DIAGNOSTIC UNDERSTANDING AND DEEP LEARNING BASED PREDICTION OF THE GENESIS OF MONSOON LOW-PRESSURE SYSTEMS

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by

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DEDICATION

To my family and my teachers

A quote that inspires me....

Vidya nigoodaguptha magu viththamu roopamu poorushaalikin,

Vidya yasassu bhogakari vidya gurundu videsa bandhudun ।

Vidya visishtadaivathamu vidyaku saati dhanambu le dilan,

Vidya nrupaala poojithamu vidya nerungani vaadu marthyude ॥

FROM THE BOOK “BHARTHUHARI SATAKAM"

Translates into English from Telugu as: This poem tells us the importance of education. The poet says that education is a hidden treasure, and no thief can steal it. Education improves when it is shared but not lost. He also says an educated person is welcome everywhere and is most respected and treated as a friend, even abroad. Education and knowledge are equal to god, and there is no treasure equal to that. So he says to worship studies and also that a person without education is equal to an animal.

THESIS CERTIFICATE

This is to certify that the thesis entitled "**Diagnostic Understanding and Deep-Learning based Prediction of Indian Summer Monsoon Low-Pressure Systems**", submitted by **Mr. Kompella Siva Santhosh Sai Srujan**, to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is an original bonafide record of the research work done by him under our guidance and supervision. He has fulfilled the requirements for the submission of this thesis. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Place: New Delhi

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ABSTRACT

The relatively weak synoptic-scale tropical storms, known as low-pressure systems (LPSs), contribute as much as 60% of the summer monsoon precipitation over the hugely populated central India. Although LPSs form over all monsoonal regions, they are more prominent over the Indian Summer Monsoon (ISM) domain with 12$\pm$2 systems every June – September period. These rain-bearing systems originating in the Bay of Bengal (BoB) help the South Asian region to meet their irrigation needs, and also, these storms have the potential to cause floods in the Indo-Gangetic regions. Despite its importance in the hydrological cycle of South Asia, the genesis mechanisms of LPSs are not fully known, and these vortices are not properly represented in the current generation climate models either. Therefore, a better understanding of the genesis mechanisms of LPSs helps in representing the LPS-related dynamics in coupled models well, which further minimises the uncertainty in ISM rainfall simulated by these models. The genesis of LPSs is broadly classified into two mechanisms: in situ (LPS_i) and downstream amplification (LPS_d). About a third of total LPSs are formed by the downstream amplification of the westward propagating atmospheric disturbances from the Pacific, and the remaining due to the in situ mechanisms over the BoB.

In chapter 3, Initially, a simple objective-based automated tracking algorithm is developed to classify LPSs into “downstream" and “in situ" LPS based on the propagation of anomaly of relative vorticity at 850 hPa (ζ_{850}) from the West North Pacific (WNP). This algorithm is applied to the models from the fifth and sixth phases of the coupled

model intercomparison project (CMIP5/6), and bulk statistics are presented. Besides the two broader genesis mechanisms (downstream and in situ), a third category named “uncertain cases" is also defined, where both the signals from BoB (for in situ) and WNP (for LPS_d) are present at the same time. Irrespective of their skill in simulating the LPSs, all models have a predominantly in situ genesis mechanism, in line with the observations, with an average of 56% systems falling under this category. Also, in CMIP5, the average downstream genesis in the models is 32%, closer to the observed 30%. Whereas the ensemble mean of CMIP6 shows 29% LPS_d genesis, which is comparable with the observations. Although the bulk statistics of the in situ and LPS_d genesis across the models in boreal summer is comparable to that of observations, substantial inter-model variability is observed in both CMIP 5 and 6. Also, it is observed that there are significant differences in the temporal distribution of downstream LPS genesis in models. Although the models realistically capture the fraction of LPS_d for the whole monsoon season, they tend to simulate a higher number of genesis in the early phase of monsoon as opposed to the observed peak in August and September, which is linked to a stronger Rossby wave activity in the models in June.

The relationship between LPS_d and WNP tropical cyclones (TCs) was investigated in the 1970s and 1980s, but a strong causality has not been established, chapter 4 of the thesis discusses the establishment of causality. In this study, TCs over WNP are grouped into six different clusters on the basis of their genesis location as well as the length and recurvature of the trajectories. This clustering is done using a polynomial mixture regression model. It is observed that the LPS_d genesis is associated with the TCs over WNP. The top four clusters of TCs over WNP, which made landfall over the South China Sea and adjoining land regions and have the least angle of recurvature, contribute to about 83% of the downstream LPS genesis. The diabatic heating from the TCs over the WNP is a major source for the genesis of Rossby waves. Therefore, causality has been established between the fluctuations of the mean sea level pressure (MSLP) over the BoB prior to the initiation of LPSs and the Rossby wave activity over WNP through a transfer entropy analysis. To examine the previously observed link between WNP TCs and LPSs further, sensitivity experiments have been performed using an atmospheric general circulation model (AGCM) by imposing sea surface temperature (SST) warming over two patches over the WNP (one patch is over the genesis locations of TCs in cluster B alone and another patch is over the genesis locations of TCs in cluster A to D) so that the model simulates TCs in desired clusters. In each experiment, the model simulated TCs in clusters, with the size of the clusters proportional to the area of SST warming patches. The LPS genesis frequency over the BoB responded strongly to the SST warming imposed over the WNP, with more sensitivity to the landfalling TC cluster in the South China Sea. It is observed with the simulation of the increased number of TCs that the diabatic heating is enhanced and results in generating/amplifying westward propagating Rossby waves. These sensitivity experiments support the observed hypothesis that the Rossby wave propagation from the WNP TCs triggers the downstream LPSs over BoB.

The ISM rainfall undergoes a cycle of enhancement and weakening, known as active and break spells. This cycle is associated with the large-scale Monsoon Intra-seasonal Oscillation (MISO), which is the dominant mode of sub-seasonal monsoon variability. The LPSs are observed to cluster in the active phase of the MISO. However, the LPS-MISO interaction in the climate models has not yet been investigated. In Chapter 5 of the thesis, the relationship between MISO and LPSs is examined in the historical simulations of 20 coupled models from the CMIP6. It is observed that, as in the observations, the LPSs tend to cluster during the active phase of ISM in the model simulations. The observations show that the frequency of LPS genesis during the active phase of ISM is 2.6 times more than that during the break phase. In the model simulations, the LPS genesis distribution is also skewed towards the positive phase of MISO, albeit with considerable inter-model variability. Irrespective of the genesis types, the LPSs are clustered in the active phase in observations and model simulations. A strong negative meridional shear of zonal wind at 850 hPa ($\frac{dU_{850}}{d\phi}$) is observed over the head BoB, the core LPS genesis region, in both observations and CMIP6 models during the active phase of ISM. The vertical shear simulated by the models differs from the observations. The vertical shear simulated by the CMIP6 models does not vary much between active and break phases. The analyses suggest that part of the uncertainty in simulating the LPSs might be linked to the skill of models in simulating the ζ_{850} pattern over the WNP, which is a key factor in triggering the downstream genesis of LPS.

Finally, considering the importance of LPS in causing floods, the prediction of these storms is important irrespective of their genesis type. Understanding both downstream and in situ LPS genesis mechanisms could lead to a substantial advancement in climate modeling in the long run. However, with the recent advancement in machine learning techniques, this could be easily achieved for immediate action. In Chapter 7 of the dissertation, a framework is developed using the LPS neural operator with a newly introduced Fourier layer (FConvLSTM) to predict the spatial structure of MSLP anomaly over the BoB at a resolution of 1°x1°. In the next step, we reconstructed the MSLP using the predicted anomaly and the climatology, which is then used to track the LPSs using a Lagrangian tracking algorithm. The median pattern correlation between the pre-

dicted and actual mean sea level pressure anomalies over the BoB is about 88%, 60%, and 50% for 24, 48, 72-hour forecasts. The proposed model improves the accuracy of predictions compared with the earlier ConvLSTM models. The pattern correlation between the observed and predicted synoptic activity index is 0.94, 0.9, and 0.87 for 1, 2, and 3-day ahead predictions, respectively. A well-trained model of FConvLSTM takes only $\sim$3.2 s to generate a one-day forecast on a one GPU node of Nvidia V100 in the PADUM supercomputer at IIT Delhi, which is computationally extremely cheap compared to the conventional numerical weather prediction models. The proposed LPS Neural Operator can advance the current operational weather forecasting substantially.

KEYWORDS: Indian Summer Monsoon; Low-Pressure systems; Tropical cyclones; Machine Learning; Bay of Bengal; Causality; Rossby waves

सारांश

अपेक्षाकृत कमजोर सिनोप्टिक-स्केल उष्णकटिबंधीय तूफान, जिन्हें निम्न-दबाव प्रणाली (एलपीएस) के रूप में जाना जाता है, अत्यधिक आबादी वाले मध्य भारत में ग्रीष्मकालीन मानसून वर्षा में 60% का योगदान करते हैं। यद्यपि एलपीएस सभी मानसूनी क्षेत्रों में बनते हैं, वे हर जून-सितंबर अवधि में 12±2 प्रणालियों के साथ भारतीय ग्रीष्मकालीन मानसून (आईएसएम) डोमेन पर अधिक प्रमुख होते हैं। बंगाल की खाड़ी (बीओबी) से उत्पन्न होने वाली ये वर्षा-अवरोधक प्रणालियाँ दक्षिण एशियाई क्षेत्र को उनकी सिंचाई आवश्यकताओं को पूरा करने में मदद करती हैं, और साथ ही, इन तूफानों से भारत-गंगा क्षेत्रों में बाढ़ आने की भी संभावना होती है। दक्षिण एशिया के जल विज्ञान चक्र में इसके महत्व के बावजूद, एलपीएस की उत्पत्ति तंत्र पूरी तरह से ज्ञात नहीं हैं, और इन भंवरों को वर्तमान पीढ़ी के जलवायु मॉडल में भी उचित रूप से प्रस्तुत नहीं किया गया है। इसलिए, एलपीएस की उत्पत्ति तंत्र की बेहतर समझ एलपीएस-संबंधित गतिशीलता का प्रतिनिधित्व करने में मदद करती है युग्मित मॉडलों में अच्छी तरह से, जो इन मॉडलों द्वारा अनुरूपित आईएसएम वर्षा में अनिश्चितता को और कम करता है। एलपीएस की उत्पत्ति को मोटे तौर पर दो तंत्रों में वर्गीकृत किया गया है: स्वस्थानी और डाउनस्ट्रीम प्रवर्धन। कुल एलपीएस का लगभग एक तिहाई हिस्सा प्रशांत क्षेत्र से पश्चिम की ओर फैलने वाले वायुमंडलीय गड़बड़ी के डाउनस्ट्रीम प्रवर्धन द्वारा बनता है, और शेष बीओबी पर सीटू तंत्र के कारण बनता है।

अध्याय 3 में, प्रारंभ में, एक सरल उद्देश्य-आधारित स्वचालित ट्रैकिंग एल्गोरिदम विकसित किया गया है। पश्चिम उत्तरी प्रशांत (डब्ल्यूएनपी) से 850 एचपीए (ζ850) पर सापेक्ष भंवर की विसंगति के प्रसार के आधार पर एलपीएस को "डाउनस्ट्रीम" और "इन सीटू" एलपीएस में वर्गीकृत करें। यह एल्गोरिदम युग्मित मॉडल इंटरकंपेरिसन प्रोजेक्ट (CMIP5/6) के पांचवें और छठे चरण के मॉडल पर लागू किया जाता है, और थोक आंकड़े प्रस्तुत किए जाते हैं। दो व्यापक उत्पत्ति तंत्रों (डाउनस्ट्रीम और इन-सीटू) के अलावा, "अनिश्चित मामलों" नामक एक तीसरी श्रेणी को भी परिभाषित किया गया है, जहां बीओबी (इन-सीटू के लिए) और डब्ल्यूएनपी (डाउनस्ट्रीम एलपीएस के लिए) दोनों सिग्नल एक ही समय पर मौजूद होते हैं। समय। एलपीएस के अनुकरण में उनके कौशल के बावजूद, सभी मॉडलों में मुख्य रूप से सीटू उत्पत्ति तंत्र होता है, अवलोकनों के अनुरूप, औसतन 56% सिस्टम इस श्रेणी में आते हैं। इसके अलावा, सीएमआईपी5 में, औसत डाउनस्ट्रीम उत्पत्ति मॉडलों में 32% है, जो देखे गए 30% के करीब है। जबकि सीएमआईपी6 का समग्र माध्य 29% डाउनस्ट्रीम एलपीएस उत्पत्ति दर्शाता है, जो अवलोकनों के साथ तुलनीय है। हालांकि मॉडलों में सीटू और डाउनस्ट्रीम एलपीएस उत्पत्ति के थोक आंकड़े बोरियल समर अवलोकनों की तुलना में है, सीएमआईपी 5 और 6 दोनों में पर्याप्त अंतर-मॉडल परिवर्तनशीलता देखी गई है। इसके अलावा, यह देखा गया है कि मॉडल में डाउनस्ट्रीम एलपीएस उत्पत्ति के अस्थायी वितरण में महत्वपूर्ण अंतर हैं। हालांकि मॉडल वास्तविक रूप से कैप्चर करते हैं पूरे मानसून सीज़न के लिए

डाउनस्ट्रीम एलपीएस का अंश, वे अगस्त और सितंबर में देखी गई चोटी के विपरीत मानसून के शुरुआती चरण में अधिक संख्या में उत्पत्ति का अनुकरण करते हैं, जो मॉडल में एक मजबूत रॉस्बी लहर गतिविधि से जुड़ा हुआ है। जून में।

एलपीएसडी और डब्ल्यूएनपी उष्णकटिबंधीय चक्रवातों (टीसी) के बीच संबंध की जांच 1970 और 1980 के दशक में की गई थी, लेकिन एक मजबूत कारणता स्थापित नहीं की गई है, थीसिस का अध्याय 4 कारणता की स्थापना पर चर्चा करता है। इस अध्ययन में, डब्ल्यूएनपी पर टीसी को उनके उत्पत्ति स्थान के साथ-साथ प्रक्षेप पथ की लंबाई और पुनरावृत्ति के आधार पर छह अलग-अलग समूहों में बांटा गया है। यह क्लस्टरिंग बहुपद मिश्रण प्रतिगमन मॉडल का उपयोग करके किया जाता है। यह देखा गया है कि डाउनस्ट्रीम एलपीएस उत्पत्ति डब्ल्यूएनपी पर टीसी के साथ जुड़ी हुई है। डब्ल्यूएनपी पर टीसी के शीर्ष चार समूह, जो दक्षिण चीन सागर और आसपास के भूमि क्षेत्रों पर भूस्खलन करते हैं और जिनमें पुनरावृत्ति का कोण सबसे कम है, डाउनस्ट्रीम एलपीएस उत्पत्ति में लगभग 83% का योगदान करते हैं। डब्ल्यूएनपी पर टीसी से डायबेटिक हीटिंग रॉस्बी तरंगों की उत्पत्ति का एक प्रमुख स्रोत है। इसलिए, स्थानांतरण एन्ट्रापी विश्लेषण के माध्यम से एलपीएस की शुरुआत से पहले बीओबी पर औसत समुद्र स्तर दबाव (एमएसएलपी) के उतार-चढ़ाव और डब्ल्यूएनपी पर रॉस्बी तरंग गतिविधि के बीच एक कारणता स्थापित की गई है। डब्ल्यूएनपी टीसी और एलपीएस के बीच पहले देखे गए लिंक की जांच करने के लिए, डब्ल्यूएनपी (एक पैच उत्पत्ति स्थानों पर है) पर दो पैच पर समुद्र की सतह के तापमान (एसएसटी) को गर्म करके वायुमंडलीय सामान्य परिसंचरण मॉडल (एजीसीएम) का उपयोग करके संवेदनशीलता प्रयोग किए गए हैं। अकेले क्लस्टर बी में टीसी की संख्या और एक अन्य पैच क्लस्टर ए से डी में टीसी के उत्पत्ति स्थानों पर है) ताकि मॉडल वांछित समूहों में टीसी का अनुकरण कर सके। प्रत्येक प्रयोग में, मॉडल ने क्लस्टर में टीसी का अनुकरण किया, जिसमें क्लस्टर का आकार एसएसटी वार्मिंग पैच के क्षेत्र के समानुपाती था। दक्षिण चीन सागर में भूस्खलन टीसी क्लस्टर के प्रति अधिक संवेदनशीलता के साथ, बीओबी पर एलपीएस उत्पत्ति आवृत्ति ने डब्ल्यूएनपी पर लगाए गए एसएसटी वार्मिंग पर जोरदार प्रतिक्रिया व्यक्त की। टीसी की बढ़ी हुई संख्या के अनुकरण के साथ यह देखा गया है कि डायबेटिक हीटिंग बढ़ जाती है और इसके परिणामस्वरूप पश्चिम की ओर फैलने वाली रॉस्बी तरंगें उत्पन्न/प्रवर्धित होती हैं। ये संवेदनशीलता प्रयोग समर्थन करते हैं परिकल्पना देखी गई कि डब्ल्यूएनपी टीसी से रॉस्बी तरंग प्रसार ट्रिगर होता है बीओबी पर डाउनस्ट्रीम एलपीएस।

आईएसएम वर्षा वृद्धि और कमजोर होने के एक चक्र से गुजरती है, जिसे सक्रिय और ब्रेक मंत्र के रूप में जाना जाता है। यह चक्र बड़े पैमाने पर मानसून इंट्रा-सीज़नल ऑसिलेशन (MISO) से जुड़ा है, जो उप-मौसमी मानसून परिवर्तनशीलता का प्रमुख तरीका है। एलपीएस को एमआईएसओ के सक्रिय चरण में क्लस्टर करते हुए देखा गया है। हालाँकि, एलपीएस जलवायु मॉडल में एमआईएसओ इंटरेक्शन की अभी तक जांच

नहीं की गई है। के अध्याय 5 में थीसिस, एमआईएसओ और एलपीएस के बीच संबंध की ऐतिहासिक सिम्यू में जांच की जाती है CMIP6 से 20 युग्मित मॉडलों का संयोजन। यह देखा गया है कि, जैसा कि प्रेक्षणों में है, मॉडल सिमुलेशन में आईएसएम के सक्रिय चरण के दौरान एलपीएस क्लस्टर होते हैं। अवलोकनों से पता चलता है कि आईएसएम के सक्रिय चरण के दौरान एलपीएस उत्पत्ति की आवृत्ति होती है ब्रेक चरण के दौरान 2.6 गुना अधिक। मॉडल सिमुलेशन में भी, LPS उत्पत्ति वितरण एमआईएसओ के सकारात्मक चरण की ओर झुका हुआ है, हालांकि इस पर विचार किया जा रहा है इरेबल अंतर-मॉडल परिवर्तनशीलता। उत्पत्ति प्रकार के बावजूद, एलपीएस क्लस्टर किए गए हैं अवलोकनों और मॉडल सिमुलेशन में सक्रिय चरण में। एक मजबूत नकारात्मक मध्याह्न 850 hPa (dU850) पर आंचलिक पवन का आयनल कतरनी प्रमुख BoB, कोर dφ पर देखा जाता है।आईएसएम के सक्रिय चरण के दौरान अवलोकन और सीएमआईपी6 मॉडल दोनों में एलपीएस उत्पत्ति क्षेत्र। मॉडलों द्वारा सिम्युलेटेड ऊर्ध्वाधर कतरनी अवलोकनों से भिन्न होती है। सीएमआईपी6 मॉडल द्वारा सिम्युलेटेड ऊर्ध्वाधर कतरनी सक्रिय और ब्रेक चरणों के बीच ज्यादा भिन्न नहीं होती है। विश्लेषण से पता चलता है कि एलपीएस के अनुकरण में अनिश्चितता का एक हिस्सा डब्ल्यूएनपी पर ζ850 पैटर्न का अनुकरण करने में मॉडल के कौशल से जुड़ा हो सकता है, जो एलपीएस की डाउनस्ट्रीम उत्पत्ति को ट्रिगर करने में एक महत्वपूर्ण कारक है।

अंत में, बाढ़ पैदा करने में एलपीएस के महत्व को देखते हुए, इन तूफानों की भविष्यवाणी उनकी उत्पत्ति के प्रकार की परवाह किए बिना महत्वपूर्ण है। डाउनस्ट्रीम और इन-सीटू एलपीएस उत्पत्ति तंत्र दोनों को समझने से लंबे समय में जलवायु मॉडलिंग में पर्याप्त प्रगति हो सकती है। हालाँकि, मशीन लर्निंग तकनीकों में हालिया प्रगति के साथ, इसे तत्काल कार्रवाई के लिए आसानी से हासिल किया जा सकता है। शोध प्रबंध के अध्याय 7 में, 1◦x1◦ के रिज़ॉल्यूशन पर बीओबी पर एमएसएलपी विसंगति की स्थानिक संरचना की भविष्यवाणी करने के लिए एक नई शुरू की गई फूरियर परत (एफसीओएनवीएलएसटीएम) के साथ एलपीएस न्यूरल ऑपरेटर का उपयोग करके एक रूपरेखा विकसित की गई है। अगले चरण में, हमने अनुमानित विसंगति और जलवायु विज्ञान का उपयोग करके एमएसएलपी का पुनर्निर्माण किया, जिसका उपयोग लैग्रेंजियन ट्रैकिंग एल्गोरिदम का उपयोग करके एलपीएस को ट्रैक करने के लिए किया जाता है। बीओबी पर अनुमानित और वास्तविक औसत समुद्र स्तर दबाव विसंगतियों के बीच औसत पैटर्न सहसंबंध 24, 48, 72-घंटे के पूर्वानुमान के लिए लगभग 88%, 60% और 50% है। प्रस्तावित मॉडल पहले के ConvLSTM मॉडल की तुलना में भविष्यवाणियों की सटीकता में सुधार करता है। प्रेक्षित और पूर्वानुमानित सिनोप्टिक गतिविधि सूचकांक के बीच पैटर्न सहसंबंध क्रमशः 1, 2, और 3-दिन आगे की भविष्यवाणियों के लिए 0.94, 0.9 और 0.87 है। FConvLSTM का एक अच्छी तरह से प्रशिक्षित मॉडल आईआईटी दिल्ली में PADUM सुपरकंप्यूटर में Nvidia V100 के एक

GPU नोड पर एक दिवसीय पूर्वानुमान उत्पन्न करने के लिए केवल ~3.2 सेकंड लेता है, जो पारंपरिक संख्यात्मक मौसम पूर्वानुमान मॉडल की तुलना में कम्प्यूटेशनल रूप से बेहद सस्ता है। प्रस्तावित एलपीएस न्यूरल ऑपरेटर वर्तमान परिचालन मौसम पूर्वानुमान को काफी हद तक आगे बढ़ा सकता है।

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ABBREVIATIONS

AGCM	Atmospheric General Circulation Model
AI	Artificial Intelligence
BoB	Bay of Bengal
CAM5	Community Atmospheric Model of version 5
CESM	Community Earth System Model
CMIP	Coupled Model Intercomparison Project
CMIP5	fifth phase of the coupled model inter-comparison project
CMIP6	sixth phase of the coupled model inter-comparison project
CNN	Convolutional Neural Network
ConvLSTM	Convolutional Long short-term memory
DL	Deep Learning
ECMRWF	European Centre for Medium-Range Weather Forecasts
ERE	Extreme Rainfall Event

EOF	Empirical Orthogonal Function
ERAI	European Center interim reanalysis
ERA5	European Centre for Medium-Range Weather Forecasts' fifth generation
IMD	India Meteorological Department
ISM	Indian Summer Monsoon
JJAS	June to September
JTWC	Joint Typhoon Warning Center
LPS	low-pressure system
LSTM	Long Sort long-Term Memory
MCZ	Maximum Cloud Zone
MISO	Monsoon Intraseasonal Oscillation
ML	Machine Learning
MSE	Mean Squared Error
MSLP	Mean Sea Level Pressure
NOAA	National Oceanographic and Atmospheric Administration

NWP	numerical weather prediction
OLR	Outgoing Longwave Radiation
PC1	leading principal component
PV	Potential Vorticity
RMSE	Root Mean Squared Error
SLP	Sea Level Pressure
SST	Sea Surface Temperature
TC	Tropical Cyclone
TE	Transfer Entropy
TRMM	Tropical Rainfall Measuring Mission
WNP	Western North Pacific
WP	West Pacific