The PALAEO-RA project

Combining an intermediate-size AGCM ensemble with historical observations and proxies to create a new dataset of the past 600 years of climate history

Stefan Brönnimann, Ralf Hand, Jörg Franke, Veronika Valler, and Andrey Martynov

Institute of Geography (Climatology Dpt.) & Oeschger Centre for Climate Change Research

2020-05-08, #shareEGU20
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- Historical Observations,…
In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- **Historical Observations,***
  - They represent „real“ states of the climate system at a certain time.
In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

**Historical Observations,**…

😊 They represent „real“ states of the climate system at a certain time.

😢 But they suffer from uncertainties and being temporarily and spatially sparse.
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- **Historical Observations,...**
  - They represent „real“ states of the climate system at a certain time.
  - But they suffer from uncertainties and being temporarly and spatially sparse.

- **Climate Models,...**
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- **Historical Observations,**
  - They represent „real“ states of the climate system at a certain time.
  - But they suffer from uncertainties and being temporarly and spatially sparse.

- **Climate Models,**
  - They are a useful tool to understand physical processes in the climate system.

Ralf Hand - The PALAEO-RA project
In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

**Historical Observations,**

- They represent „real“ states of the climate system at a certain time.
- But they suffer from uncertainties and being temporarily and spatially sparse.

**Climate Models,**

- They are a useful tool to understand physical processes in the climate system.
- But individual simulations only represent a „possible state“ of the climate system, rather than „reality“.
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

**Historical Observations,**
- They represent „real“ states of the climate system at a certain time.
- But they suffer from uncertainties and being temporarily and spatially sparse.

**Climate Models,**
- They are a useful tool to understand physical processes in the climate system.
- But individual simulations only represent a „possible state“ of the climate system, rather than „reality“.

**Data Assimilation,**
- ... allows to combine informations from models and observations.
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- **Data Assimilation**.
  - Allows to combine informations from models and observations.

- **Historical Observations**.
  - They represent „real“ states of the climate system at a certain time.
  - But they suffer from uncertainties and being temporarily and spatially sparse.

- **Climate Models**.
  - They are a useful tool to understand physical processes in the climate system.
  - But individual simulations only represent a „possible state“ of the climate system, rather than „reality“.

In PALAEO-RA we use different kinds of observations to combine them into a comprehensive dataset for covering the past 600 years. See slide 4 for details on our observations!
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- Data Assimilation,...
  - ... allows to to combine informations from models and observations.

- Historical Observations,...
  - They represent „real“ states of the climate system at a certain time.
  - But they suffer from uncertainties and being temporarily and spatially sparse.

- Climate Models,...
  - They are a useful tool to understand physical processes in the climate system.
  - But individual simulations only represent a „possible state“ of the climate system, rather than „reality“.

In PALAEO-RA we use a 30+ member ensemble of simulations with an atmospheric general circulation model to represent the range of realistic atmospheric states under a transient forcing and to acquire informations about spatial correlations.

See slides 5 & 6 for details on our simulations!
Motivation & Overview

In PALAEO-RA we combine an ensemble of model simulations with historical simulations to create a new, global, monthly, physically consistent, 3-dimensional data set for the climate of the past 600 years:

- **Historical Observations**:
  - They represent "real" states of the climate system at a certain time.
  - But they suffer from uncertainties and being temporarily and spatially sparse.

- **Climate Models**:
  - They are a useful tool to understand physical processes in the climate system.
  - But individual simulations only represent a "possible state" of the climate system, rather than "reality".

- **Data Assimilation**:
  - ... allows to combine informations from models and observations.

In PALAEO-RA we will use Ensemble Kalman Fitting to combine the historical observations with the ensemble of model simulations. See slide 7 for details on our assimilation procedure!

Understanding the climate of the past is crucial to improve the knowledge about the underlying processes and, consequently, to improve climate predictions.

To reach this aim, we can use:

- **Data Assimilation**
- **Climate Models**
- **Historical Observations**
The Observations
A comprehensive set of historical climate data

In PALAEO-RA we combine different types of data into one large database:

**Historical data**
We will assimilate monthly resolved temperature, precipitations and sea level pressure data from existing existing as well as newly digitized early instrumental data and documentary data (e.g. cherry blossom and grape harvest dates) and complement them with newly digitized data.

**Climate proxies**
Additionally we use annually resolved climate proxies, e.g. tree rings and corals.

© University of Bern

Arnoldius (Wikimedia commons)
The Model Set Up

Configuration of our experiments

We will use an atmospheric general circulation model with prescribed SST and Sea Ice forcings.
ECHAM 6.3.05-LR horizontal resolution: T63 vertical resolution: L47
ECHAM 6.3.05-HR (to be used in a later project phase) horizontal resolution: T127 vertical resolution: L47
Configuration was chosen to be +/- consistent with the PMIP4 past 2k simulations, but...

- ... with prescribed ocean conditions (instead of a dynamically coupled ocean)
- ... without dynamic vegetation
The Ensemble
30+ members for the past 600 years

- **Set 1: 10 members low resolution (completed)**
  - SST/SIC: 10 realisations of HadISST
  - Initialization: 10 different initializations
  - Radiative forcings & volcanoes: PMIP4

- **Set 2: 10 members low resolution (completed)**
  - SST/SIC: same as set 1
  - Initialization: another 10 different initializations
  - Radiative forcings & volcanoes: PMIP4

- **Set 3: 16 members low resolution (completed)**
  - SST/SIC: linear combinations of 10 HadISST realisations
  - Initialization: as set 1
  - Radiative forcings & volcanoes: PMIP4

- **30 members low resolution (in prep.)**
  - SST/SIC: 30 novel SST/SIC reconstructions
    (for details: Samakinwa et al, EGU2020-8744)
  - Initialization: 30 different initializations
  - Radiative forcings & volcanoes: PMIP4

- **4 members high resolution (planned)**
  - SST/SIC: novel SST/SIC reconstructions
    (for details: Samakinwa et al, EGU2020-8744)
  - Radiative forcings: PMIP4
  - volcanoes: PMIP4 and/or additional realizations

The simulations are supposed to represent the range of atmospheric states that is possible under given boundary conditions.

Additional time chunk experiments to increase the ensemble size after major volcanic eruptions to account for uncertainties in the volcanic forcings.
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

Example for the assimilation of an observation in the mediterranean region

We start from the the uncorrected ensemble mean.

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

Example for the assimilation of an observation in the mediterranean region

We start from the the uncorrected ensemble mean.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We start from the uncorrected ensemble mean.
To eliminate effects from spurious correlation with grid cells far away, we additionally apply a localization matrix that gives high weights to grid cells in the close neighbourhood and zero weight to grid cells far away.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

Example for the assimilation of an observation in the mediterranean region

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We start from the uncorrected ensemble mean.

To eliminate effects from spurious correlation with grid cells far away, we additionally apply a localization matrix that gives high weights to grid cells in the close neighbourhood and zero weight to grid cells far away.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

Example for the assimilation of an observation in the mediterranean region

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We start from the the uncorrected ensemble mean.

To eliminate effects from spurious correlation with grid cells far away, we additionally apply a localization matrix that gives high weights to grid cells in the close neighbourhood and zero weight to grid cells far away.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

We now assimilate the first observation (x) as part of an observation network (o +)

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We start from the uncorrected ensemble mean. To eliminate effects from spurious correlation with grid cells far away, we additionally apply a localization matrix that gives high weights to grid cells in the close neighbourhood and zero weight to grid cells far away.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

Example for the assimilation of an observation in the mediterranean region

Combining the observation error with the localized background error covariance matrix gives us the Kalman gain that is applied as a correction term to update the ensemble mean towards the observation.

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We start from the uncorrected ensemble mean.

To eliminate effects from spurious correlation with grid cells far away, we additionally apply a localization matrix that gives high weights to grid cells in the close neighbourhood and zero weight to grid cells far away.

The background error covariance matrix was computed from the ensemble. It represents spatial correlations of the deviation from the ensemble mean in a distinct grid cell with the anomalies in all other grid cells.

Example for the assimilation of an observation in the mediterranean region

Adding the observation weighted by the Kalman gain then gives us the updated ensemble. Afterwards the whole procedure is repeated to update the anomalies of all ensemble members accordingly.

Combining the observation error with the localized background error covariance matrix gives us the Kalman gain that is applied as a correction term to update the ensemble mean towards the observation.

We now assimilate the first observation (x) as part of an observation network (o +)

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

Example for the assimilation of an observation in the mediterranean region

The updated ensemble mean then is the starting point for the assimilation of the next observation

© all figures on this page: The authors. All rights reserved
The Application: Ensemble Kalman Fitting
An offline approach for the serial assimilation of observations

We assimilate data twice per year. This is beyond the typical memory of the atmosphere. Thus, in contrast to the conventional use of Ensemble Kalman Filters, the assimilation can be done offline (i.e. after the ensemble simulations are finished), which makes the problem computationally feasible. For details on the method see Bhend. et al, 2012; doi:10.5194/cp-8-963-2012.
The Dataset

Accessibility

More information? Click here to visit the PALAEO-RA Website