

## Nonlinear atmospheric variability in the winter northeast Pacific associated with the Madden-Julian oscillation

Cédric Jamet and William W. Hsieh

Department of Earth and Ocean Sciences, University of British Columbia, Vancouver, British Columbia, Canada

Received 17 May 2005; accepted 13 June 2005; published XX Month 2005.

[1] The Madden-Julian Oscillation (MJO), the primary mode of large-scale intraseasonal variability in the tropics, is known to relate to the mid-latitude atmospheric variability. Using neural network techniques, a nonlinear projection of the MJO onto the precipitation and 200-hPa wind anomalies in the northeast Pacific during January–March shows asymmetric atmospheric patterns associated with different phases of the MJO. For precipitation, the strength of the nonlinear effect to the linear effect was 0.94 (in terms of the squared anomalies and averaged over all phases of the MJO), indicating strong nonlinearity, while for the 200-hPa wind, the ratio was 0.55, indicating moderate nonlinearity. In general, anomalous winds blowing from the north or from land were associated with negative precipitation anomalies, while winds from the south or from the open ocean, with positive precipitation anomalies. The nonlinear effects generally induced positive precipitation anomalies during all phases of the MJO. **Citation:** Jamet, C., and W. W. Hsieh (2005), Nonlinear atmospheric variability in the winter northeast Pacific associated with the Madden-Julian oscillation, *Geophys. Res. Lett.*, *32*, LXXXXX, doi:10.1029/2005GL023533.

### 1. Introduction

[2] The Madden-Julian Oscillation (MJO) is the dominant mode of the subseasonal tropospheric variability over the tropical Indian and Pacific Oceans. The MJO was originally identified as a coherent, eastward-propagating perturbation in the tropical sea level pressure, upper level zonal wind and atmospheric convection, with a relatively broad spectral peak of 30–90 days [Madden and Julian, 1994]. The impact of the MJO on the atmospheric circulation outside of the tropics has been of considerable interest. There is evidence that deep tropical convection forces the mid-latitude flow both directly [Hoskins and Karoly, 1981; Horel and Wallace, 1981] and indirectly [Schubert and Park, 1991]. Connections have been found between mid-latitude weather variations and the MJO [Higgins and Mo, 1997; Mo and Higgins, 1998; Jones, 2000; Bond and Vecchi, 2003, hereinafter referred to as BV]. Most of the studies on the MJO used an index to present and explain the MJO life cycle in the tropics and extratropics. These studies worked with linear methods, e.g. phase sum composite, correlation, regression [Hendon and Salby, 1994; Knutson and Weickmann, 1987; Rui and Wang, 1990; Maloney and Hartmann, 1998; BV]. Recently, a multiple linear regression model has been used to analyse the relationships

between eastward- and westward-moving intraseasonal modes by Roundy and Frank [2004], who concluded that the regression model produced physically valid analyses that revealed processes of partly nonlinear wave interactions in the tropical atmosphere.

[3] In recent years, neural network (NN) methods have been increasingly applied to nonlinearly study the atmosphere and oceans, with reviews given by Hsieh and Tang [1998] and Hsieh [2004]. In this study, we apply fully nonlinear NN techniques to create a nonlinear composite life cycle and try to separate the linear and nonlinear responses of the atmosphere to the MJO. The association between the MJO and the climate in the northeast Pacific is investigated by applying a nonlinear projection (i.e. nonlinear regression) of the BV MJO index onto the 200-hPa wind and precipitation anomalies during winter (January–March). If  $x$  denotes the MJO index and  $y$ , the atmospheric response to MJO, the nonlinear response function  $y = f(x)$  can be obtained via NN [Wu and Hsieh, 2004] (the nonlinear projection by NN is simply called an *NN projection* thereafter). In contrast to the linear projection, the NN projection detects the fully nonlinear atmospheric variability associated with MJO. As the effects of the MJO over northeast Pacific and the northwestern part of North America (esp. western Canada) is not well documented, the purpose of this study is to reveal the nonlinear association between the winter precipitation and 200 hPa wind anomalies in the northeast Pacific and the tropical MJO.

### 2. Data and Methods

[4] To characterize the state of the MJO, we used the MJO index developed by Bond and Vecchi [2003], available for the period from January 1, 1980 to December 31, 2003. This index is composed of an amplitude  $A$  and a phase  $\Phi$  based on the two leading principal components of the intraseasonal 850-hPa zonal wind in the 5°S–5°N band. An MJO event is defined as a period of 30 or more days during which  $A$  exceeds 0.7 standard deviation and during which  $\Phi$  corresponds to eastward propagation for the entire period. In the  $A$  and  $\Phi$  time series, values are only defined during MJO events.

[5] For the variability in northeast Pacific, we examined the daily 200-hPa wind from the NCEP-NCAR extended reanalysis product [Kalnay et al., 1996] and the daily MSU precipitation (both downloadable from <http://www.cdc.noaa.gov>). The precipitation data, available during 1979–1995, were derived from channel 1 of the microwave sounding unit, which is sensitive to emission by cloud water and rainfall in the lowest few kilometers of the

104 atmosphere [Spencer, 1993]. The MSU precipitation prod-  
 105 uct is only usable over the ocean. For both datasets, the  
 106 daily climatological means were subtracted from the daily  
 107 values to yield the anomalies. To obtain intraseasonal  
 108 anomalies, a Lanczos response bandpass filter with 240  
 109 weights and cutoff periods at 35 and 120 days was applied  
 110 to the wind and precipitation anomalies [Duchon, 1979]. We  
 111 studied the period 1980–1995 during the months January,  
 112 February and March for both datasets and the MJO index.  
 113 The analysis was performed only when MJO events were  
 114 present, thus shrinking the data record to 968 days. Our  
 115 study is focused on the northeast Pacific area, between  
 116 30°N–60°N and 150°W–112.5°W.

117 [6] After removing the linear trend, a combined prin-  
 118 cipal component analysis (PCA) was used to compress  
 119 the meridional and zonal wind anomalies, with the  
 120 8 leading principal components (PC) (accounting for  
 121 95.2% of the variance) retained. For the precipitation  
 122 anomalies, the 8 leading PCs, accounting for 64.4% of  
 123 the variance, were retained. Analysis using different  
 124 number of PCs showed that our results were not sensitive  
 125 to the number of modes retained as long as 8 or more  
 126 PCs were used.

127 [7] The multi-layer perceptron NN model with 1-hidden  
 128 layer used here has a similar structure to the multivariate  
 129 nonlinear regression model used for ENSO prediction by  
 130 our group [Hsieh and Tang, 1998]. Here, the NN model has  
 131 two inputs (predictors)  $A \cos \Phi$  and  $A \sin \Phi$  (from the MJO  
 132 index) and 8 output variables (the 8 leading PCs of the  
 133 200-hPa wind anomalies or precipitation anomalies). The  
 134 inputs were first nonlinearly mapped to intermediate vari-  
 135 ables  $h_j$  (called hidden neurons), which were then linearly  
 136 mapped to the 8 output variables  $p_k$ , i.e.

$$h_j = \tanh(w_j A \cos \Phi + \tilde{w}_j A \sin \Phi + b_j),$$

$$p_k = \sum_j \tilde{w}_{jk} + \tilde{b}_k,$$

140 where  $\tilde{w}_j$ ,  $w_j$ ,  $\tilde{w}_{jk}$ ,  $b_j$  and  $\tilde{b}_k$  are the model parameters. With  
 141 enough hidden neurons, the NN model is capable of  
 142 modeling any nonlinear continuous function to arbitrary  
 143 accuracy. Starting from random initial values, the NN  
 144 model parameters were optimized so that the mean square  
 145 error (MSE) between the 8 model outputs and the  
 146 8 observed PCs was minimized. To avoid local minima  
 147 during optimization [Hsieh and Tang, 1998], the NN  
 148 model was trained repeatedly 25 times from random initial  
 149 parameters and the solution with the smallest MSE was  
 150 chosen.

151 [8] To reduce the possible sampling dependence of  
 152 a single NN solution, we repeated the above calculation  
 153 100 times with a bootstrap approach. A bootstrap sample  
 154 was obtained by randomly selecting data (with replacement)  
 155 968 times from the original record of 968 days, so that on  
 156 average about 63% of the original record was chosen in a  
 157 bootstrap sample [Efron and Tibshirani, 1993]. The ensemble  
 158 mean of the resulting 100 NN models was used as the  
 159 final NN solution, found to be insensitive to the number of  
 160 hidden neurons, which was varied from 2 to 10 in a  
 161 sensitivity test. Results from using 4 hidden neurons are

presented. For comparison, the linear regression (LR) model  
 is simply

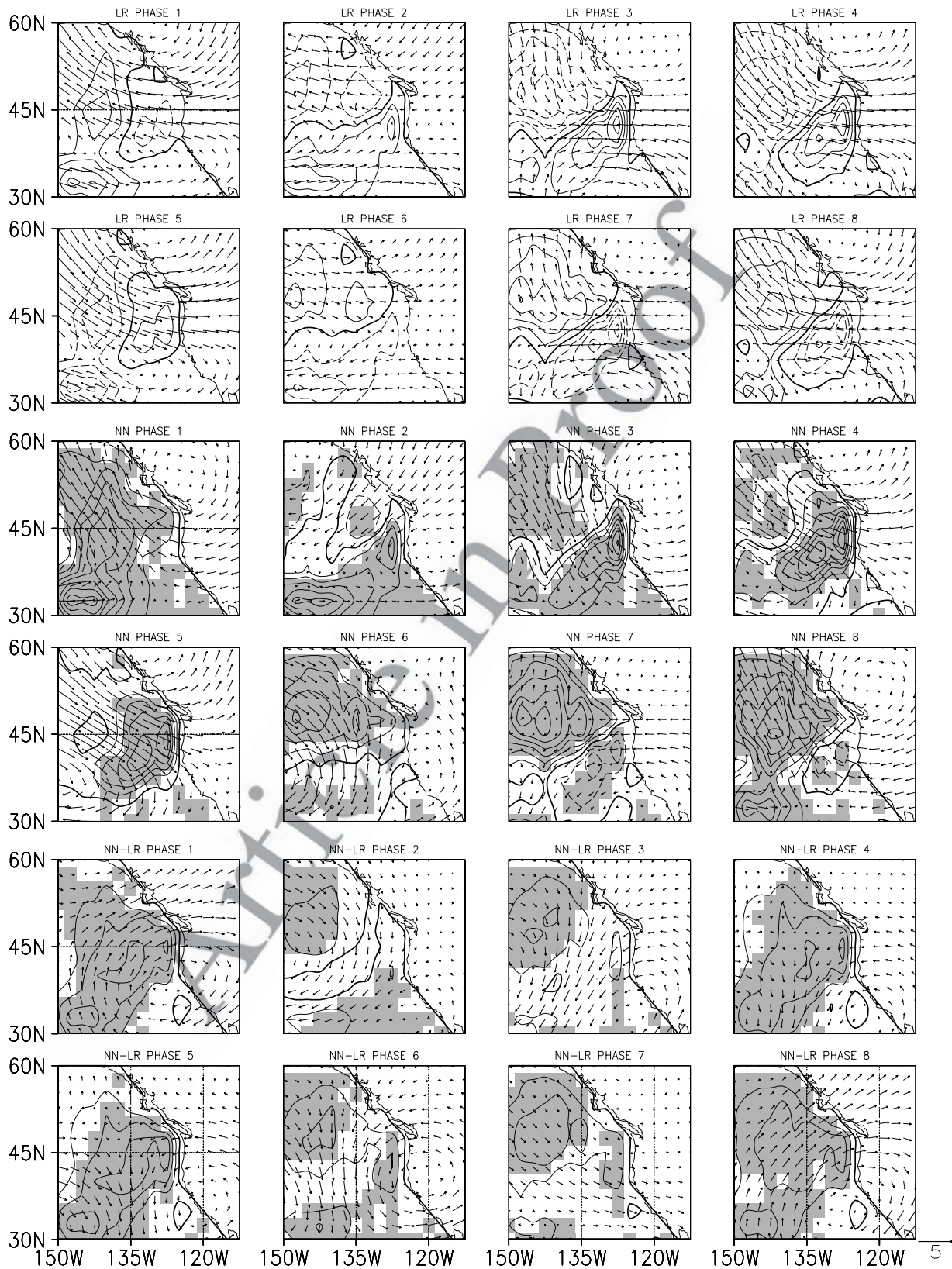
$$p_k = w_k A \cos \Phi + \tilde{w}_k A \sin \Phi + b_k.$$

### 3. Results

[9] The output signal from the NN projection is man-  
 ifested by a surface in the 8 dimensional space spanned by  
 the PCs; in contrast, the linear projection from LR is  
 manifested by a plane in the same 8-D space (not shown).  
 The phase of the MJO was binned into eight equal parts as  
 in BV, phase 1 ( $-\pi \leq \Phi < -3\pi/4$ ), ..., phase 8 ( $3\pi/4 \leq$   
 $\Phi < \pi$ ). of the model outputs were computed for each  
 phase bin by averaging all data with  $\Phi$  falling within a given  
 bin. Also by combining the PCs with their corresponding  
 spatial patterns (the empirical orthogonal functions) yielded  
 the spatial anomalies during each phase of the MJO. The  
 composite spatial anomalies of the 200-hPa wind and  
 precipitation are shown during the 8 MJO phases in Figure 1,  
 where the top two rows are the LR results, the middle two  
 rows, the NN results, and the bottom two rows, the nonlin-  
 ear residual (i.e. the NN projection minus the LR projec-  
 tion). The corresponding tropical behaviour of the MJO  
 during the 8 phases are shown in Figure 1 of BV.

[10] With the LR projection, the composites for two out-  
 of-phase bins (e.g. bin 1 and 5, 2 and 6, 3 and 7, 4 and 8)  
 gave essentially the same spatial patterns but with oppo-  
 sitely signed anomalies (Figure 1), due to the limitations of  
 the LR method. In contrast, for the NN projection, the  
 patterns and the amplitudes of the 200-hPa wind and  
 precipitation anomalies changed as the phase of the MJO  
 varied across the bins, without showing the strict antisym-  
 metry between two out-of-phase bins. For instance, during  
 phase 1 with LR projection, there is a dipole structure in the  
 precipitation anomalies, with negative anomalies along the  
 coast and positive anomalies further west. The superim-  
 posed wind composite shows wind blowing from the land  
 north of 40°N (Figure 1). In the NN projection during phase  
 1, there is no dipole structure in the precipitation anomalies,  
 but only a large tongue of positive anomalies in the open  
 ocean with a maximum value of 0.7 mm day<sup>-1</sup>, much  
 greater than the maximum of 0.4 mm day<sup>-1</sup> found in the LR  
 phase 1 projection. In the NN phase 1, there is an anticy-  
 clonic cell over British Columbia, centered just north of  
 Vancouver Island. Generally, over all 8 phases and for both  
 the NN and LR projections, there is quite good agreement  
 between the wind anomalies and the precipitation anomalies  
 (Figure 1), with wind blowing from the north and from land  
 associated with negative precipitation anomalies, and wind  
 blowing from the south and from the open ocean, with  
 positive precipitation anomalies, as expected.

[11] By subtracting the LR projection from the NN  
 projection, the nonlinear residual (bottom two rows of  
 Figure 1) represents the purely nonlinear response after  
 the removal of the linear response. The nonlinear residual  
 for precipitation shows weak nonlinearity during phase 2  
 and 3 (with maximum anomalies about 0.1 mm day<sup>-1</sup>) and  
 strong nonlinearity during phase 1, 4 and 5, with anomalies  
 reaching about 0.3 mm day<sup>-1</sup>. The lack of comparable  
 negative anomalies in the nonlinear residual indicates that



**Figure 1.** Composites during the 8 phases of the MJO for the LR projection (top two rows), the NN projection (middle two rows) and the nonlinear residual (NN-LR) (bottom two rows), with precipitation anomalies shown in contour maps and 200-hPa wind anomalies by vectors. With negative contours dashed and zero contours thickened, the contour interval is  $0.1 \text{ mm day}^{-1}$ , and the scale for the wind ( $5 \text{ m s}^{-1}$ ) given beside the bottom right panel. The shaded areas indicate statistical significance for the precipitation anomalies at the 5% level based on the bootstrap distribution.

221 the nonlinear effects tend to induce positive precipitation  
222 anomalies over all phases of the MJO.

223 [12] We next computed the average of the squared  
224 precipitation anomalies in each panel in Figure 1, and let  
225  $r$  be the ratio between this computed value for the nonlinear  
226 residual and that for the LR projection during a given phase.  
227 For phase 1 to phase 8, the values of  $r$  are 1.69, 0.25, 0.26,  
228 1.18, 1.79, 0.86, 0.56 and 0.96, respectively, which supports  
229 our claim that nonlinearity is weak during phase 2 and 3,  
230 but strong during phase 1, 4 and 5, where  $r$  actually exceeds  
231 1 in all three phases (meaning that the squared anomalies of  
232 the nonlinear residual averaged over the spatial domain  
233 exceeds the corresponding value from the linear projection).

234 [13] For the wind speed anomalies, the  $r$  values are 0.37,  
235 0.52, 0.69, 0.15, 0.19, 1.74, 0.28 and 0.43 during phase 1 to  
236 phase 8, respectively. The nonlinear effect is weakest during  
237 phase 4 and 5 and strongest during phase 6, where there is a  
238 strong cyclonic cell on the West Coast. Averaged over all  
239 8 phases,  $r$  is 0.55, versus an average  $r$  of 0.94 for  
240 precipitation. Thus the overall nonlinear effect is stronger  
241 in the precipitation than in the wind. We expect precipitation  
242 to be more nonlinear than wind, as precipitation depends on  
243 temperature and moisture convergence besides wind, and  
244 latent heat, which is governed by a step function, introduces  
245 strong nonlinearity into precipitation.

#### 246 4. Conclusion

247 [14] This study has applied a fully nonlinear technique to  
248 study the nonlinear association between the MJO and the  
249 northeast Pacific variability of precipitation and 200-hPa  
250 wind during January–March. By projecting from the MJO  
251 index to the variables in the northeast Pacific, the linear and  
252 nonlinear response to MJO were found. For precipitation,  
253 the strength of the nonlinear effect to the linear effect was  
254 0.94 (in terms of the squared anomalies and averaged over  
255 all phases of the MJO). This means the nonlinear effect was  
256 essentially of the same strength as the linear effect. For the  
257 200-hPa wind, the ratio was 0.55, indicating moderate  
258 nonlinearity. In general, anomalous winds blowing from  
259 the north or from land were associated with negative  
260 precipitation anomalies, while winds from the south or from  
261 the open ocean, with positive precipitation anomalies. The  
262 nonlinear effects generally induced positive precipitation  
263 anomalies during all phases of the MJO. Follow-on work  
264 could further explore time lags between MJO and variables  
265 in the northeast Pacific.

266 [15] **Acknowledgments.** The authors would like to thank Dr. Gabriel  
267 Vecchi for providing his MJO index, and Drs. Phil Austin and Aiming Wu

for their useful comments. The authors acknowledge the support from the 268  
Natural Sciences and Engineering Research Council of Canada via research 269  
and strategic grants. 270

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W. W. Hsieh and C. Jamet, Department of Earth and Ocean Sciences, 326  
University of British Columbia, 6339 Stores Road, Vancouver, BC, Canada 327  
V6T 1Z4. (whsieh@eos.ubc.ca; cjamet@eos.ubc.ca) 328