Decadal Climate Variability and Prediction

1. Introduction to Decadal Climate Variability

2. The AMO

3. The PDO

4. Decadal Prediction
"Climate is now recognized as being continuously variable, on all scales of time"

J. Murray Mitchell Jr., Quaternary Research, 1976
Bartlein, Encyclopedia of Quaternary Science, 2006
Example 1: Global temperature

NEWSWEEK published an article in 1975 worried about global cooling and a new ice age!!

*this was not the scientific consensus at the time though

From www.metoffice.gov.uk
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It is important to consider decadal variations on top of any long term trend.

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It is important to consider decadal variations on top of any long term trend.

Decadal variability alternately disguises and accentuates the secular warming trend.

From www.metoffice.gov.uk
Example 2: The US Dust Bowl

During 1930s, US experienced one of the most devastating droughts of the past century. Affected ~2/3 of US, parts of Mexico and Canada.

Drought is a example of decadal climate variability that the public understand. Multiple years of low rainfall reduce the amount of available water in the earth system (water table, rivers, soil etc.).
Example 3: Sahel Drought

Wet conditions in 50s and 60s

Drought in 70s and 80s:
* Affected 20 countries, 150 million people
* 30 million were in urgent need of food aid
* 10 million refugees seeking food and water
* 100,000 to 250,000 deaths
“An improved understanding of decadal climate variability is very important because stakeholders and policymakers want to know the likely climate trajectory for the coming decades for applications to water resources, agriculture, energy, and infrastructure development.”

Mehta et al., BAMS, 2011
2) The AMO:

Atlantic Multidecadal Oscillation
Positive signal over whole North Atlantic – horseshoe pattern
Weak SST signal across over global ocean regions
The AMO Index

The AMO index is the *detrended* SST anomalies in the North Atlantic.

Removing basic global warming signal – we want the decadal climate variability.

Wang, State of the Climate 2010, BAMS, 2011
The AMO index: SST anomalies averaged over 0° - 70°N, 75° - 10°W
detrended
low-pass-filtered (extracts the decadal variations)
Did the AMO exist before 1900?

12 tree ring sites (1567-1990), detrended

Calibration period (1922-1990)

Verification period (1856-1921)

Reconstruct a time series of the AMO index that agrees with SST instrument measurements but can be extended back into the past

Gray et al., Geophys. Res. Lett., 2004
AMO Reconstruction from Tree Ring Data

- SST observations (in-situ/satellite)
- AMO Index from tree rings
- Warm/Cold AMO periods
The Thermohaline Circulation (THC)

Meridional Overturning

Global Ocean Conveyor Circulation

In order to balance the excess heating in the Tropics, the oceans transports heat (in the form of warm, salty water) from low to high latitudes.
Current mode:

1) warm water (red) flows northward in the upper ocean along the East Coast of the U.S. toward Iceland

2) Warm water exchanges heat with the cooler air, becoming cooler and saltier

3) Near Iceland, water becomes more dense (cool and salty) than the water below and sinks, flowing southward along the floor of the Atlantic = North Atlantic Deep Water Formation
What can General Circulation Models models tell us?

Long (~1400 year) model integrations with HadCM3 able to simulate the observed pattern and amplitude of the AMO (Knight et al., 2005)

Model did not include any fluctuations in external forcing (greenhouses gases, aerosols, etc.)

→ suggests AMO is a genuine quasi-periodic cycle of internal climate variability persisting for many centuries

→ Model hints that AMO results from variability in the oceanic THC
Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability

Ben B. B. Booth¹, Nick J. Dunstone¹*, Paul R. Halloran¹*, Timo I.

Systematic climate shifts have been linked to multidecadal variability in observed sea surface temperatures in the North Atlantic Ocean. These links are extensive, influencing a range of climate processes such as hurricane activity² and African Sahel³–⁵ and Amazonian⁶–⁸ droughts. The variability is distinct from historical global-mean temperature changes and is commonly attributed to natural ocean oscillations⁹–¹⁰. A number of studies have provided evidence that aerosols can influence long-term changes in sea surface temperatures¹¹–¹², but climate models have so far failed to reproduce these interactions⁹–¹⁰ and the role of aerosols in decadal variability remains unclear. Here we use a state-of-the-art Earth system climate model to show that aerosol emissions and periods of volcanic activity explain 76 per cent of the simulated multidecadal variance in detrended 1860–2005 North Atlantic sea surface temperatures. After 1950, simulated variability is within observational estimates; our estimates for 1910–1940 capture twice the warming of previous generation models but do not explain the entire observed trend. Other processes, such as ocean circulation, may also have contributed to variability in the early twentieth century. Mechanistically, we find that inclusion of aerosol–cloud microphysical effects, which were included in few previou multimodel ensembles, dominates the magnitude (80 per cent) and the spatial pattern of the total surface forcing in the North Atlantic. Our findings suggest that anthropogenic aerosol emissions influenced a range of societally important historical climate events such as peaks in hurricane activity and Sahel drought. Decadal-scale model predictions of regional Atlantic climate will probably be improved by incorporating aerosol–cloud microphysical interactions and estimates of future concentrations of aerosols, emissions of which are directly addressable by policy actions.

External forcing as a metronome for Atlantic multidecadal variability

Odd Helge Ottera¹,²,³*, Mats Bentsen¹,²,³, Helge Drange¹,²,⁴ and Lingling Suo²,³

Instrumental records, proxy data and climate modelling show that multidecadal variability is a dominant feature of North Atlantic sea-surface temperature variations¹⁰–¹⁴, with potential impacts on regional climate¹⁵. To understand the observed variability and to gauge any potential for climate predictions it is essential to identify the physical mechanisms that lead to this variability, and to explore the spatial and temporal characteristics of multidecadal variability modes. Here we use a coupled ocean–atmosphere general circulation model to show that the phasing of the multidecadal fluctuations in the North Atlantic during the past 600 years is, to a large degree, governed by changes in the external solar and volcanic forcings. We find that volcanoes play a particularly important part in the phasing of the multidecadal variability through their direct influence on tropical sea-surface temperatures, on the leading mode of northern-hemisphere atmosphere circulation and on the Atlantic thermohaline circulation. We suggest that the implications of our findings for decadal climate prediction are twofold: because volcanic eruptions cannot be predicted a decade in advance, longer-term climate predictability may prove challenging, whereas the systematic post-eruption changes in ocean and atmosphere may hold promise for shorter-term climate prediction.

Is it all natural?

Otter et al., Nat. Geosci., 2010

AMO Impacts

- Warm SSTs over N. Atlantic

- What potential impacts are there on surrounding regions?
One method of looking at impacts is to make composite (or averages) of warm and cold period and take the difference (e.g. 1931/60 – 1961/90)

So, when the AMO is in a warm period:

Low SLP across Atlantic and N. America

Wet in West Africa, Europe, dry in central US

Warm in East US

Sutton and Hodson, Science, 2005
Impacts

Globally

rainfall is highly correlated with All India Summer Rainfall [Parthasarathy et al., 1994]. Over west central India, the multidecadal wet period is in phase with the positive AMO phase (warm North Atlantic) during the middle of the 20th century (1926–1965); the dry periods are in phase with the negative AMO phase during both the early (1901–1926) and the late 20th century (1965–1995) (Figures 1a and 1c). The time series of west central India summer rainfall is in phase with Sahel summer rainfall (Figures 1b and 1c). The leading spatial pattern (EOF 1, from Empirical Orthogonal Function analysis, Figure 2a) of observed 20th century summer rainfall anomalies over the region covering both Africa and India also suggests an in-phase relationship between India and Sahel summer rainfall. The time series of this spatial pattern is in phase with the observed AMO index (Figures 1a and 1d).

The observed AMO Index is also in phase with the observed time series of the number of major Atlantic hurricanes and the Hurricane Shear Index (Figures 1a and 1e), consistent with previous studies [Gray, 1990; Landsea et al., 1999; Goldenberg et al., 2001]. Here the Hurricane Shear Index is defined as the anomalous 200-hPa–850-hPa vertical shear of the zonal wind multiplied by 1, computed during Hurricane season, August to October.

Figure 1. Observed and modeled variability. The color shading is the low-pass filtered (LF) data and the green dash line is the unfiltered data. (a) Observed AMO Index derived from HADISST [Rayner et al., 2003]. (b) Observed JJAS Sahel rainfall anomalies (averaged over 20W-40E, 10–20N). All observed rainfall data is from Climate Research Unit (CRU), University of East Anglia, United Kingdom (CRU-TS_2.1). (c) Observed JJAS west central India rainfall anomalies (averaged over 65–80E, 15–25N). (d) Observed time series of the dominant pattern (PC 1) of LF JJAS rainfall anomalies. (e) Observed anomalous Atlantic major Hurricane number (axis on the left, original data from the Atlantic basin hurricane database—HURDAT, with no bias-type corrections from 1944–1969 as recently recommended by Landsea [2005], there is no reliable data before 1944), and observed Hurricane Shear Index (1958–2000), derived from ERA-40 [Simmons and Gibson, 2000] (m/s, brown solid line for LF data, brown dash line for unfiltered data, axis on the right). (f) Modeled AMO Index. (g) Modeled JJAS Sahel rainfall anomalies. (h) Modeled JJAS west central India rainfall anomalies. (i) Modeled PC 1 of LF JJAS rainfall anomalies. (j) Modeled Hurricane Shear Index. All LF data in this paper were filtered using the Matlab function ‘filtfilt’, with a Hamming window based low-pass filter and a frequency response that drops to 50% at the 10-year cutoff period. All rainfall time series are normalized by the SD of the corresponding LF data, i.e. 9.1 and 5.5 mm/month for Figures 1b and 1g; 12.5 and 7.1 mm/month for Figures 1c and 1h, 371 and 261 mm/month for Figures 1d and 1i. Light blue lines mark the phase-switch of AMO.

Figure 2. Leading spatial pattern of the 20th century low frequency JJAS rainfall anomalies over Africa and India. (a) EOF 1 (31%) of observed LF JJAS rainfall anomalies. (b) EOF 1 (67%) of modeled LF JJAS rainfall anomalies. (c) Regression of observed LF JJAS rainfall anomalies on observed AMO Index. (d) Regression of modeled LF JJAS rainfall anomalies on modeled AMO Index. The observed rainfall is from CRU-TS_2.1. The original regressions correspond to 1 SD of the AMO index, Figures 2a and 2c are normalized by the SD of observed time series of the dominant pattern, i.e. PC1 (371 mm/month), and Figures 2b and 2d are normalized by the SD of modeled PC1 (261 mm/month). The modeled EOF1 explains much higher percentage of variance due to ensemble average.

You can also look at correlations between time series:

- Sahel rainfall
- Indian monsoon rainfall
- Hurricane numbers

AMO Impacts in the US

So, when the AMO is in a warm period:

- Dry conditions in Central US, especially in Fall
- Wet conditions in Central America and Florida
- Changes in wind accompany rainfall changes

The AMO and the Dust Bowl


SHADES: GP Precip in the above marked red box (83–103W, 30–50N)
Correlation (GP Precip Red box, AMO PC) = -0.78
Correlation (GP Precip RBN box, AMO PC) = -0.72
Correlation (GP Precip Schubert et al. box, AMO PC) = -0.67

Dust Bowl

Warm N. Atlantic

Observed Dust Bowl Precipitation Anomaly

Schubert et al., 2004
**The AMO and Hurricanes**

**Cold AMO period**
- 1971 – 1994
- Cold N. Atlantic and small Atlantic warm pool
- 15 major hurricanes, few hit US
- Cheap insurance
- Little public and industry awareness of climate risk shifts

**Warm AMO period**
- Warm N. Atlantic and large Atlantic warm pool
- 33 major hurricanes, lots hit US
- Expensive insurance
- More public and industry awareness of climate risk shifts

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**Essential to consider decadal changes in hurricanes when assessing impact of climate change**
Summary: AMO Impacts on Climate

- AMO plays an important role in modulating climate on multidecadal time scales in US and Europe, especially during boreal summer and fall
  - Low pressure centers over SE US and UK
  - Enhanced rain in western Europe, Florida, Sahel and N. Africa
  - Reduced rain central US and Mexico
  - Warm surface temperature anomalies over US and central Europe
- May affect not only mean climate but also frequency of extreme events (US droughts, hurricanes, heat waves)
- Phase change of AMO around 1960 may have caused summertime cooling in US and Europe
- Most recent phase change (around 1990) may have contributed to rapid warming

MUST CONSIDER THESE DEcadal CHANGES WHEN ASSESSING CLIMATE CHANGE
3) The PDO:

Pacific Decadal Oscillation

- The PDO is a long-lived El Niño-like pattern of Pacific climate variability.

- The term PDO was first used in 1996 by a fisheries scientist researching connections between Alaska salmon production cycles and Pacific climate.

- When considering the pattern for the whole Pacific ocean it is often called the IPO: Inter-decadal Pacific Oscillation

- There is no scientific consensus for the cause and dynamics of the PDO
Pacific Decadal Oscillation: SST Pattern

Warm phase

Cold Phase

ENSO-like pattern but strongest SST changes in extratropics

See http://jisao.washington.edu/pdo
PDO and ENSO are on different time scales

Time series have similarities but are not identical
Note that the PDO and AMO operate on different time scales too!

McCabe et al., PNAS, 2004
PDO Impacts in US

Warm PDO:

- Wet S, SW US
- Dry in NW, Great Lakes
- Warm in E. Canada, Alaska
- Cold in E US
- Snow pack and streamflow in NW US is reduced
- Winter and spring flood risk in NW US is reduced

Mantua and Hare, J. Oceanog., 2002
Combined Impacts

• PDO, AMO and ENSO all impact US climate on different timescales

• Need to consider phase of each to make a forecast or decadal prediction

  e.g. Will they act together to cause a mega drought or cancel each other to make average conditions?
The PDO and AMO combined: Drought Frequency

McCabe et al., PNAS, 2004
PDO vs. AMO impacts in the US

- AMO+ (warm): much of US under drought conditions, regardless of PDO state

More than half (52%) of spatio-temporal variance in multidecadal drought frequency over US attributable to combined PDO / AMO influence

Recent US droughts (1996, 1999–2002) associated N. Atlantic warming (positive AMO) and NE and tropical Pacific cooling (negative PDO)

→ Much of the long-term predictability of drought frequency may reside in the multi-decadal behavior of the N. Atlantic

McCabe et al., 2004
“The decadal time scale offers a critical bridge for informing adaption strategies as climate varies and changes”

Meehl et al., BAMS, 2009
Decadal Prediction

Now we know about ways the climate varies on decadal timescales so the next questions are:

- Is it predictable?
- Can we predict it?

The decadal time scale is widely recognized as a key planning horizon for governments, businesses, and other societal entities.
Decadal Predictability

Daily Weather Forecasts  
Seasonal to ~1 Year Outlooks  
Decadal Predictions  
Multi-Decadal to Century Climate Change Projections

Initial Value Problem  
Forced Boundary Condition Problem

Figure 2. Schematic illustrating progression from initial value problems with daily weather forecasts at one end, and multidecadal to century projections as a forced boundary condition problem at the other, with seasonal and decadal prediction in between.

Figure 3. The relative importance of different sources of uncertainty in IPCC GCM projections of decadal-mean global-mean surface air temperature in the twenty-first century is shown by the fractional uncertainty (i.e., the prediction uncertainty divided by the expected mean change, relative to the 1971–2000 mean). Model uncertainty is the dominant source of uncertainty for lead times up to 50 yr, with internal variability being important for the first decade or so. Scenario uncertainty becomes important at multidecadal lead times (from Hawkins and Sutton 2009a).

Meehl et al., BAMS, 2009
Decadal Predictability

Daily Weather Forecasts
Seasonal to ~1 Year Outlooks
Decadal Predictions
Multi-Decadal to Century Climate Change Projections

Initial Value Problem
Forced Boundary Condition Problem

Predictability of the 1st kind
Predictability of the 2nd kind
Predictability of the ?? kind

Meehl et al., BAMS, 2009
Decadal Predictability

At decadal scales:
Internal variability and model uncertainty have more importance than scenario

At centennial scales:
Scenario uncertainty is dominant

ORANGE
Internal Variability: Natural fluctuations in the climate system. AMO, PDO, ENSO etc.

BLUE
Model Uncertainty: Different models respond differently to the same forcing

GREEN
Scenario Uncertainty: Changes in future greenhouse gas emission

Hawkins and Sutton, BAMS, 2009
Decadal Hindcast Example

Hindcast: run a model to assess how well it predicts what has already happened. Compare results to the real world.

10 year hindcasts of the Atlantic meridional circulation:

Some are better than others!

Are some periods more predictable than others?

Mignot et al., 2011
Decadal Hindcast Example

ANN SCREEN TEMPERATURE GLOBAL (K)
annual means

Kirtman, 2011
Decadal Prediction and the IPCC (Intergovernmental Panel on Climate Change)

They have begun exploring decadal predictions with lots of new model experiments in the newest climate change models (CMIP5). However...

“Users of CMIP5 model output should take note that decadal predictions with climate models are in an exploratory stage.... The experiments aim to advance understanding of predictability”

Taylor et al., BAMS, 2012
Decadal Prediction Challenges

1) **Initializing**: we need to know the current conditions of the atmosphere and ocean

2) **Improved climate models**: Need climate models to be more accurate, especially in regions with high decadal variability

3) **Ensembles and Uncertainty**: How to represent errors in the initial conditions

4) **Hindcasts and Evaluation**: How to measure how good or bad a prediction is

5) **Providing regional information to users**: Even if we can make a perfect prediction, how do we tell the people who need to know (governments, water managers, businesses etc.)

*Murphy et al., 2012*
“An improved understanding of decadal climate variability is very important because stakeholders and policymakers want to know the likely climate trajectory for the coming decades for applications to water resources, agriculture, energy, and infrastructure development.”

Mehta et al., BAMS, 2011