INTRODUCTION

Atmospheric Rivers (ARs) are responsible for 40% of calm transport of water vapor across the eastern Pacific (SE and SW North America). They are a source of the water content of tropical cyclones. ARs are defined by the water vapor content of the transport (WVT) of at least 1,000 kg/m² at z = 0.03 hPa, with no minimum at z = 0.5 hPa. ARs are responsible for bringing significant precipitation to Western North America and replenishing water resources. A strong correlation exists between the occurrence of ARs and the ENSO cycle. Because of the importance of water for water resources management, it is necessary to analyze the characteristics of different types of ARs over a suitable period of time.

OBJECTIVES

(1) Extend the previous study with a climatological characterization for the month of November over the same twenty-year period, 1996-2015. Compare and contrast with those from February ARs.

(2) Design and deploy a machine learning technique for the identification of ARs across a multi-landfall for a long-term dataset.

(3) Explore the challenging task of the identification and characterization of ARs using machine learning techniques.

MATERIALS & METHODS

Data is obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim Reanalysis ( ERA-INTERIM ) dataset for February and November 1996-2015 at a resolution of 0.5° x 0.5°. ARs are defined as having a WVT of at least 1,000 kg/m² at z = 0.03 hPa, with no minimum at z = 0.5 hPa. The raw AR data values are first converted to WVT values using the formula: WVT = (IVT) / (DP) in kg m⁻¹ s⁻¹. ARs are defined as having a WVT of at least 1,000 kg/m² at z = 0.03 hPa, with no minimum at z = 0.5 hPa.

RESULTS

Climatology of AR Events

AR Events: February & November, 1996-2015 (Multiple Location)

Similar to the single point analysis, Fig. 4 shows that there are more recorded AR events in November than in February. While this multi-point analysis, a few more ARs that were not present appear here. For example, the February 2005 AR event is not present in Fig. 4 (a) and (b), while the November 2005 event is present in both of Fig. 4 (a) and (b). Likewise, some ARs, such as the first event of November 1996, are still not captured in both the IVT and WVT data. This is to be expected as the ARs identified in this study include a certain amount of uncertainty, especially for ARs that are close to the coast. ARs identified in this study include a certain amount of uncertainty, especially for ARs that are close to the coast.

REFERENCES


ACKNOWLEDGMENTS

The authors of this study would like to acknowledge the contributions of the following individuals: Dr. Robert B. Schmunk (NASA Goddard) for providing a special beta version of Panoply. This work was supported by the National Science Foundation (NSF) under grant number IIA-1526858.

APPLICATIONS

Machine Learning: Opportunities & Challenges

Traditional methods of detecting ARs in large climate data sets can be tedious and may involve human subjectivity. Instead, “looking” a machine to identify these events can yield faster results and potentially reduce costs. A recent study has explored machine learning for this purpose (Severson et al. 2016). However, the diversity among ARs can be difficult to classify—both for humans and computers. It is likely that a human would not define the same AR in the same way. This is a challenging task to automate the methods of AR identification.

CONCLUSIONS

A previous study focused on characterizing the AR event in early February and considered this event as a model for the entire period of study. This study has an extended 20-year period from 1996-2015. For the February event, the maximum ARs are present in the month of February. For the November event, the maximum ARs are present in the month of November. ARs are classified as having a WVT of at least 1,000 kg/m² at z = 0.03 hPa, with no minimum at z = 0.5 hPa.

These comprehensive results come from a large volume of data, which can be used to support various applications. For example, ARs can be used to improve weather forecasting, aid in disaster management, and support water resource management. The potential applications of this study include improving weather forecasting, disaster management, and water resource management.