Application of artificial neural networks on North Atlantic tropical cyclogenesis potential index in climate change

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Major objectives:

• Project possible changes in tropical cyclone genesis frequency in the Atlantic Basin for the period 2000 – 2099.

• Develop analysis method to alleviate known limitations in TC climate change projections

Two common approaches:

a. Analyze change in TC-like vortexes in GCMs

b. Environmental parameterization for TC and study how the parameters change in GCMs

PROs and CONs?
Revised genesis potential index


\[ GPI \equiv \left| 10^5 \cdot \eta \right|^{\frac{5}{2}} \chi'^4 (1 + 0.2 \cdot \text{shear})^{-4} \]

where

\[ \chi' = \frac{V_{pot}^2}{100 \cdot \text{MAX}(7 m^2 s^{-2} K^{-1}, \frac{L_v q^*}{T} (1 - H) + R_v H q^* \ln H)} \]

\( \eta \) Absolute vorticity at 850hPa (s\(^{-1}\))

\( q^* \) Saturation spec humidity at 600hPa

\( \text{shear} \) Vertical wind shear 850-200 hPa (ms\(^{-1}\))

\( T \) Temperature at 600hPa (K)

\( V_{pot} \) Potential intensity (ms\(^{-1}\))

\( H \) Relative humidity at 600hPa (%)

\( L_v \) Latent heat of vaporization (jkg\(^{-1}\))

\( R_v \) Gas constant for water vapour
TC parameterizations:

New GPI
Emanuel (2010)

TCG
Tippett et al. (2010)

GPI
Emanuel (2007)
Data:

- ECMWF ERA40 (1960-2010)
- Output from 10 IPCC AR4 GCMs (1960 – 2099)

Prelim trend Analysis:

1. No statistically significant trends
2. Peaks due to localized extreme high values
3. Non-systematic
Synoptic typing:

- All summer months of 1960-2099 according to 6 GPI parameters anomalies (output from 10 GCMS)
- Study typical/dominant patterns of genesis environment
- By taking difference between frequency of a pattern in present and future climate
Self organizing maps (SOMs):

• Neural network using unsupervised competitive learning
• Distribution of nodes represents the multi-dimensional distribution function of the data
• With more nodes in data dense regions and fewer at data sparse regions
• Each node represent its features in its nearest measurements and less from far away measurements
• Learns from examples instead of prescribed distributions
• Preserve topology – continuum of states
Back-propagating neural network:
Peak season GPI archetypes
(Aug)

Vertical shear relevance

Peak season vertical shear archetypes
Peak season GPI archetypes (Sept)

Vertical shear relevance

Relative humidity (600hPa) relevance
Peak season GPI archetypes (Sept)

Peak season vertical shear archetypes (Sept)

Peak season relative humidity (600hPa) archetypes (Sept)
### Projection summary:

<table>
<thead>
<tr>
<th>TC season</th>
<th>Spatial change</th>
<th>Magnitude (%)</th>
<th>Main contributor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early season (Jun, Jul)</td>
<td>GPI decrease in common development region (CDR)</td>
<td>-4.353 -29.693</td>
<td>Decreasing relative humidity</td>
</tr>
<tr>
<td>Peak Season (Aug, Sep)</td>
<td>GPI decrease in CDR</td>
<td>-9.175 -19.946</td>
<td>P1: Decreasing relative humidity (600hPa) P2: Increasing vertical shear</td>
</tr>
<tr>
<td>Late Season (Oct, Nov)</td>
<td>GPI decrease in basin centre and Caribbean</td>
<td>-8.199 -15.317</td>
<td>Increasing vertical shear</td>
</tr>
</tbody>
</table>
Conclusion:

- Developed alternate method to project possible changes in TC genesis frequency using existing data and models.
- The 2 types of neural networks combines to alleviate some known limitations in TC climate change projections and capitalize on existing data and methods.
- Expecting less frequent TC genesis but more intense TCs in peak and late TC season.
- Vertical shear and mid-level relative humidity are major contributors.
- Need to experiment with other NN and analyze the physical mechanisms involved in the projected change in mid-level relative humidity and vertical wind shear.