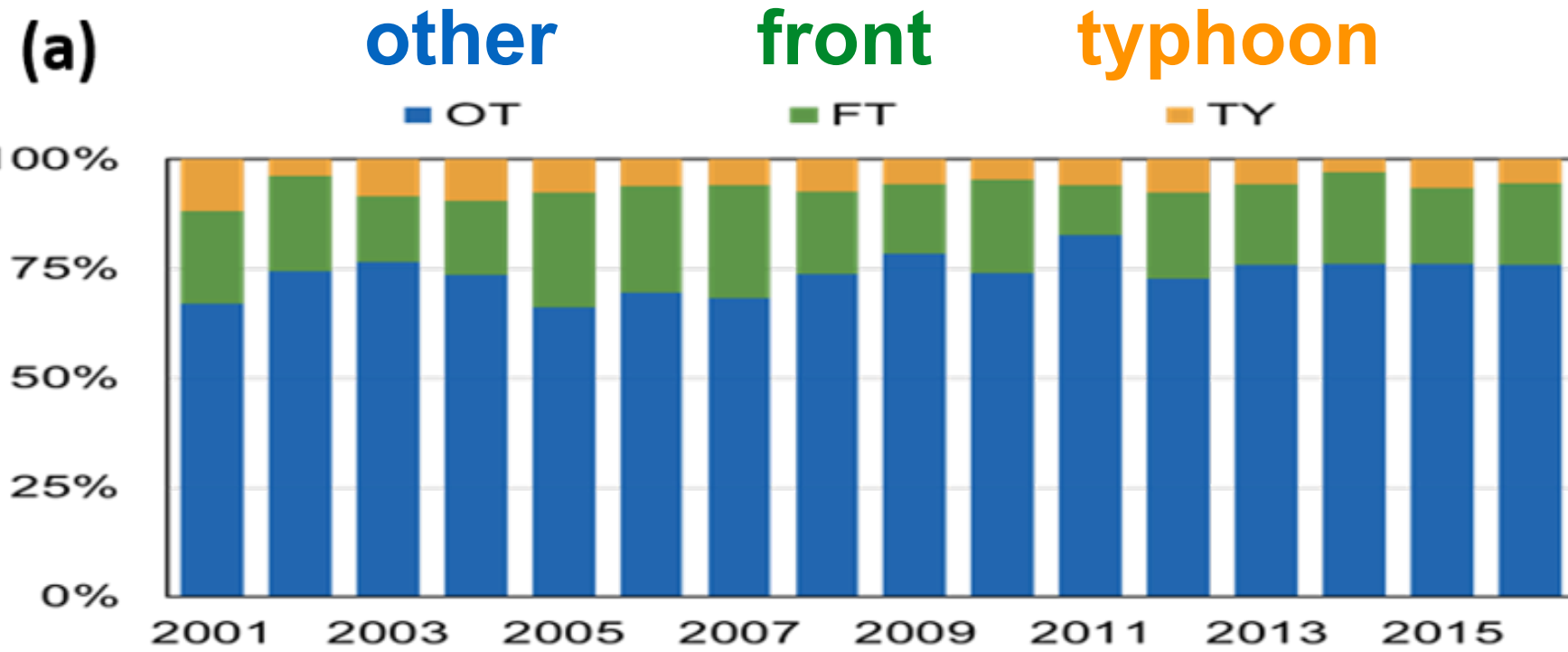
Collaborators: Chien-Ting Chiang and Kao-Yuan Liu

# Annual precipitation in Taiwan >2500mm

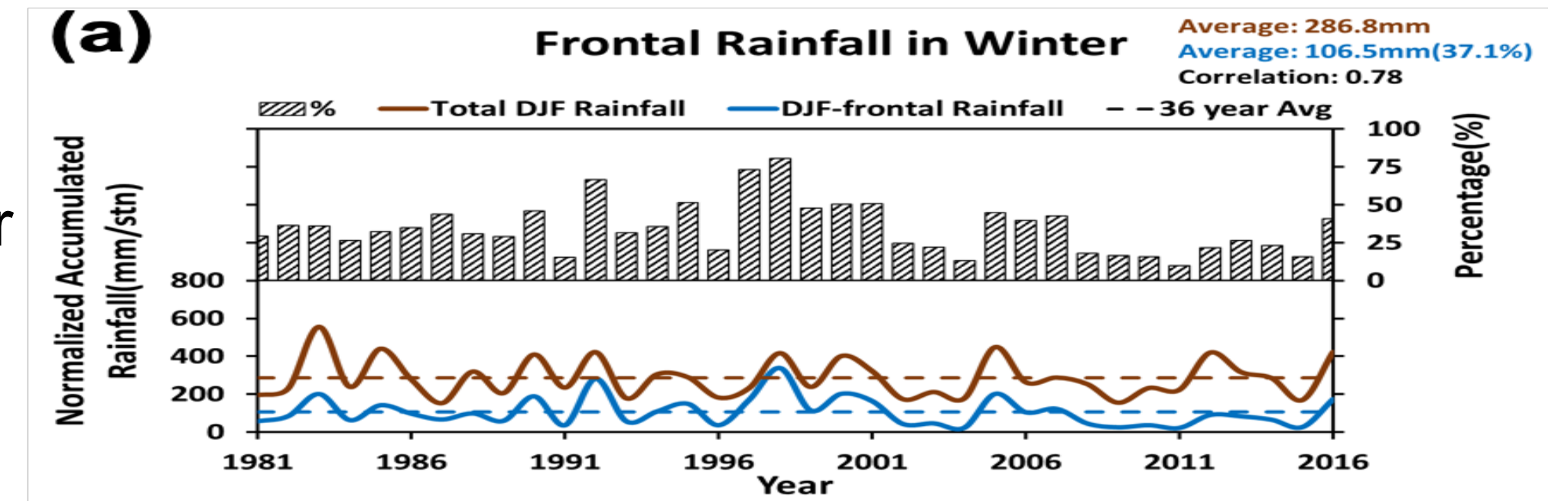
~3X of the world average

only ~20% are available

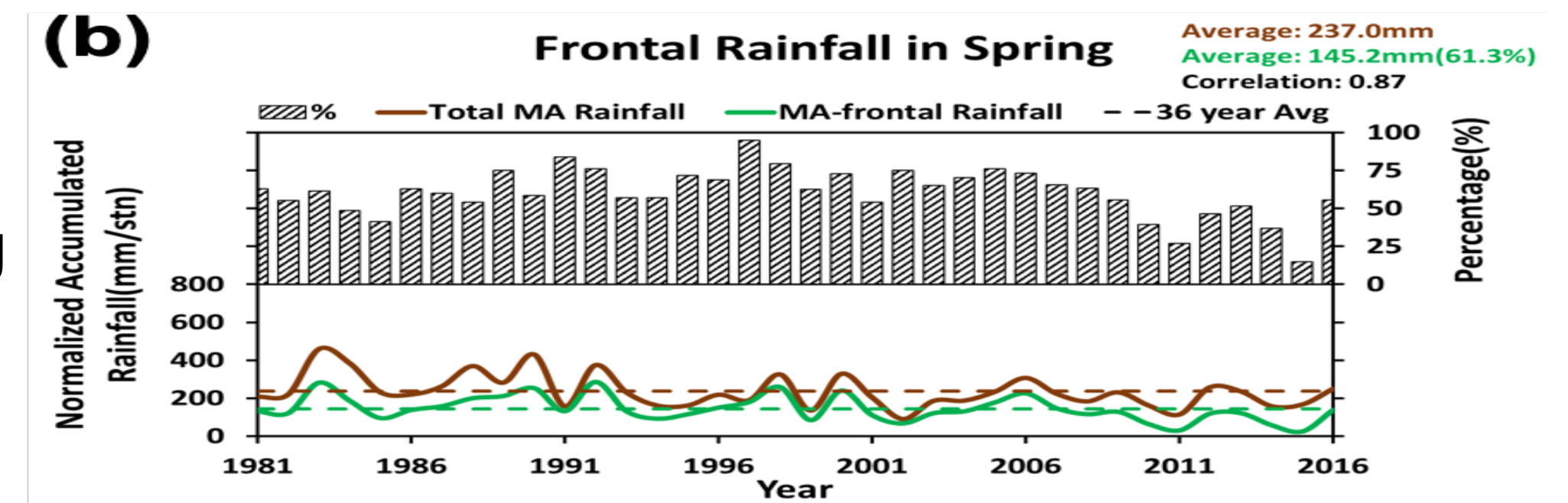
(ATs, NE, SWF...)



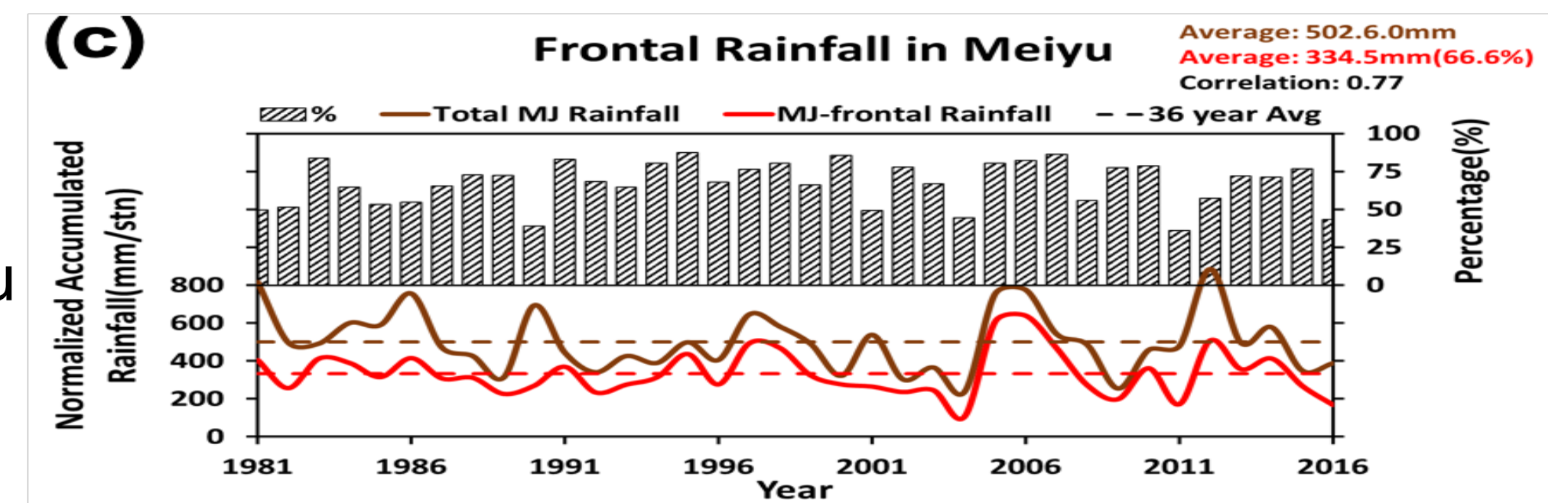
Winter



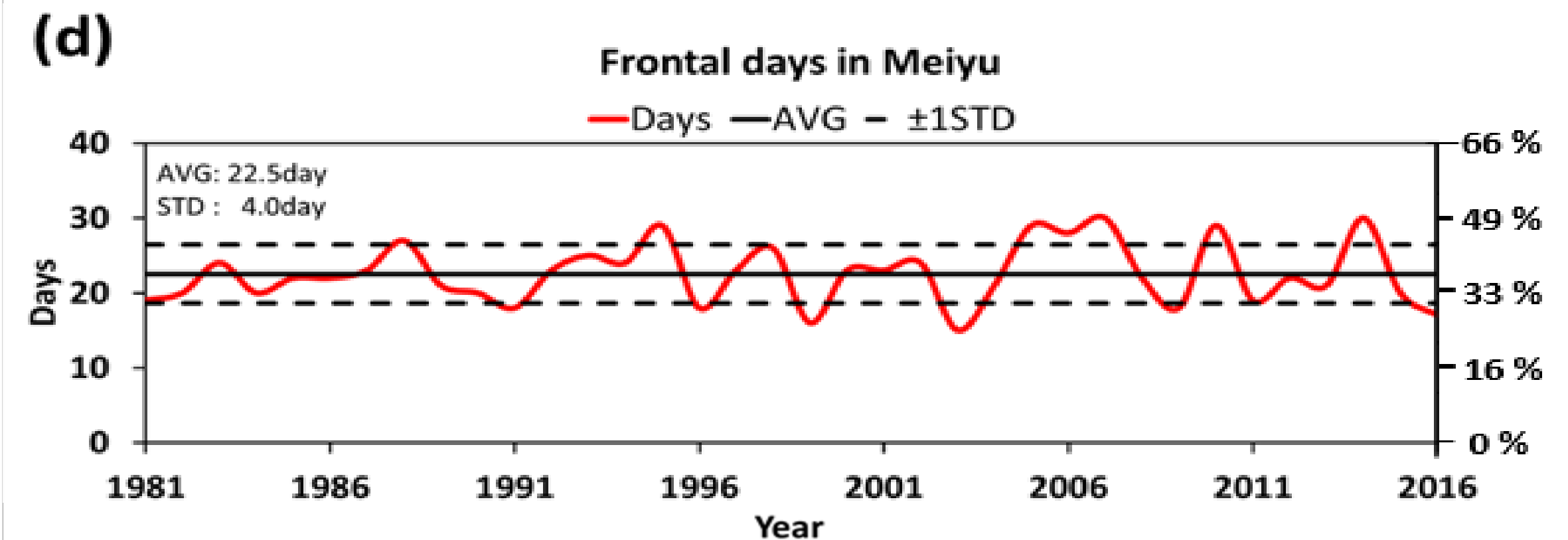
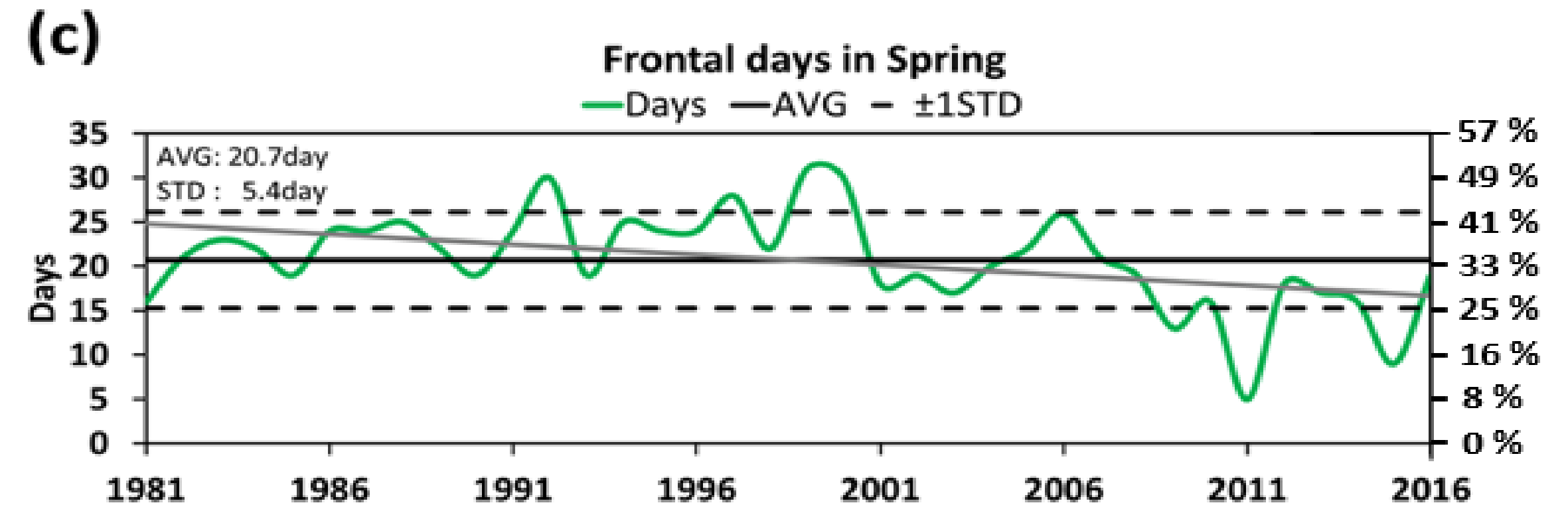
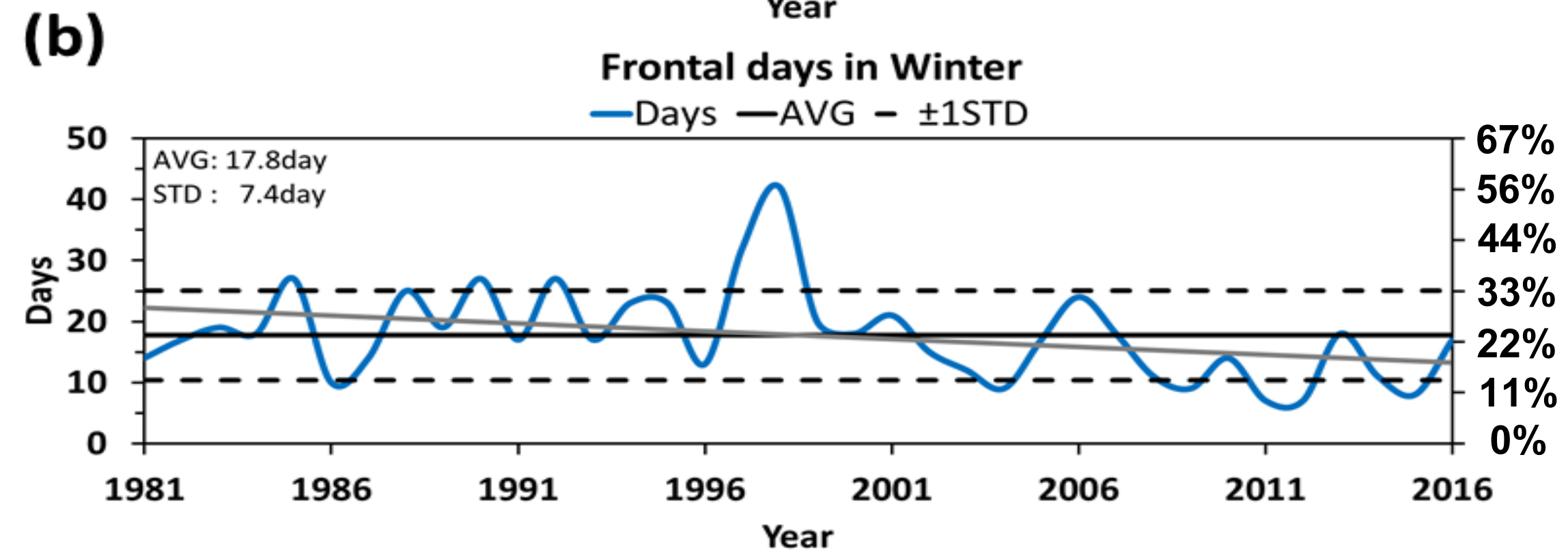
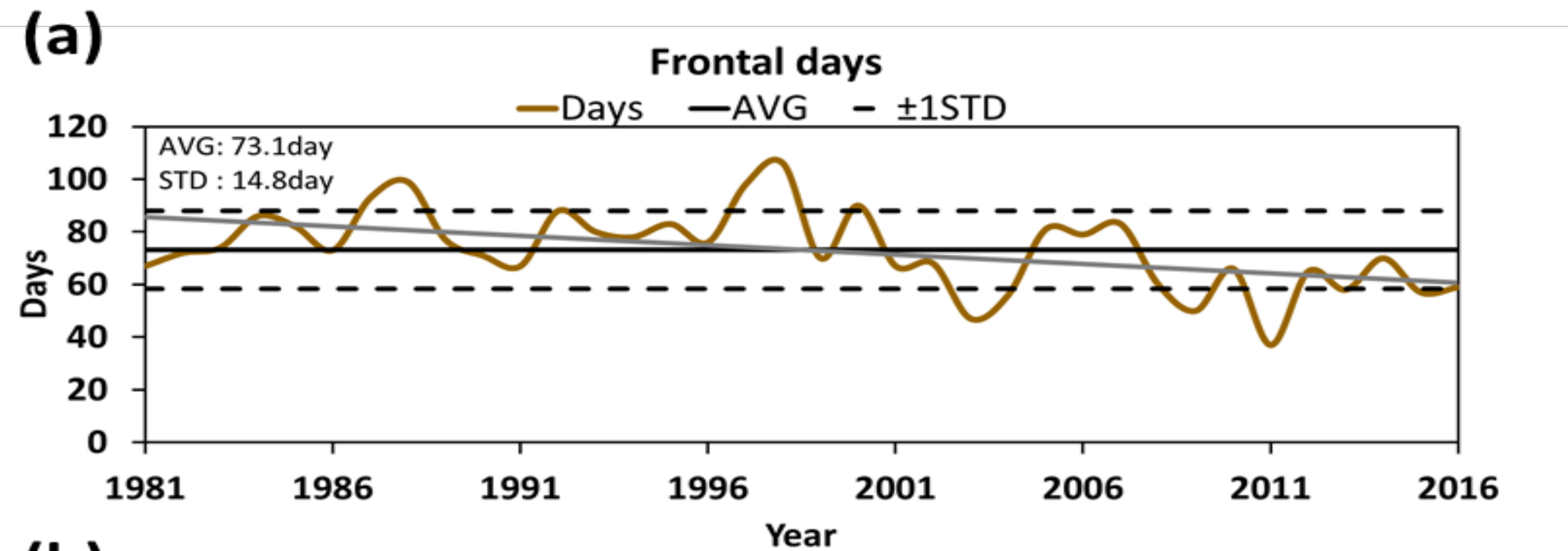
Spring



Mei-Yu



# Long-term trend and annual variations



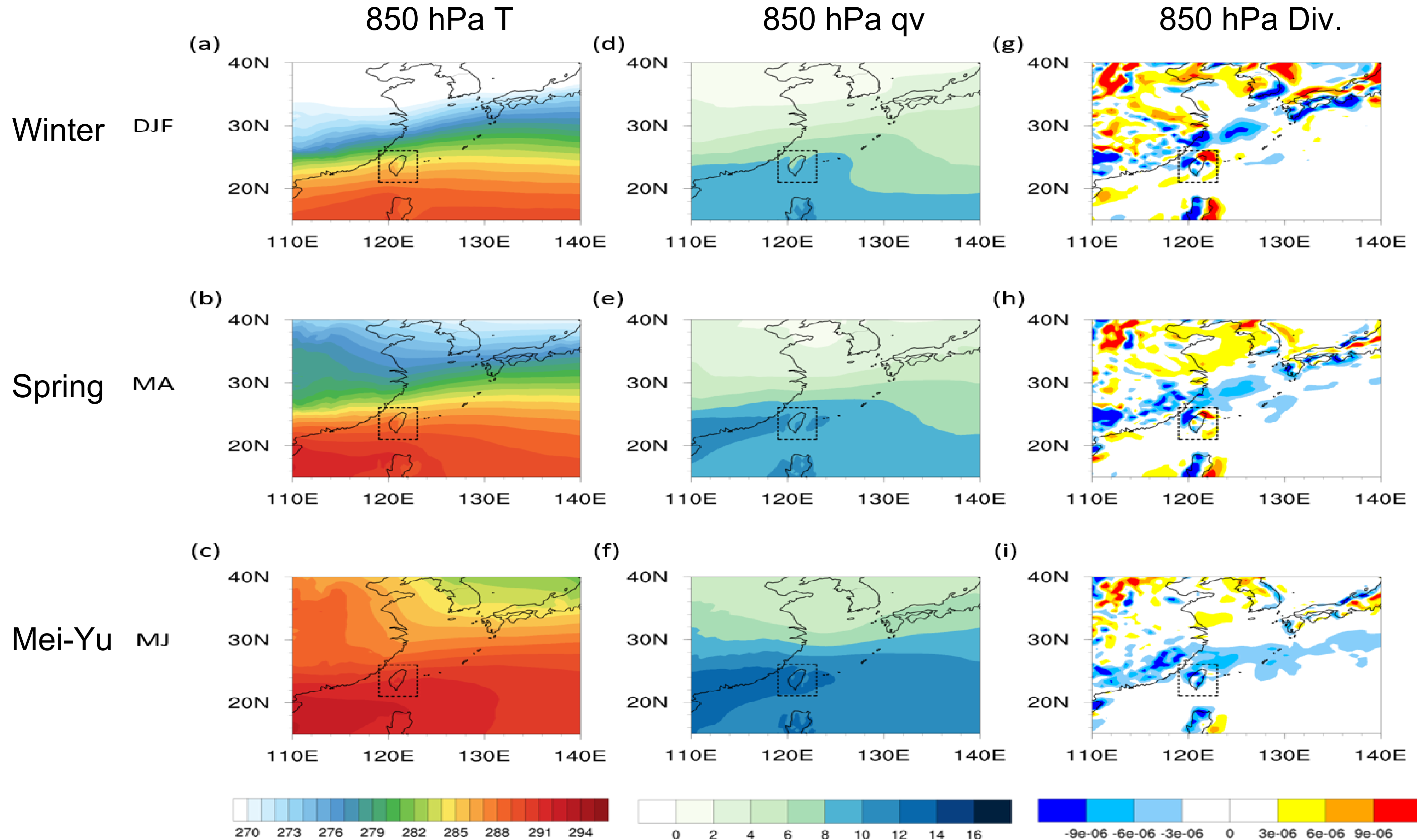
The frequency of front was decreasing significantly in past 36 years.

**Winter: -2.2 days per decade (DJF)**

**Spring: -2.5 days per decade (MA)**

Weather events are coming from Taiwan Atmospheric events Database (TAD)  
Su et al.(2018), Chang et al. (2019) Atmos. Sci.(in Chinese w/ English abstract)

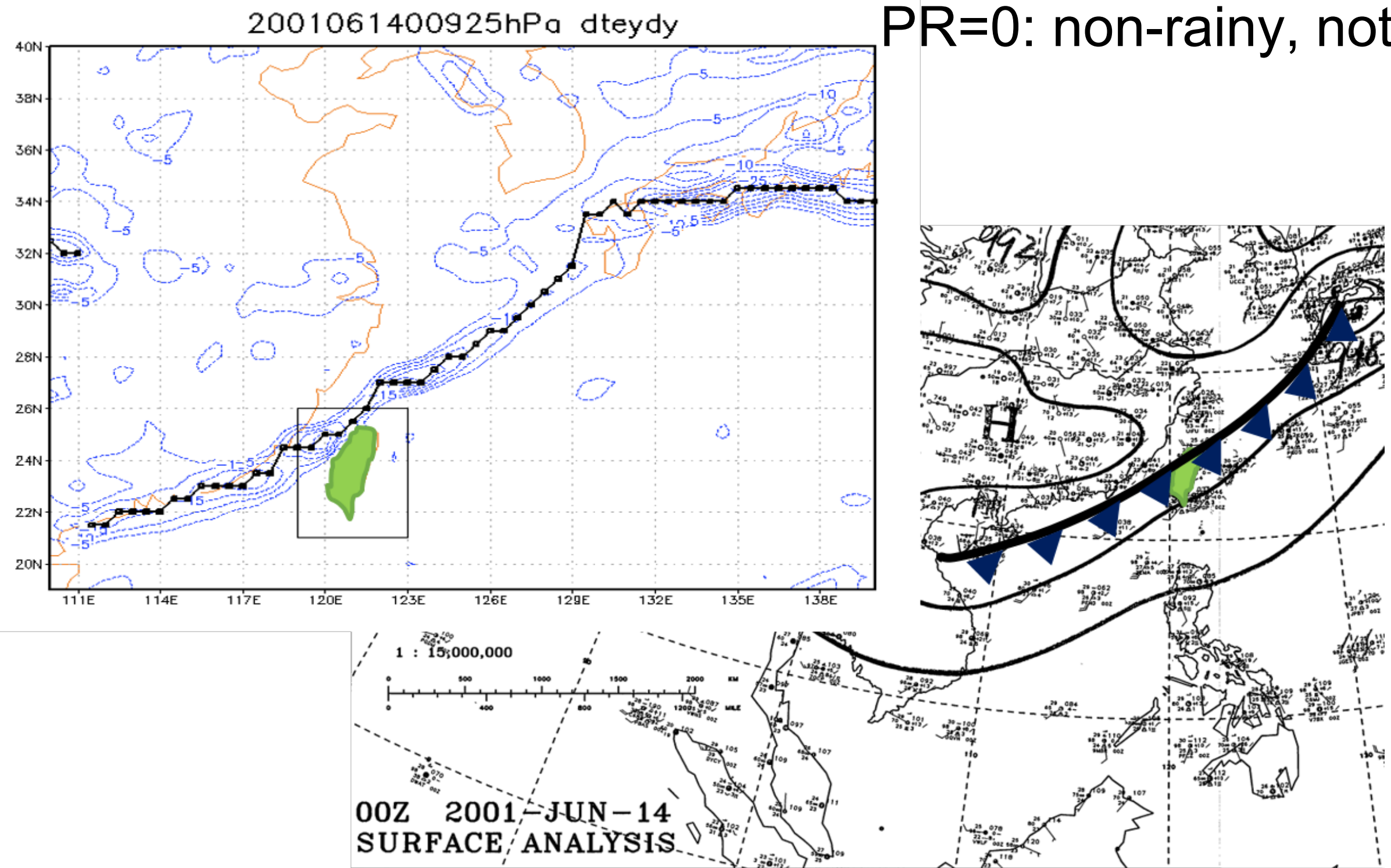
# Composite of frontal days in 1981-2016



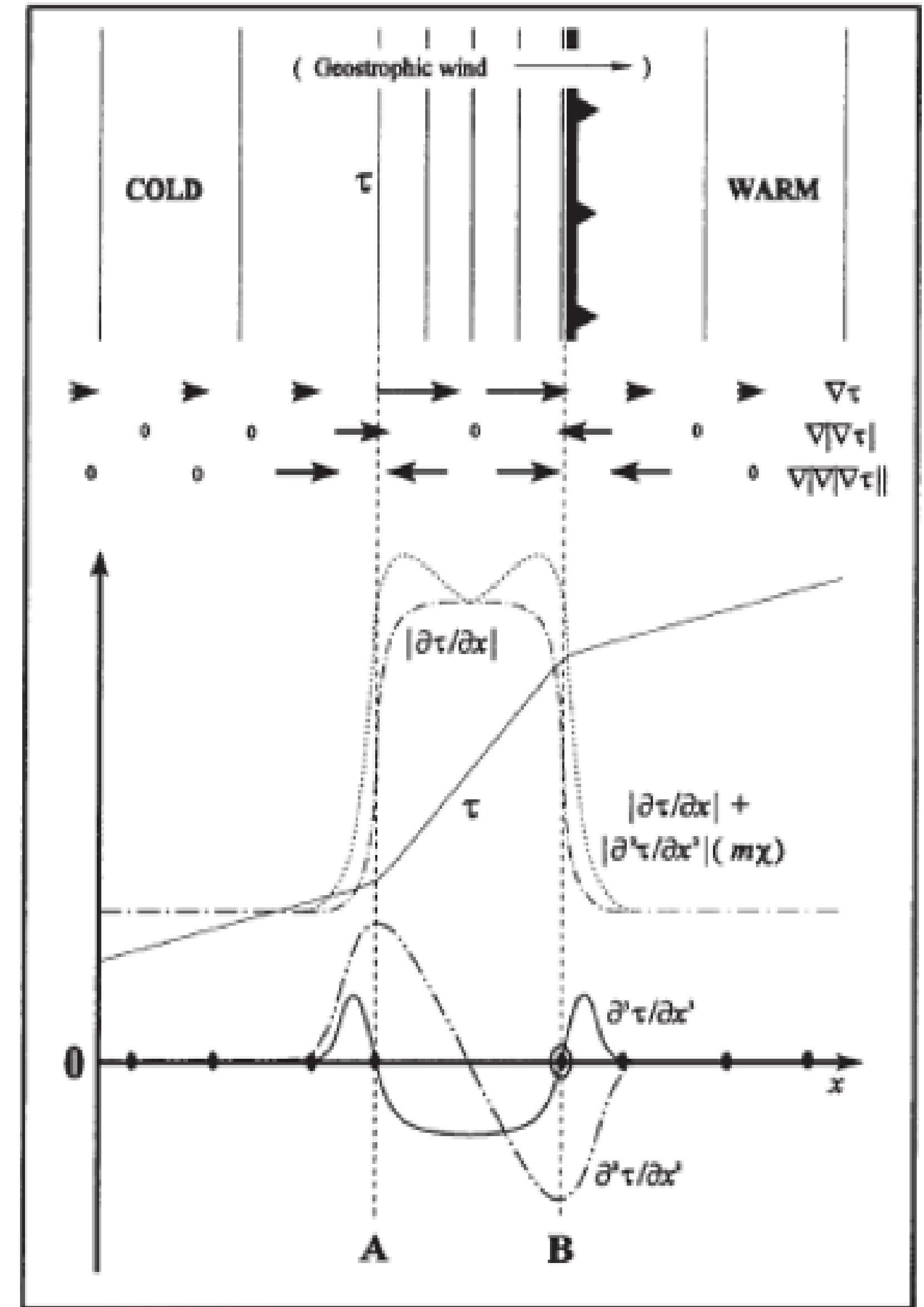
# Traditional objective analysis by thermal frontal parameter (TFP)

maximum 925 hPa  $\nabla\theta_e \times PR$  (precipitation rate)

PR=0: non-rainy, not a front

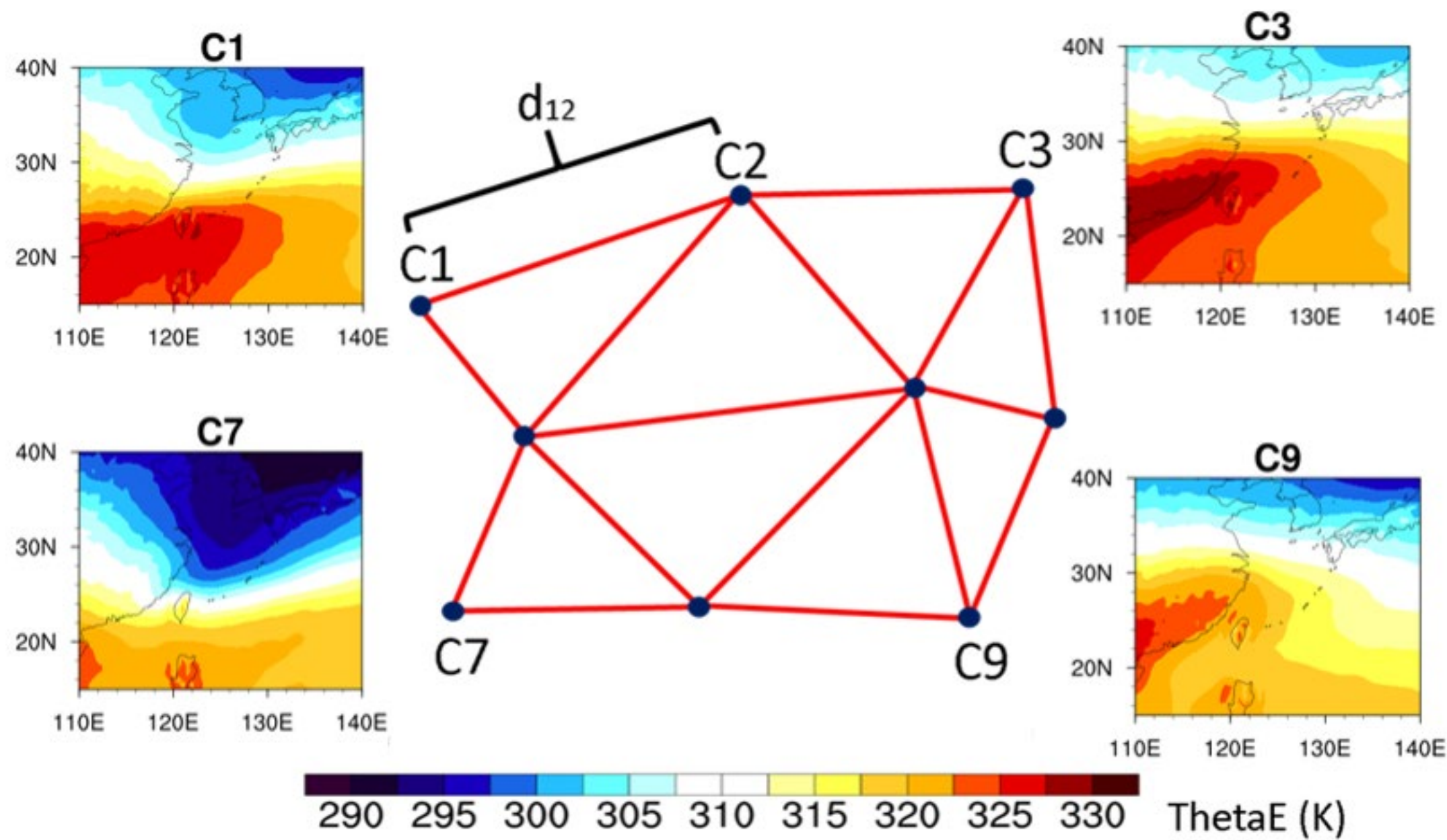


Chang et al. (2019) Atmos. Sci. (in Chinese w/ English abstract)  
劉高源, 2017

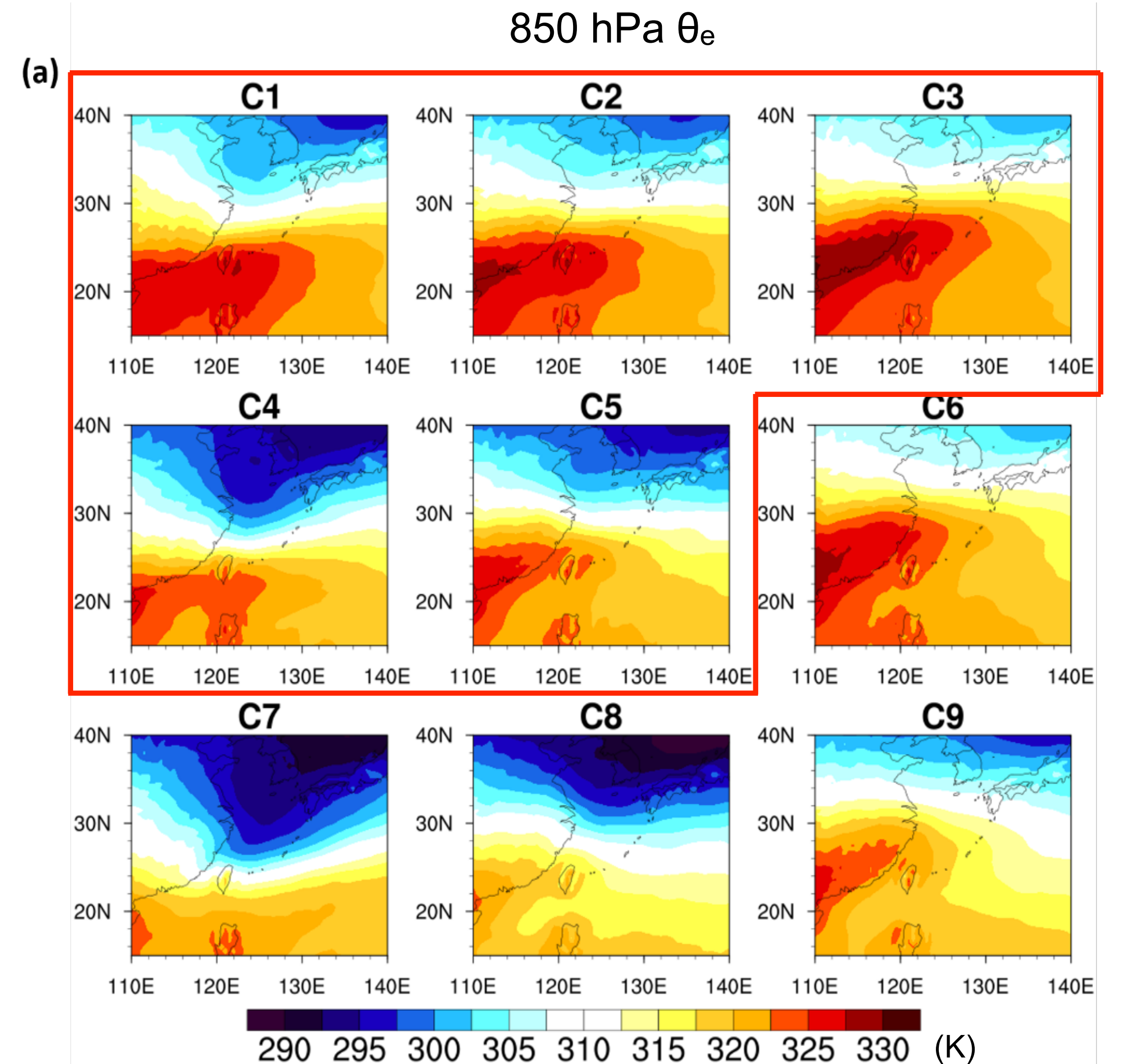


Hewson (1998)

# Unsupervised clustering analysis for atmospheric features with self-organized map (SOM) clustering methods



Input data: 850hPa U, V, T, RH in MJ, 1981-2016  
(CFSR reanalysis)  
Target: Mei-yu fronts

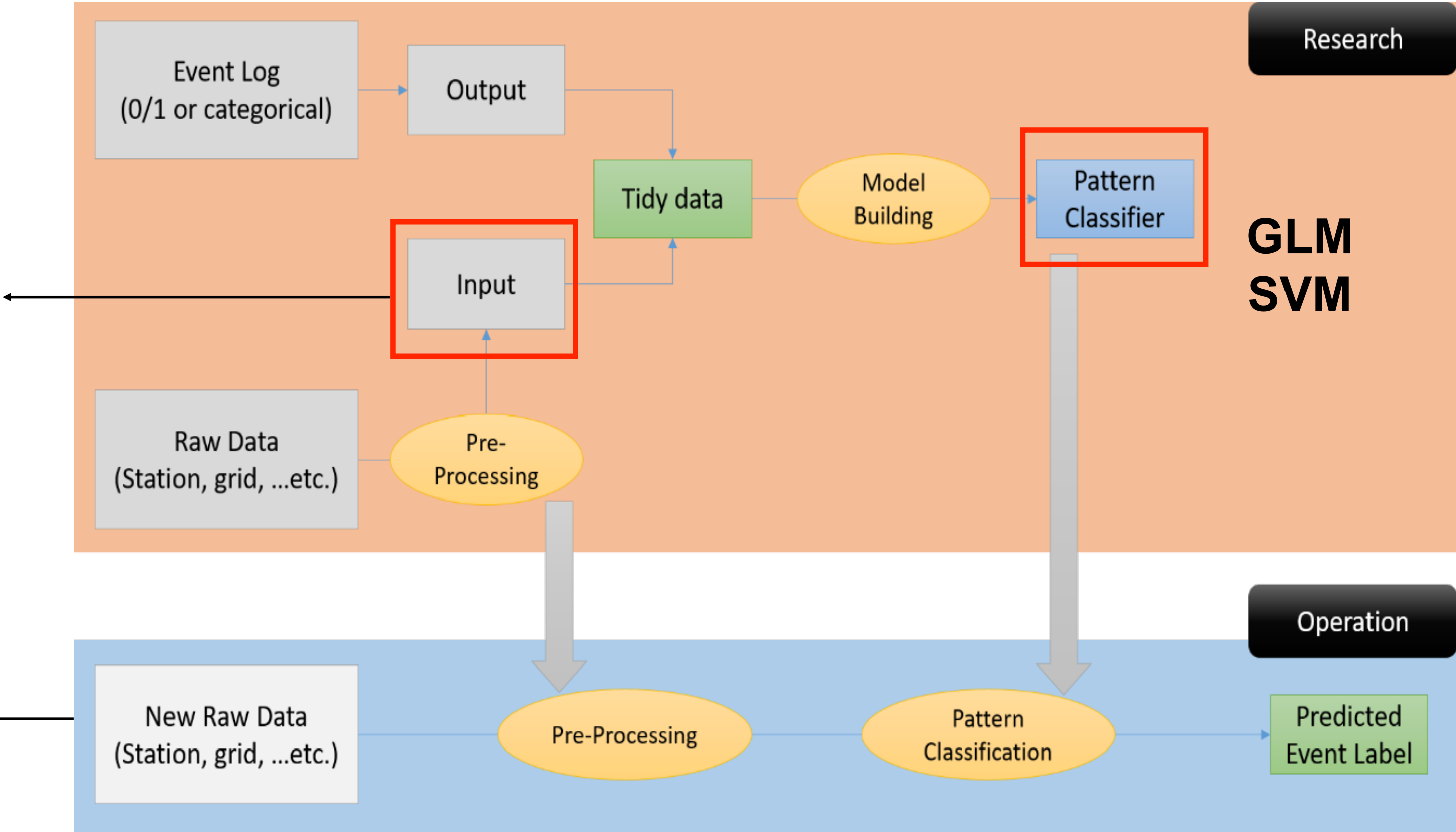


# Advanced objective diagnosing procedure with machine learning method

PC 1-20 of

- 200 hPa => U, V, T
- 500 hPa => geopotential height
- 700, 800, 925 hPa => U, V, T
- MSLP

(2001-2010 CFSR reanalysis)

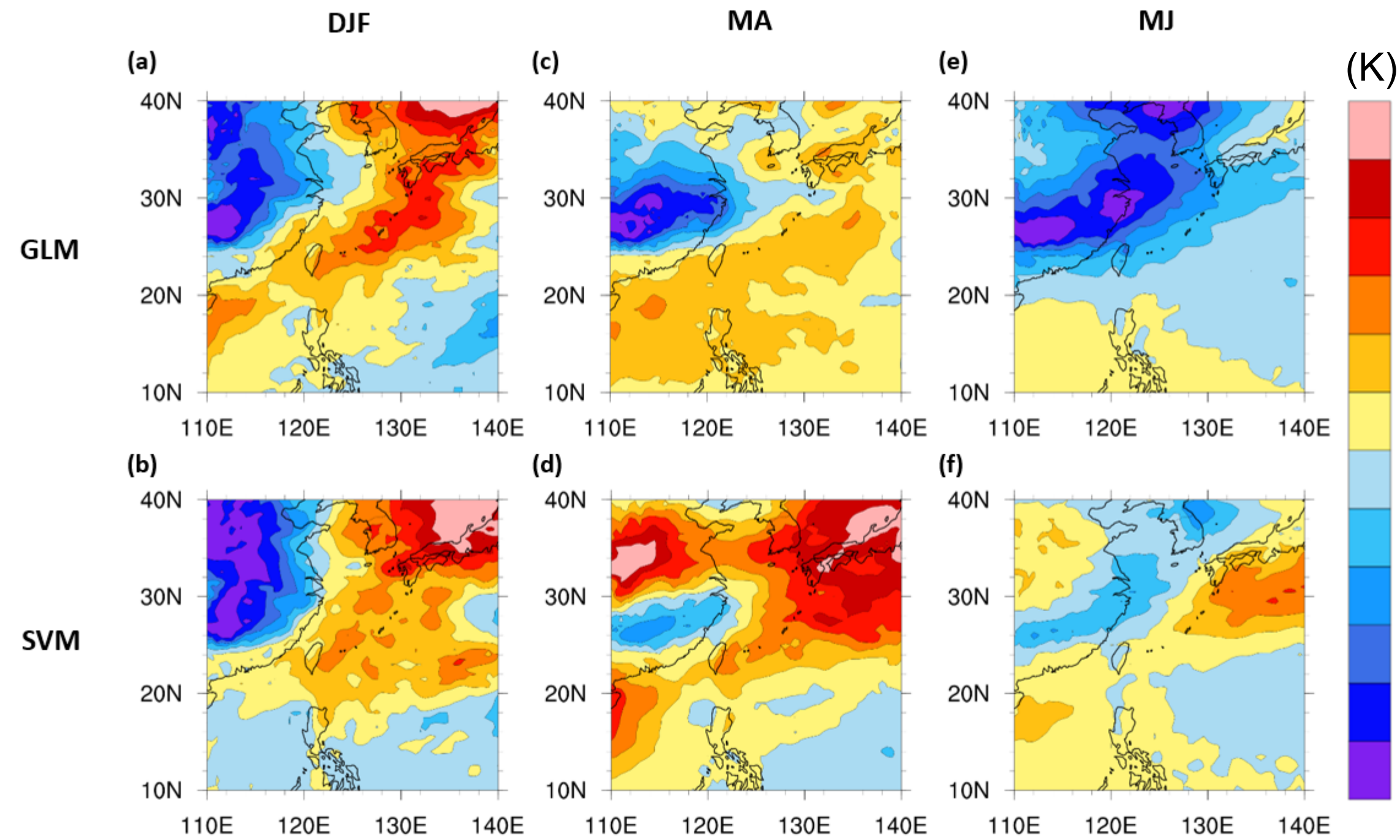


(2011-2016 CFSR reanalysis)

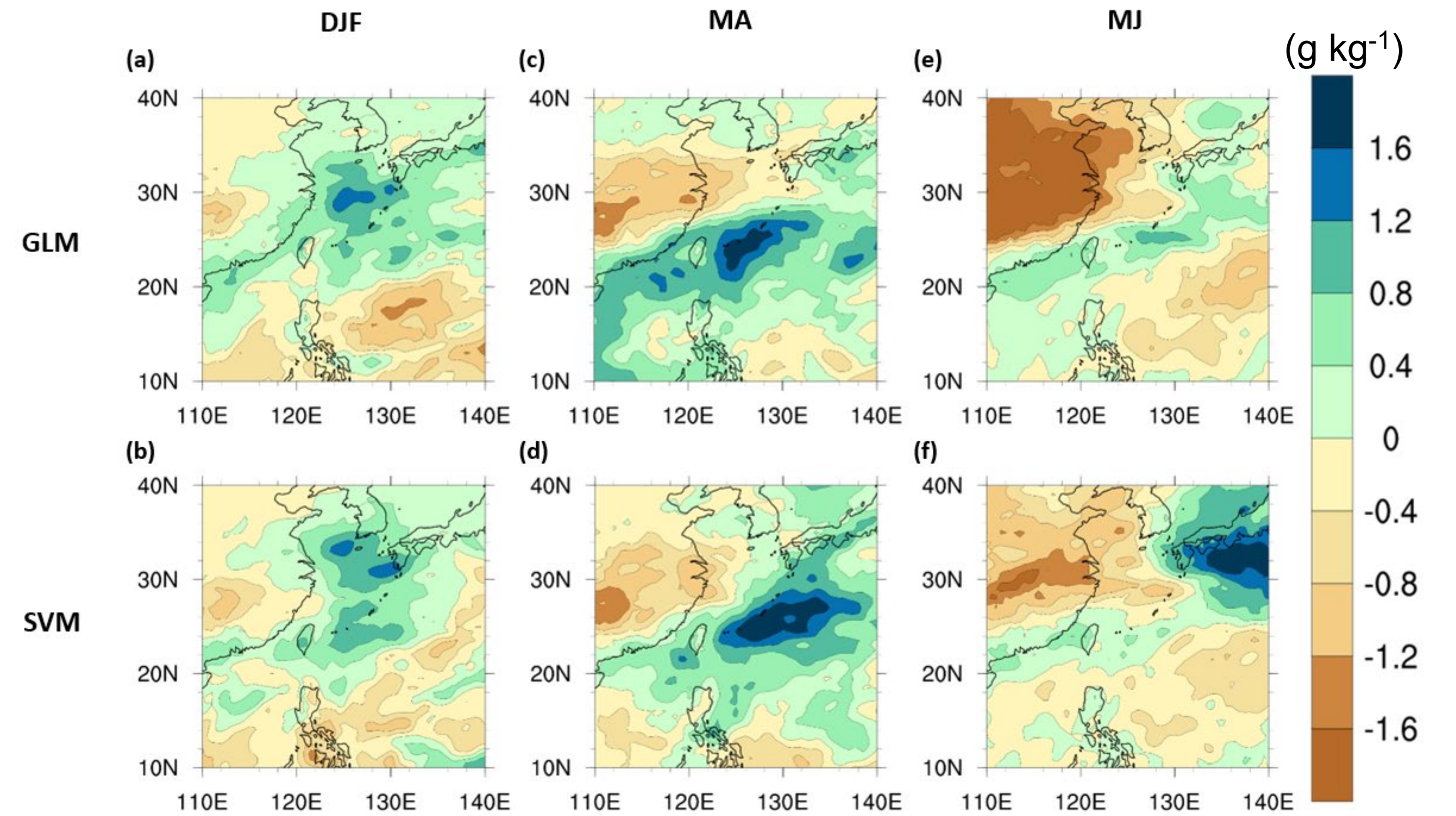
Su et al. (2018) ASL  
 Chang et al. (2019) Atmos. Sci.(in Chinese w/ English abstract)

# Hits - misses

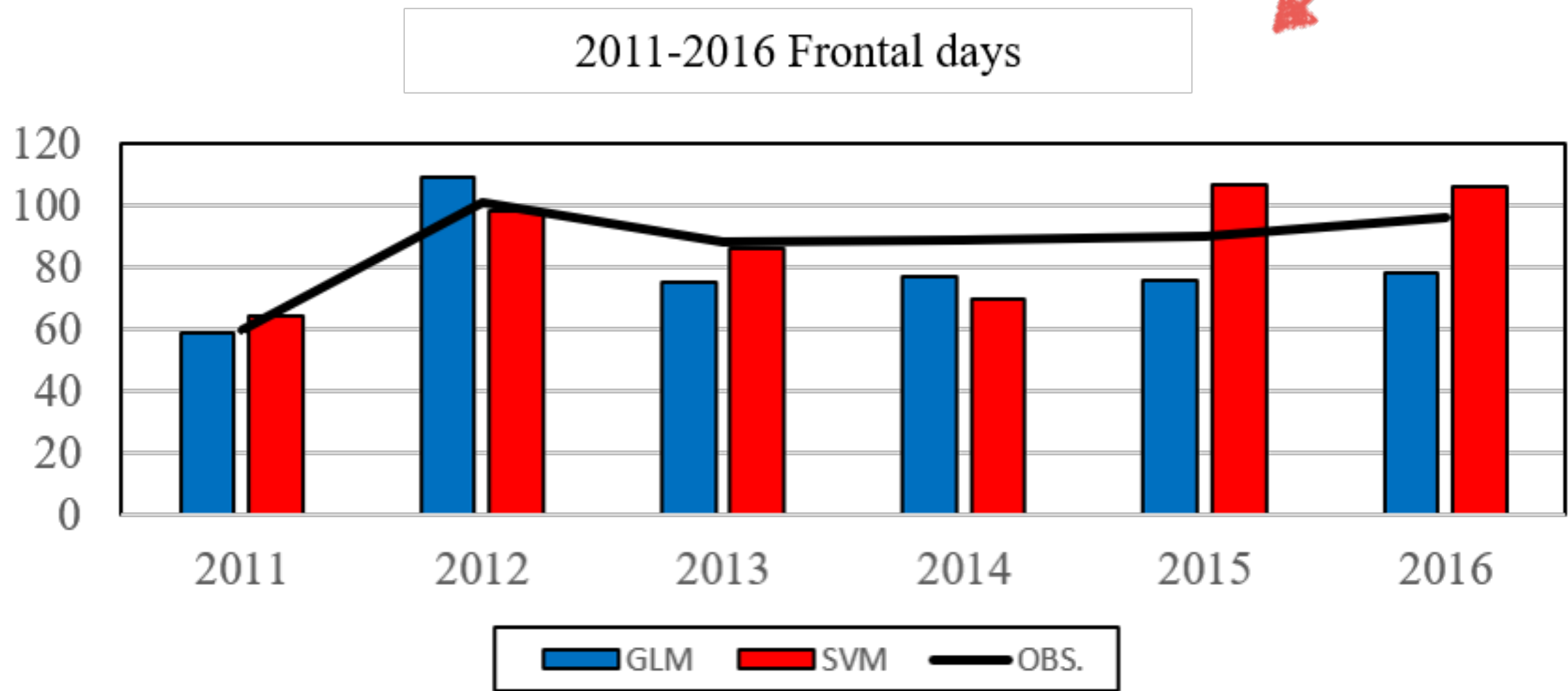
## 850 hPa $\theta_e$



## 850 hPa $q_v$





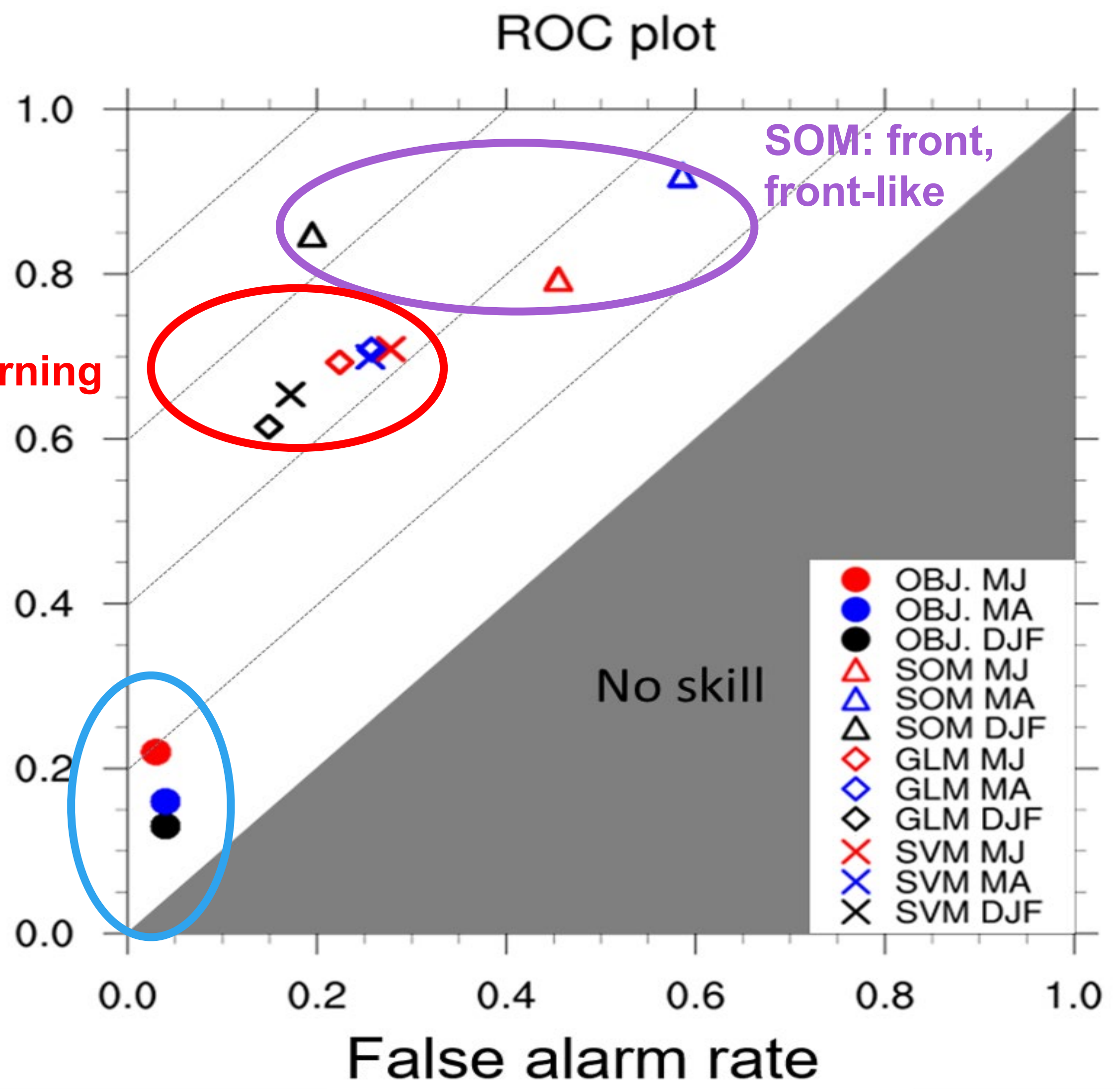


Both the two classifiers showed good correlation with the observed long-term frequency of the front.  
 GLM: 0.8  
 SVM: 0.74

Machine Learning



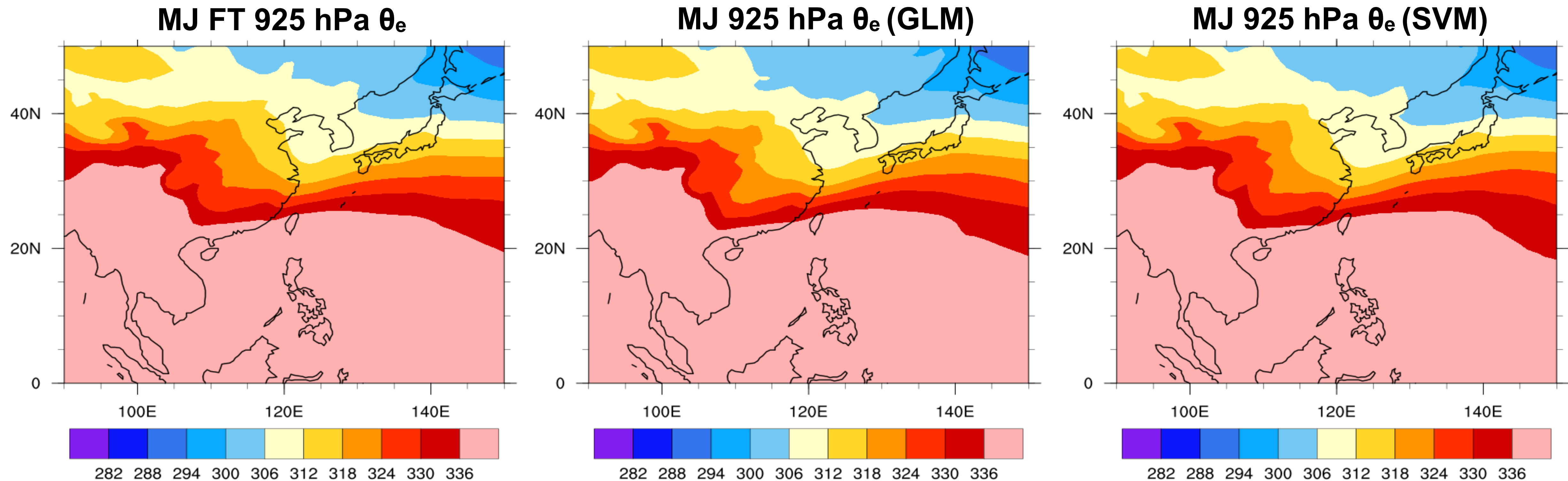
TFP



Inputs(X, vector or predictor): 1991-2016 ERA-Interim reanalysis data

Outputs(Y, target): Front days in Mei-Yu season

With Generalized linear model (**GLM**) and Support vector machine (**SVM**)



**The ML model showed good performance in diagnosing the frontal system near Taiwan!**

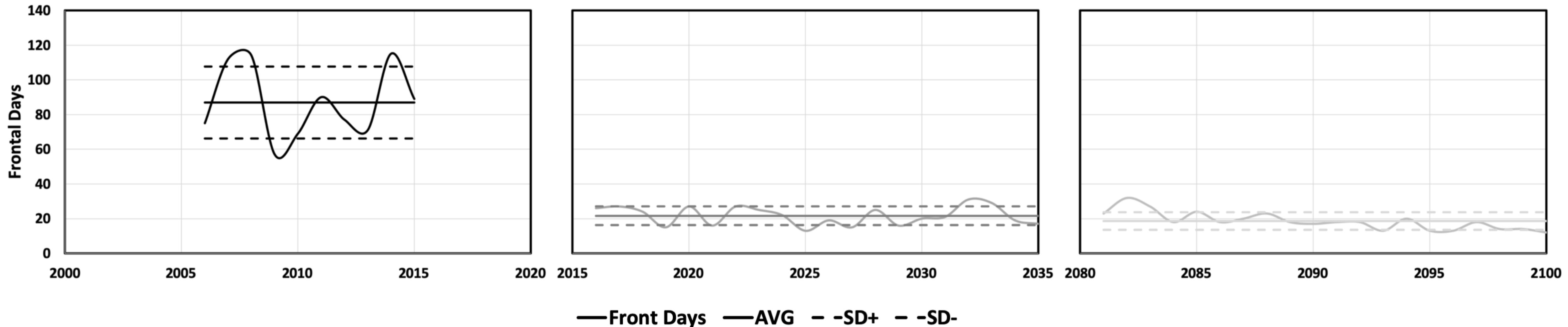
# How about the long-term frontal system variation for future climate projections ?

## MRI-CGCM3 RCP8.5 Frontal Days

Historical run

Near Future run

Far Future run

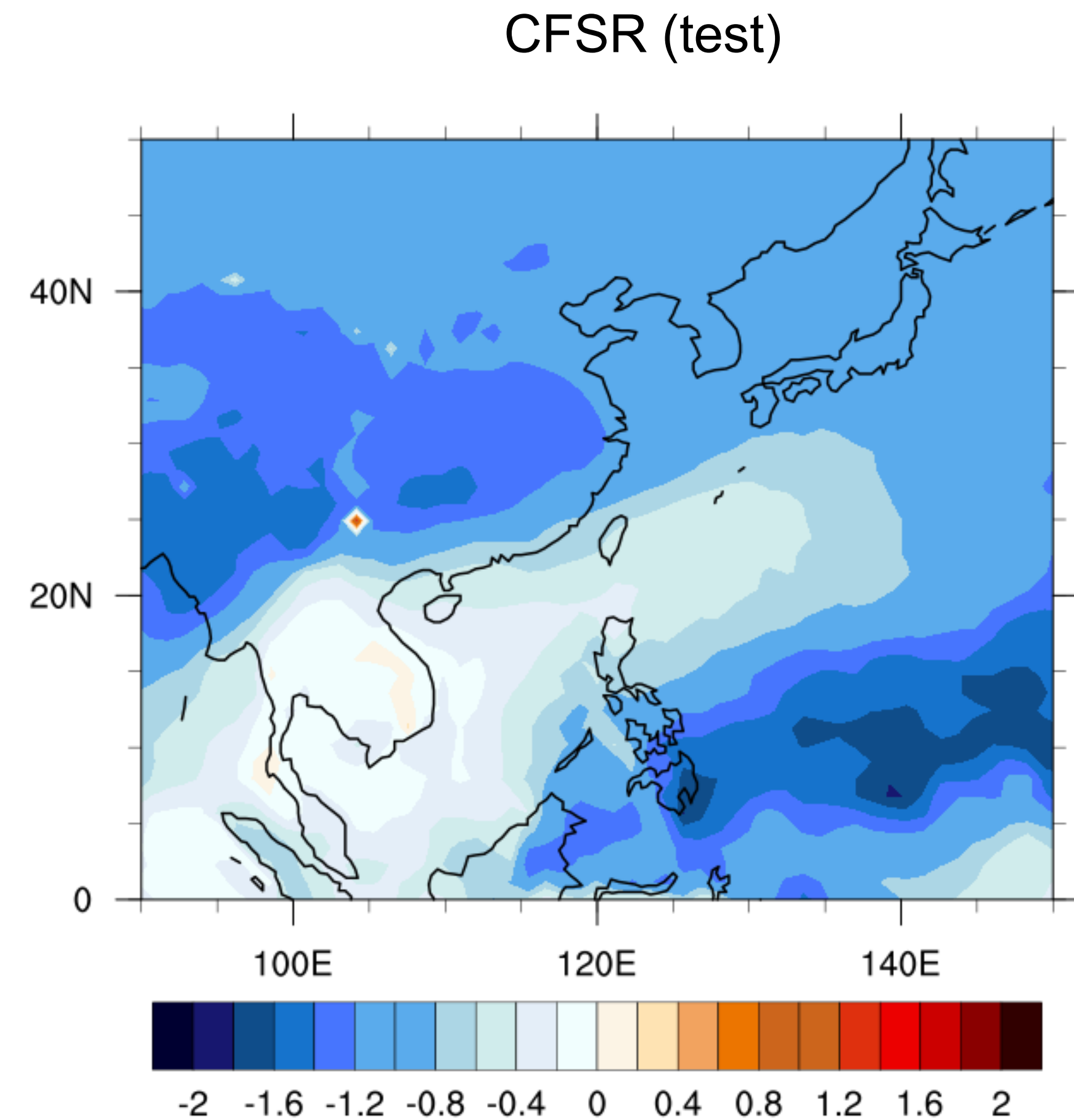
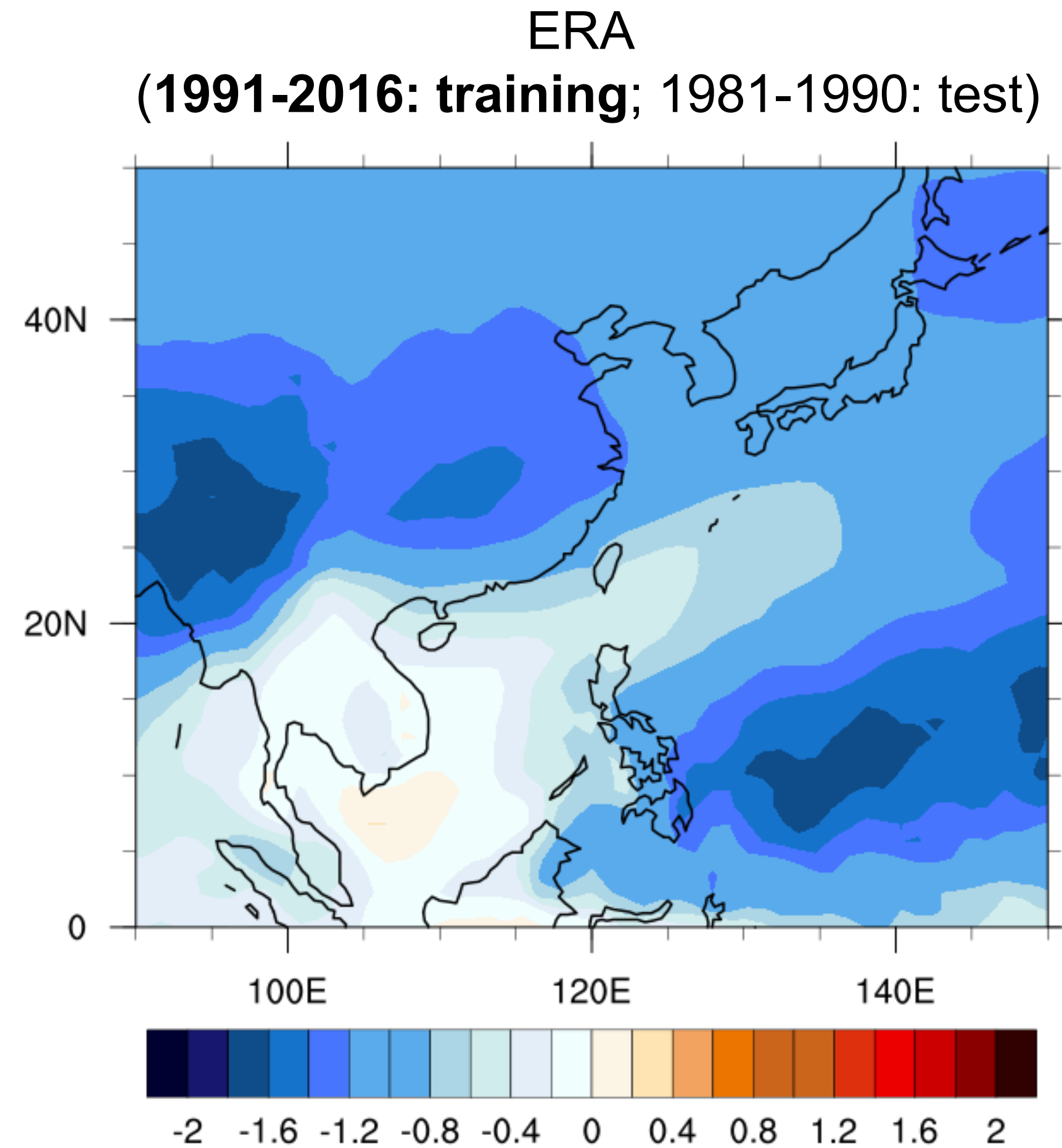


with SVM

Will the frontal days decrease/disappear in the future within RCP8.5 scenarios ?

We took advantage of previous experiments  
which using the numerical model outputs for climate projection

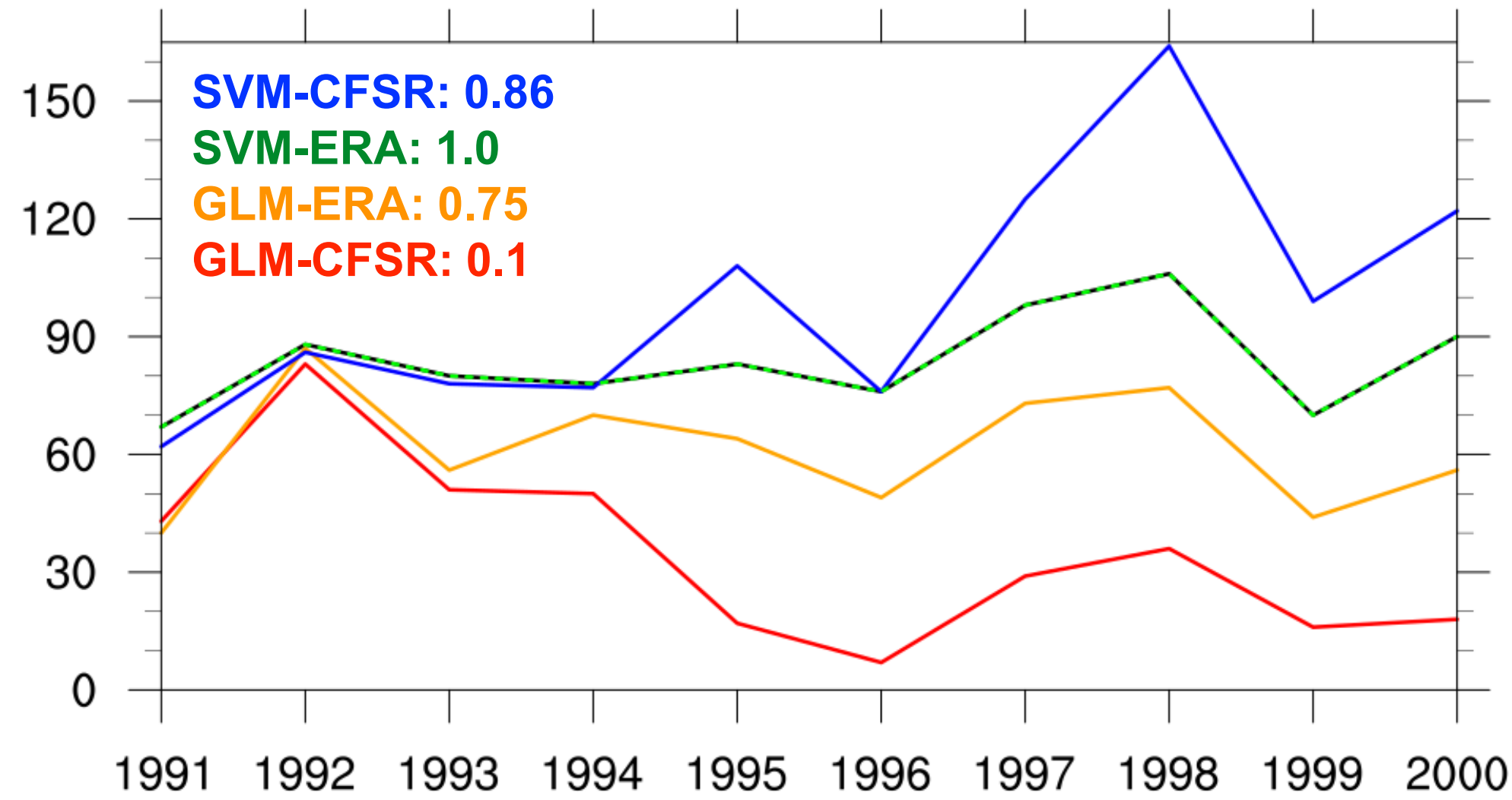
if the model bias is consistent, then using "anomaly" fields can represent the short term variation better than the absolute value



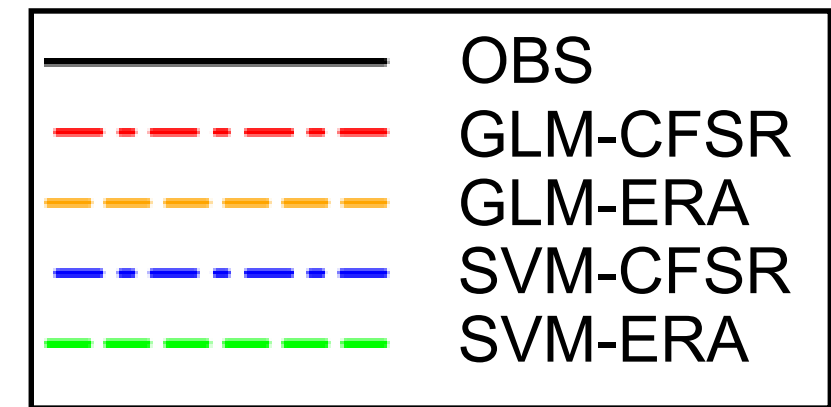
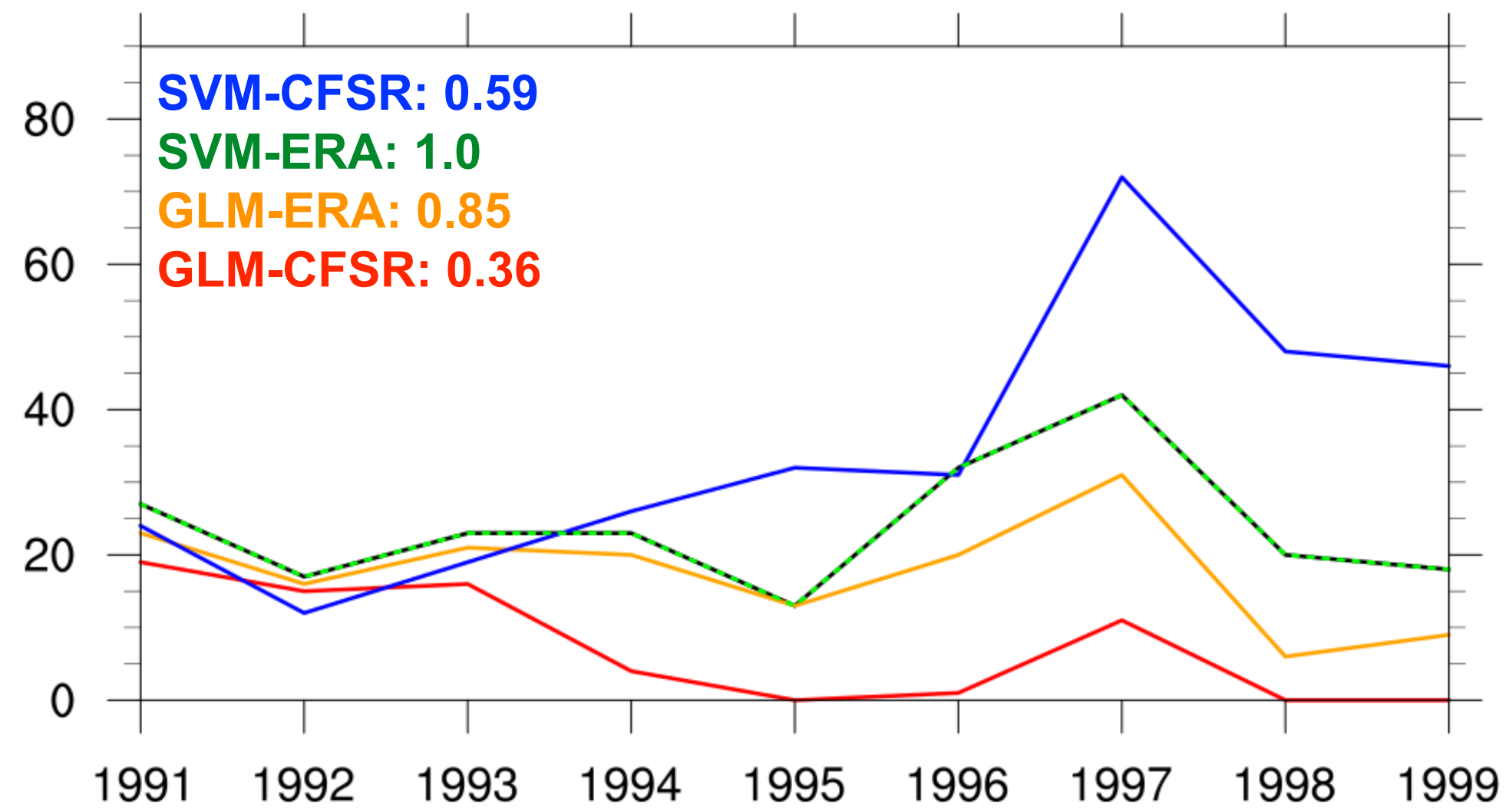
DJF frontal days composite with 850 hPa temperature "anomaly"

# The performances of ML classifier (with training data)

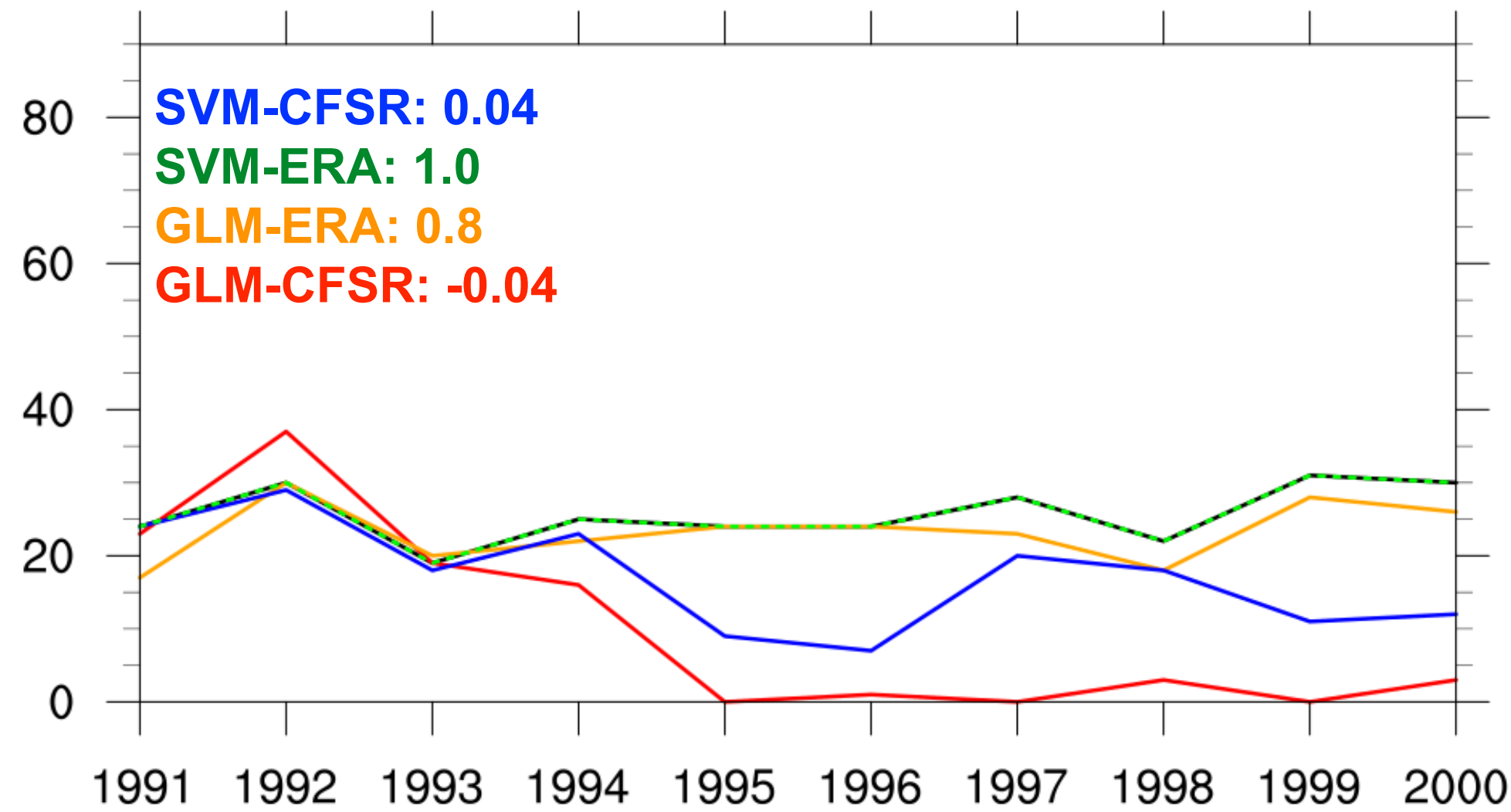
1991-2000 FT days



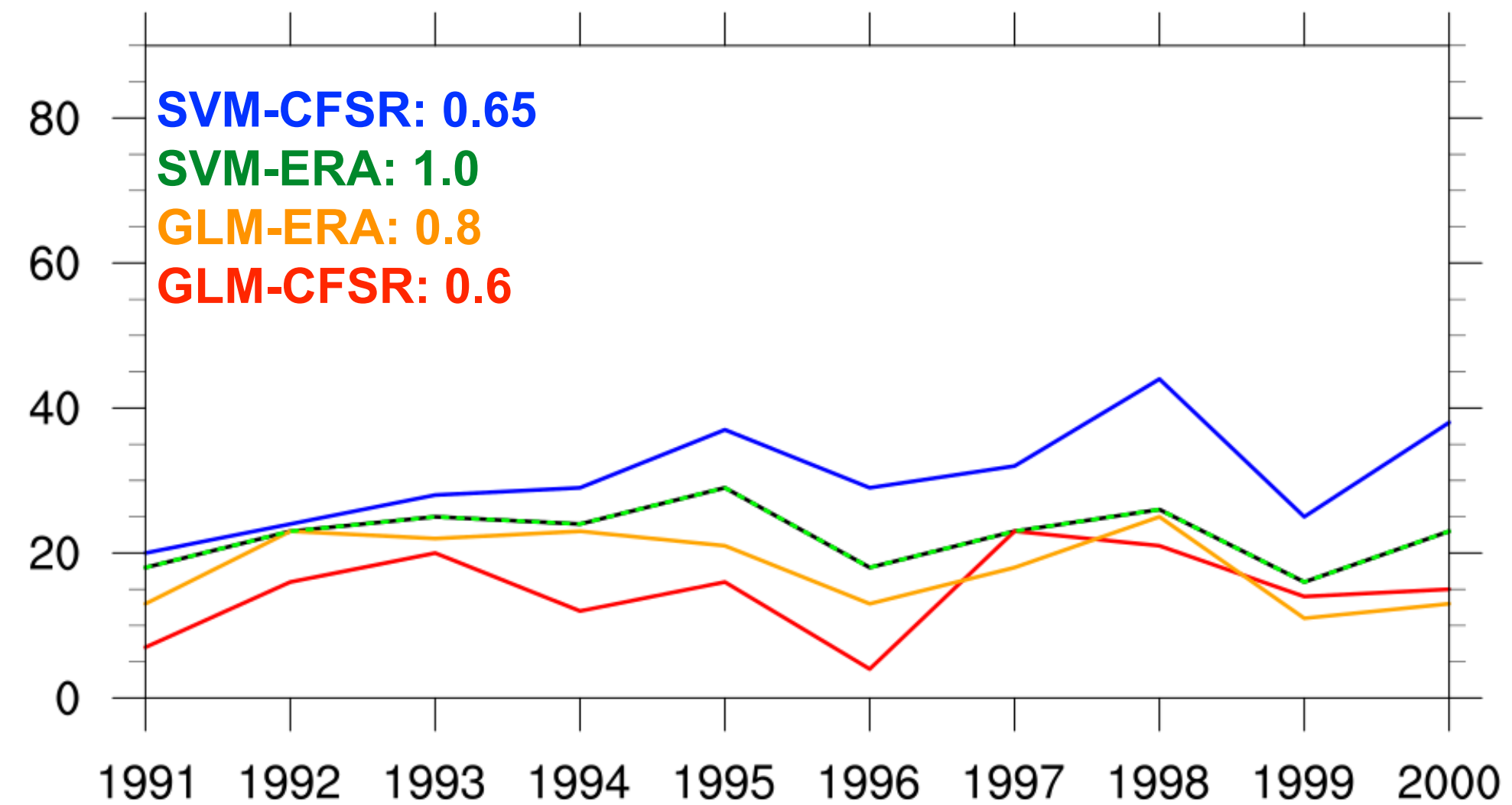
1991-2000 DJF FT days



1991-2000 MA FT days

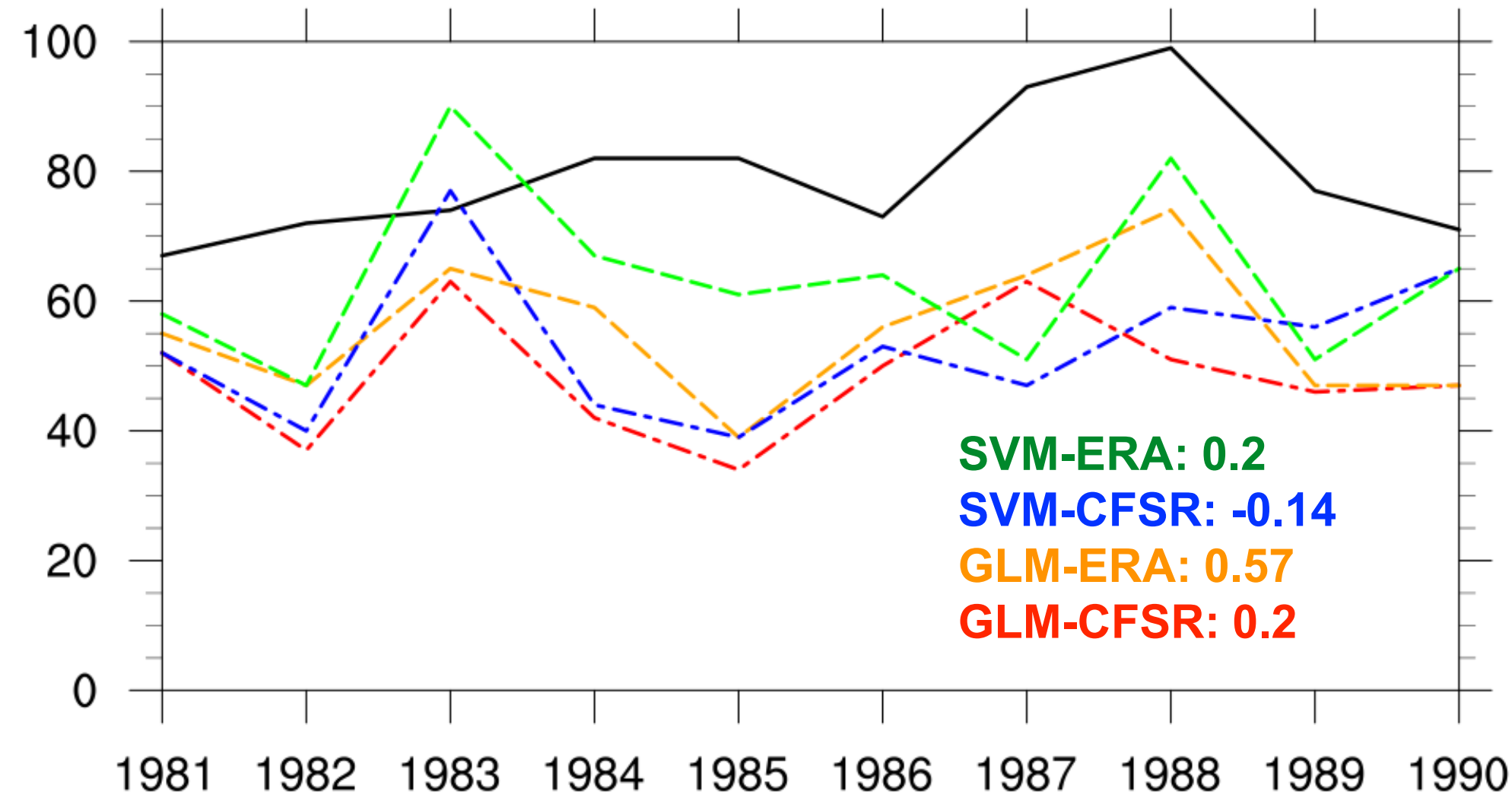


1991-2000 MJ FT days

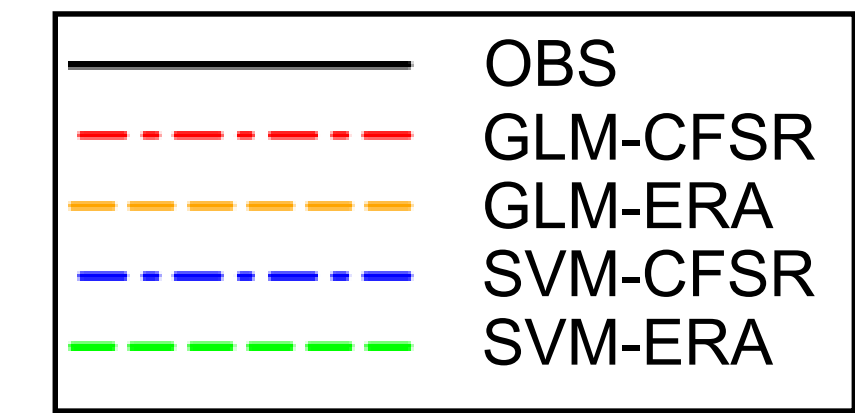
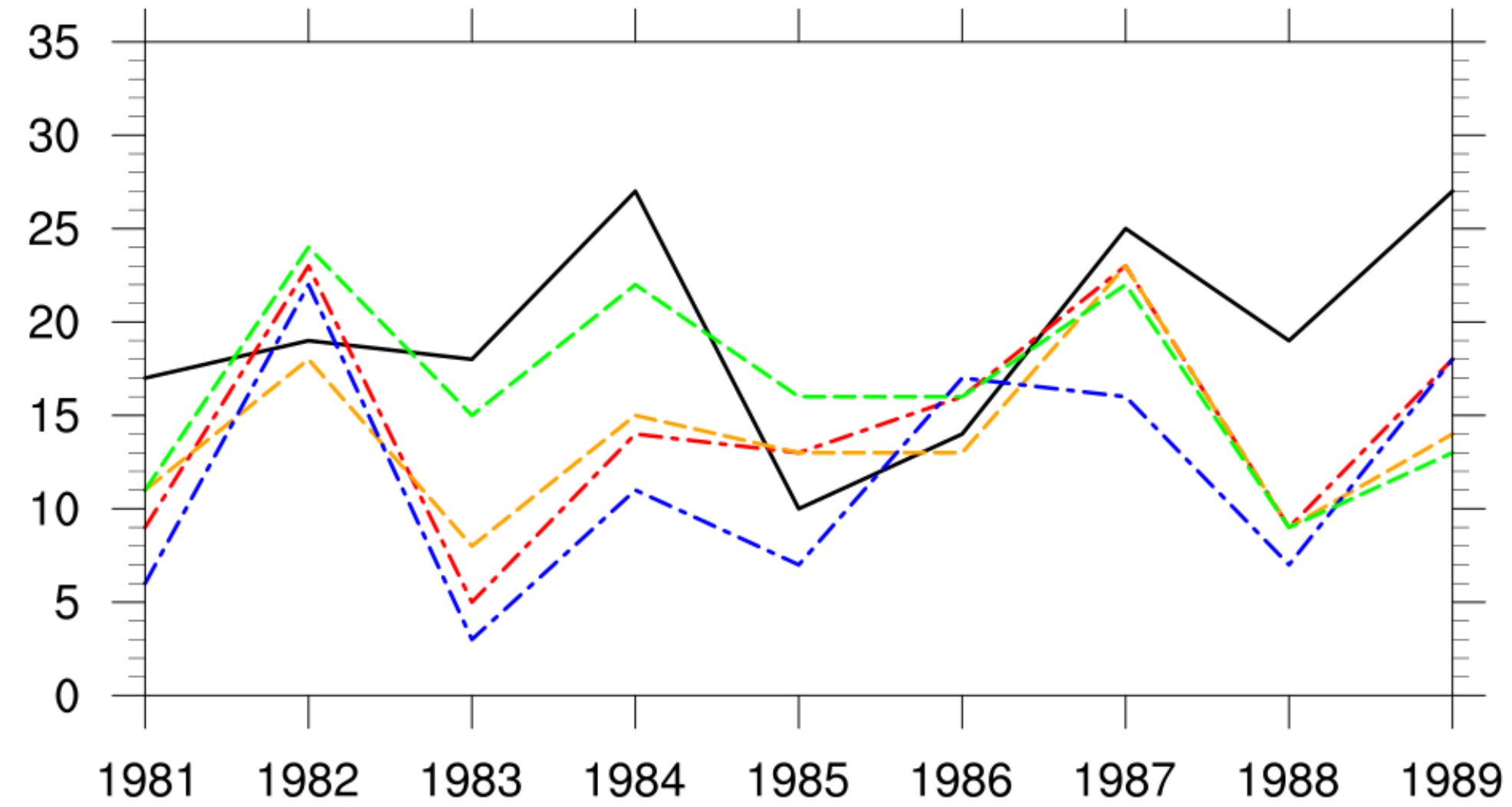


# The performances of ML classifier (with testing data)

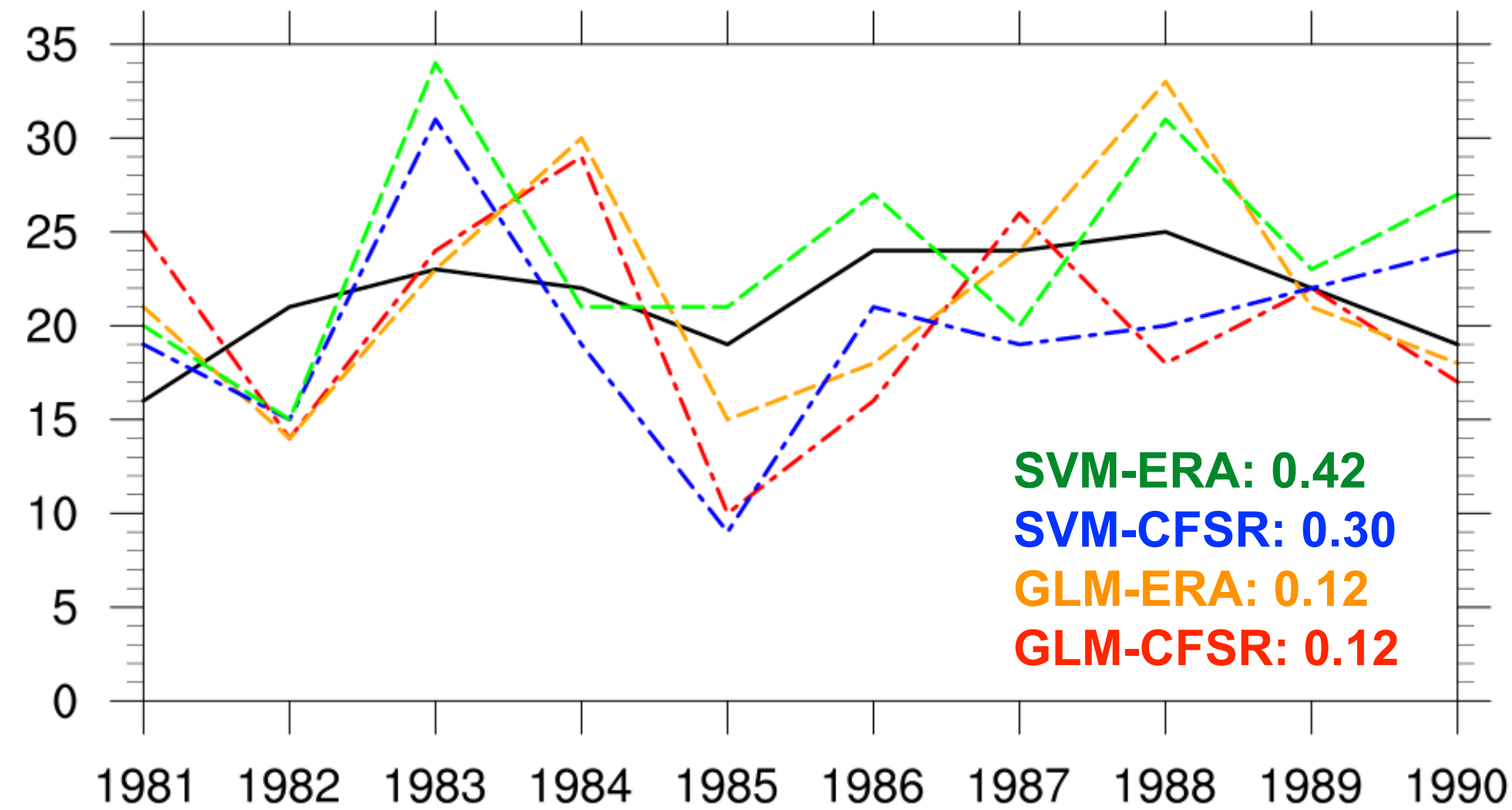
1981-1990 FT days



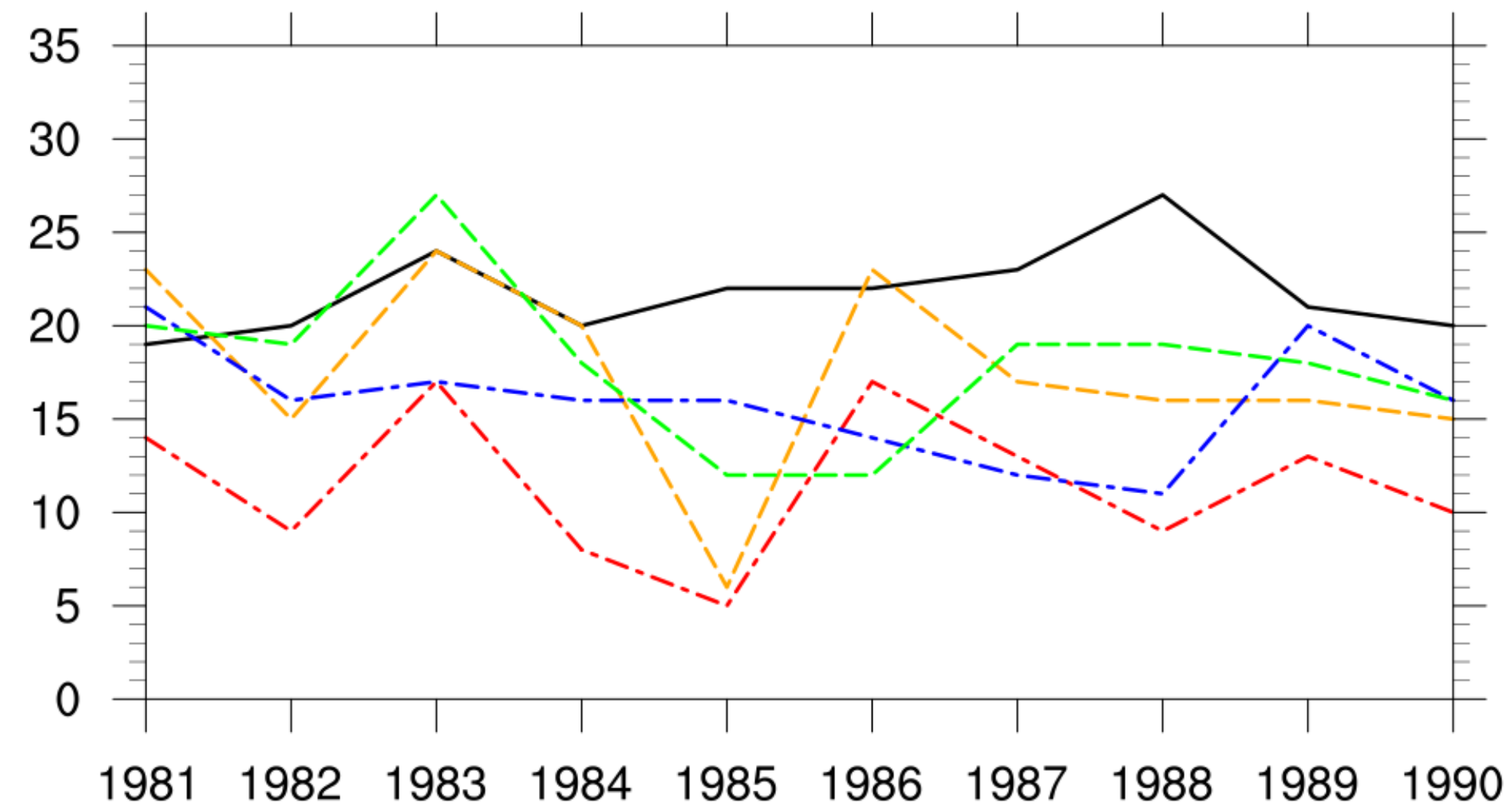
1981-1990 DJF FT days



1981-1990 MA FT days



1981-1990 MJ FT days



# Summary and ongoing work

1. The frontal system classifier with machine learning method outperformed methods based on the traditional objective diagnosis. It tends to identify the features of the baroclinic fronts and performs better in winter.
2. The frontal frequency of CMIP5 data had a large variance between different models, using an anomaly fields as the input variables can help reduce the impact of model bias on front diagnosing. (GLM would be the better tool.)
3. Selecting CMIP6 models via hierarchical clustering algorithm.

## Major work:

- Chang, C. W., Chiang, C. T., Liu, K. Y., and Su, S. H., 2019: The comparison of objective diagnose methods for Taiwan frontal system classification. *大氣科學*, 47(1), 1-29.
- 江建霆，2019：臺灣地區梅雨鋒面之氣候特徵-利用自組織映射分析（碩士論文）。臺北市，中國文化大學。
- Su, S. H., Chu, J. L., Yo, T. S., & Lin, L. Y., 2018, Identification of synoptic weather types over Taiwan area with multiple classifiers. *Atmo. Sci. Lett.*, e861.
- 劉高原，2017：2001-2016年影響臺灣鋒面系統之時空變化（碩士論文）。臺北市，中國文化大學。