Improving Climate Predictions and Reducing Their Uncertainties Using a Sequential Learning Algorithm

Ehud Strobach[1] and Golan Bel[2]

Department of Environmental Physics, Blaustein Institutes for Desert Research

Ben Gurion University, Israel

[1]udistr@gmail.com
[2]golanbel@gmail.com

Ben-Gurion University of the Negev

1. INTRODUCTION

Ensembles of climate models can improve climate predictions and reduce their uncertainties. Here, a new method from the field of decision making, which is based on a weighted average, is introduced. The weighted average is generated by comparing, during a learning period, the hindcasts of climate models with reanalysis data (considered here as true values), in one experiment, and real measurements, in a second experiment. It is shown that this method improves the predictions of global and regional climate models and reduces their uncertainties.

2. BASIC CONCEPT

The forecaster is a mathematical algorithm that takes advantage of several available model predictions (experts) and the knowledge of their past performance to generate a set of improved predictions in a sequential manner:

All experts have equal weights at $t=0$
↓
Experts give their advice concerning a future event at $t+1$
↓
The forecaster makes its decision
↓
The event outcome is revealed
↓
Each expert incurs a loss
↓
A new weight is generated

The forecaster's goal is to minimize the cumulative regret with respect to each one of the climate models. This is defined, for expert E, by the quantity:

$$R_{E,t} \equiv \sum_{n=0}^{t} \left(l(p_t, y_t) - l(f_{E,t}, y_t) \right) \equiv L_t - L_{E,t}$$

l - loss function, a measure of the difference between the predicted and the true values.

y_t - true value at time t.

p_t - predicted value by the forecaster at time t.

$f_{E,t}$

3. FORECASTERS

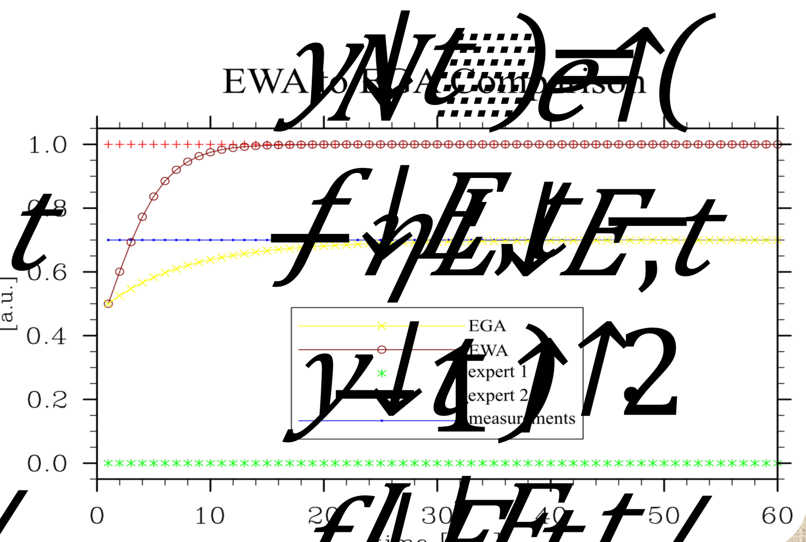
EGA
Exponentiated Gradient Average
Converges to the measurements

$$p_t \equiv \sum_{E=1}^{N} e^{-\eta L_{E,t}} f_{E,t} \Big/ \sum_{i=1}^{N}$$

η – learning parameter, large η – fast learning.

EWA
Exponential Weighted Average
Converges to the best model

$$p_t \equiv \sum_{E=1}^{N} e^{-\eta\, l(f_{E,t}, y_t)} f_{E,t} \Big/ \sum_{i=1}^{N}, \quad (f_{E,t} - y_t)^2$$

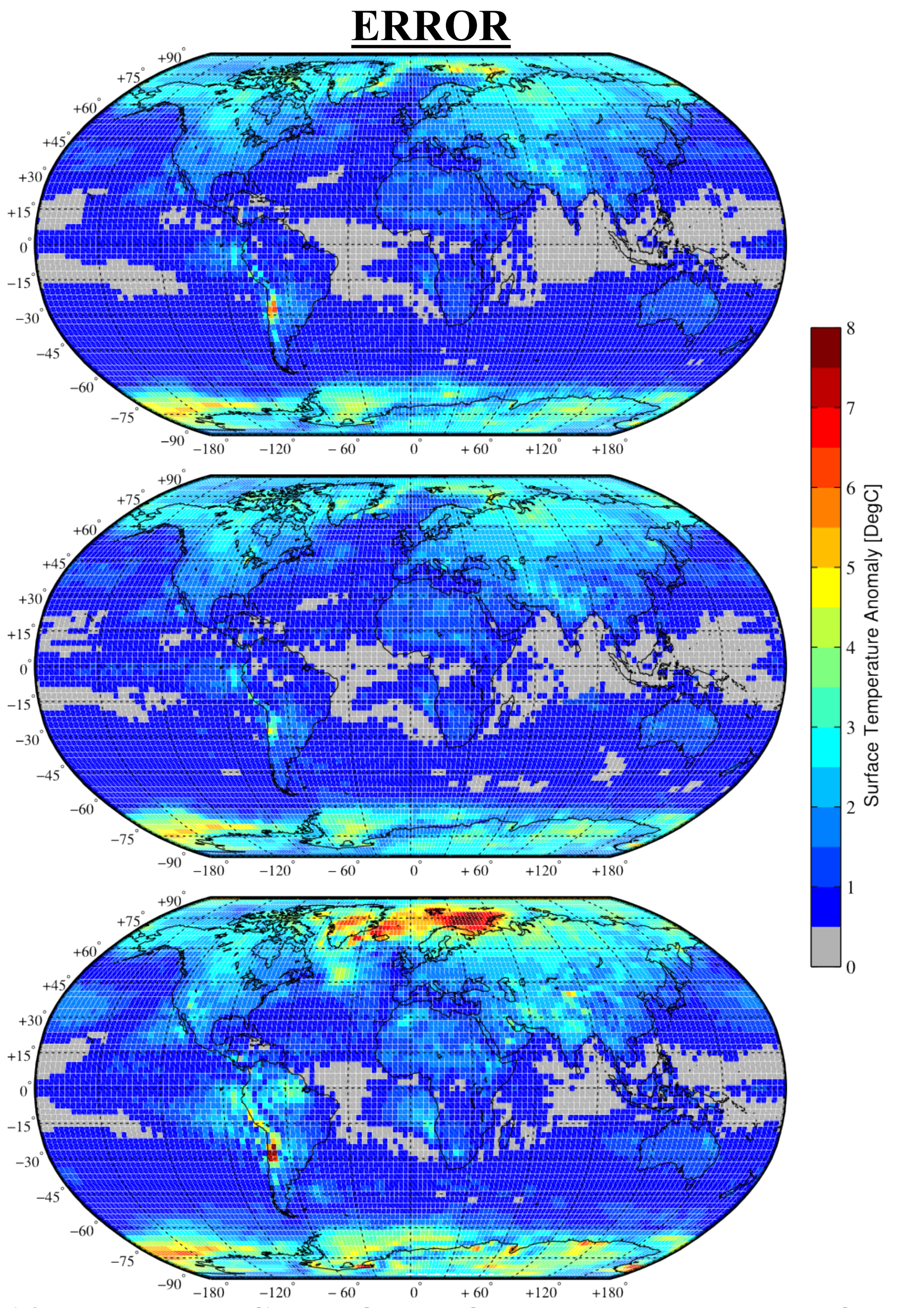


5. GLOBAL – MULTI-MODEL ENSEMBLE

EXPERIMENTAL SETUP

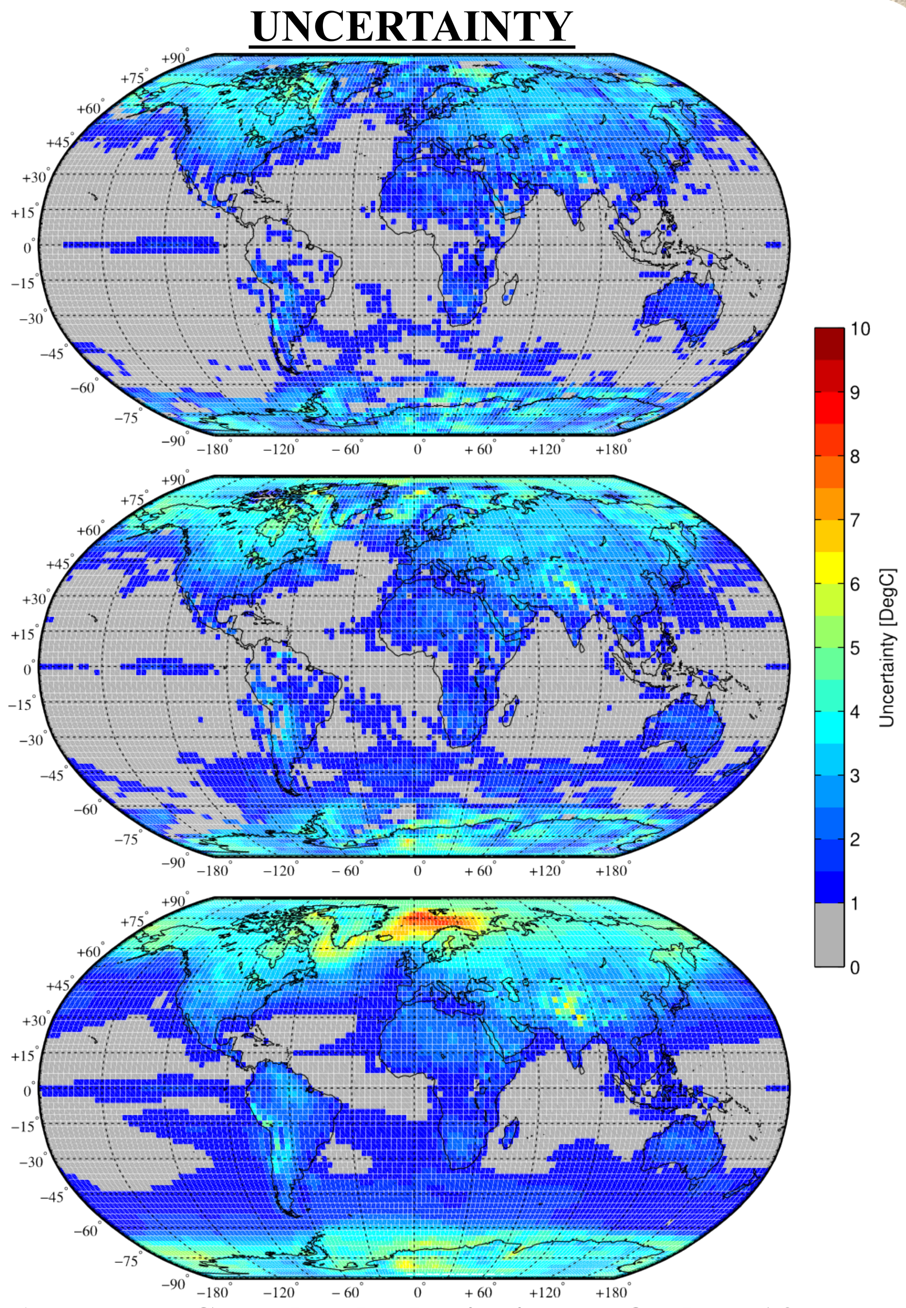
- Multi-model ensemble of 8 global climate model simulations from the CMIP5 decadal project.
- Thirty-year (1981-2011) simulation.
- NCEP reanalysis data considered as true values.
- Monthly averages of surface temperature.
- Twenty years of learning period (the weights are updated every month).
- Ten years of validation of the forecasters (the weights are constant).

ERROR



10-year RMSE of surface temperature for three forecasting methods - (a) EWA, (b) EGA, and (c) Simple average. The RMSE was calculated from the prediction period with constant weight as was determined by the last step of the learning period. Both forecasters improve the predictions of the simple average.

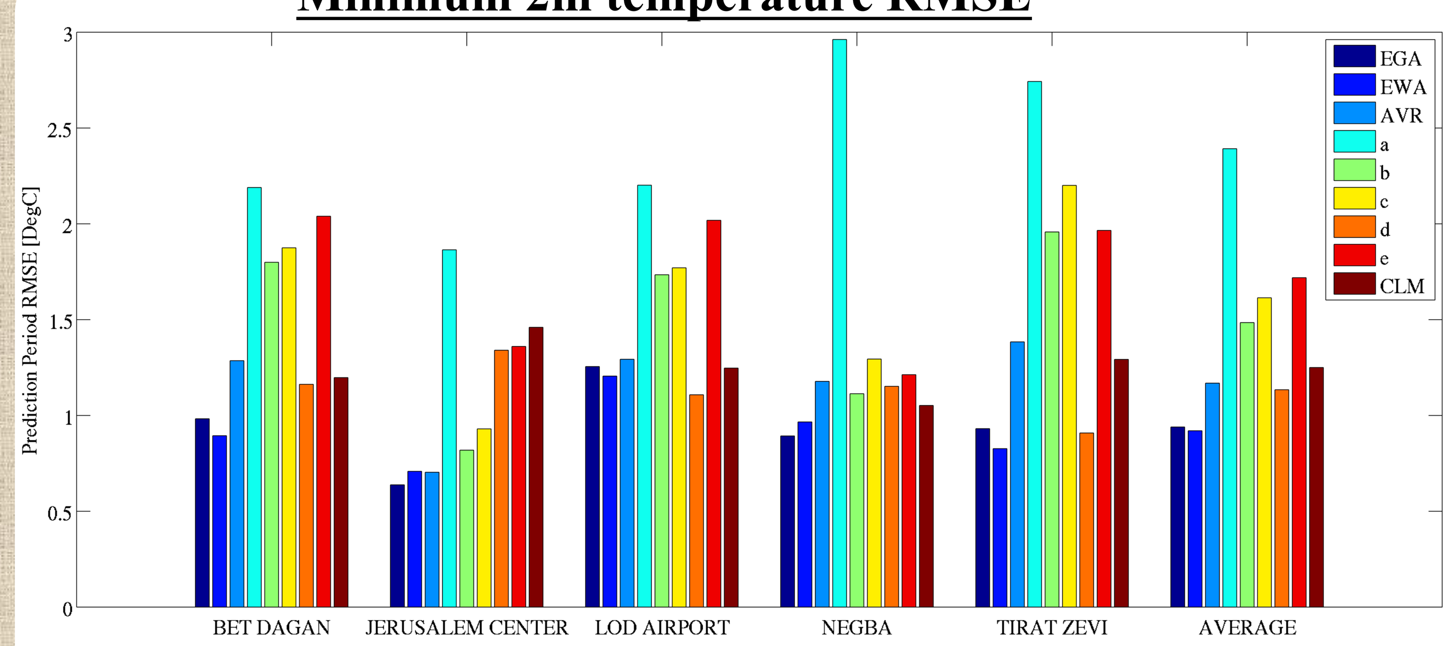
UNCERTAINTY



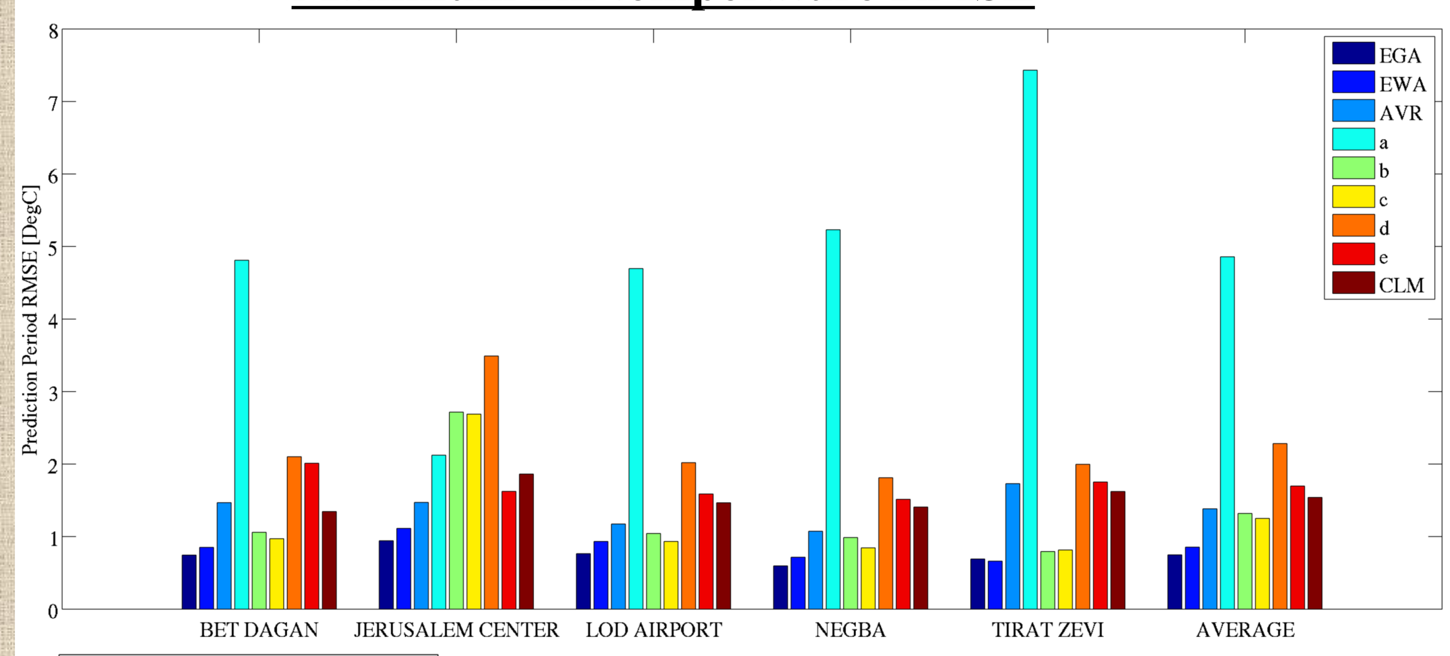
Average Standard deviation of the 10-year monthly surface temperature for three forecasting methods - (a) EWA, (b) EGA, and (c) Simple average. The STD was calculated from the prediction period with constant weight as was determined by the last step of the learning period. Both forecasters reduce the uncertainties of the simple average.

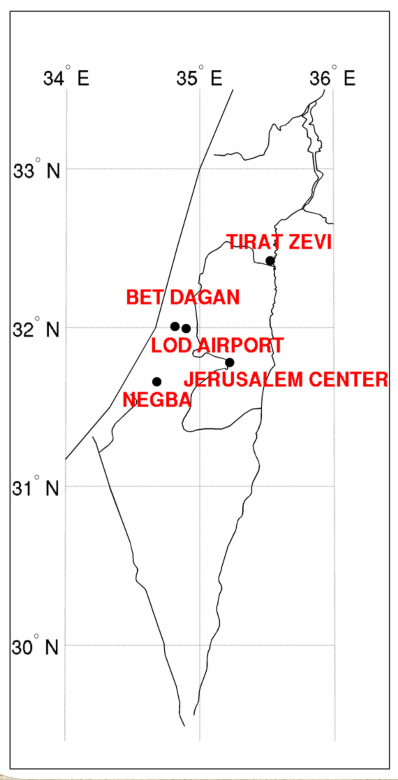
6. REGIONAL – MODEL ENSEMBLE

Minimum 2m temperature RMSE



Maximum 2m temperature RMSE





Monthly average of minimum and maximum daily 2m temperature for the prediction period. The results for five locations and an average of them are presented. AVR represents a simple average, a-e are the five different parameterizations of the model and CLM is the climatology of the learning period. Except from two cases for EGA and one case for EWA in the minimum temperature, both forecasters improve the results of the individual models and their simple average.

EXPERIMENTAL SETUP

- Model ensemble generated from the regional WRF model concentrated on Israel based on 5 different land surface parameterization schemes*.
- Initialized with the NCEP Climate Forecast System Reanalysis (CFSR).
- All ensemble members include assimilation of the greenhouse gases mixing ratio (CLWRF) and have 4km horizontal grid resolution.
- Learning period climatology as an additional 6th expert.
- Ten-year simulation (1981-1991).
- Israel Meteorological Service (IMS) station measurements as true values.
- Monthly averages of min and max 2m daily temperature.
- Six years of learning period
- Four years of validation of the forecasters.

*Parameterizations

Microphysics - WRF Single-Moment 6-class scheme
Long/short wave radiation - CAM scheme
Cumulus Parameterization - Kain-Fritsch scheme

	Land Surface	Surface Layer	Planetary Boundary Layer
a	5-layer thermal diffusion	Eta similarity	MYJ
b	Noah-LSM	Eta similarity	MYJ
c	Noah-MP	MM5 similarity	Yonsei University
d	Pleim-Xiu LSM	Pleim-Xiu SL	ACM2 PBL
e	RUC LSM	MM5 similarity	Yonsei University

7. CONCLUSIONS

- In the global experiment, averaged over the globe and compared to a simple average, EWA and EGA have reduced surface temperature error by about 18% and uncertainties by 36% and 25% respectively.
- In the regional experiment, averaged over five locations and compared to the best model, EGA have reduced error by 19% and 41% and EWA have reduced error by 17% and 32% for min and max temperature respectively.

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