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

4 Cédric Jamet and William W. Hsieh

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

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8 [1] The Madden-Julian Oscillation (MJO), the primary mode of large-scale intraseasonal variability in the tropics, 9 is known to relate to the mid-latitude atmospheric 10variability. Using neural network techniques, a nonlinear 11 projection of the MJO onto the precipitation and 200-hPa 12 wind anomalies in the northeast Pacific during January-13 March shows asymmetric atmospheric patterns associated 14 with different phases of the MJO. For precipitation, the 15 strength of the nonlinear effect to the linear effect was 0.94 16(in terms of the squared anomalies and averaged over all 17phases of the MJO), indicating strong nonlinearity, while for 18 the 200-hPa wind, the ratio was 0.55, indicating moderate 1920nonlinearity. In general, anomalous winds blowing from the north or from land were associated with negative 21precipitation anomalies, while winds from the south or 22from the open ocean, with positive precipitation anomalies. 23The nonlinear effects generally induced positive 24precipitation anomalies during all phases of the MJO. 25Citation: Jamet, C., and W. W. Hsieh (2005), Nonlinear 26atmospheric variability in the winter northeast Pacific associated 27with the Madden-Julian oscillation, Geophys. Res. Lett., 32, 2830 LXXXXX, doi:10.1029/2005GL023533.

31 **1. Introduction**

[2] The Madden-Julian Oscillation (MJO) is the domi-32 nant mode of the subseasonal tropospheric variability over 33 the tropical Indian and Pacific Oceans. The MJO was 34originally identified as a coherent, eastward-propagating 35perturbation in the tropical sea level pressure, upper level 36 zonal wind and atmospheric convection, with a relatively 37 broad spectral peak of 30-90 days [Madden and Julian, 38 1994]. The impact of the MJO on the atmospheric circula-39 40 tion outside of the tropics has been of considerable interest. There is evidence that deep tropical convection forces the 41 mid-latitude flow both directly [Hoskins and Karoly, 1981; 42 Horel and Wallace, 1981] and indirectly [Schubert and 43 Park, 1991]. Connections have been found between mid-44 latitude weather variations and the MJO [Higgins and Mo, 451997; Mo and Higgins, 1998; Jones, 2000; Bond and 46Vecchi, 2003, hereinafter referred to as BV]. Most of the 47studies on the MJO used an index to present and explain the 48 MJO life cycle in the tropics and extratropics. These studies 49worked with linear methods, e.g. phase sum composite, 50correlation, regression [Hendon and Salby, 1994; Knutson 51and Weickmann, 1987; Rui and Wand, 1990; Maloney and 52Hartmann, 1998; BV]. Recently, a multiple linear regres-53sion model has been used to analyse the relationships 54

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between eastward- and westward-moving intraseasonal 55 modes by *Roundy and Frank* [2004], who concluded that 56 the regression model produced physically valid analyses 57 that revealed processes of partly nonlinear wave interactions 58 in the tropical atmosphere. 59

[3] In recent years, neural network (NN) methods have 60 been increasingly applied to nonlinearly study the atmo- 61 sphere and oceans, with reviews given by Hsieh and Tang 62 [1998] and Hsieh [2004]. In this study, we apply fully 63 nonlinear NN techniques to create a nonlinear composite 64 life cycle and try to separate the linear and nonlinear 65 responses of the atmosphere to the MJO. The association 66 between the MJO and the climate in the northeast Pacific is 67 investigated by applying a nonlinear projection (i.e. nonli- 68 near regression) of the BV MJO index onto the 200-hPa 69 wind and precipitation anomalies during winter (January- 70 March). If x denotes the MJO index and y, the atmospheric 71 response to MJO, the nonlinear response function y = f(x) 72 can be obtained via NN [Wu and Hsieh, 2004] (the 73 nonlinear projection by NN is simply called an NN 74 projection thereafter). In contrast to the linear projection, 75 the NN projection detects the fully nonlinear atmospheric 76 variability associated with MJO. As the effects of the 77 MJO over northeast Pacific and the northwestern part of 78 North America (esp. western Canada) is not well docu-79 mented, the purpose of this study is to reveal the 80 nonlinear association between the winter precipitation 81 and 200 hPa wind anomalies in the northeast Pacific 82 and the tropical MJO. 83

2. Data and Methods

[4] To characterize the state of the MJO, we used the 85 MJO index developed by *Bond and Vecchi* [2003], available 86 for the period from January 1, 1980 to December 31, 2003. 87 This index is composed of an amplitude A and a phase Φ 88 based on the two leading principal components of the 89 intraseasonal 850-hPa zonal wind in the 5°S-5°N band. 90 An MJO event is defined as a period of 30 or more days 91 during which A exceeds 0.7 standard deviation and during 92 which Φ corresponds to eastward propagation for the entire 93 period. In the A and Φ time series, values are only defined 94 during MJO events.

[5] For the variability in northeast Pacific, we examined 96 the daily 200-hPa wind from the NCEP-NCAR extended 97 reanalysis product [*Kalnay et al.*, 1996] and the daily 98 MSU precipitation (both downloadable from http:// 99 www.cdc.noaa.gov). The precipitation data, available 100 during 1979–1995, were derived from channel 1 of the 101 microwave sounding unit, which is sensitive to emission by 102 cloud water and rainfall in the lowest few kilometers of the 103

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atmosphere [Spencer, 1993]. The MSU precipitation prod-104uct is only usable over the ocean. For both datasets, the 105daily climatological means were subtracted from the daily 106values to yield the anomalies. To obtain intraseasonal 107 108 anomalies, a Lanczos response bandpass filter with 240 109weights and cutoff periods at 35 and 120 days was applied to the wind and precipitation anomalies [Duchon, 1979]. We 110 studied the period 1980-1995 during the months January, 111 February and March for both datasets and the MJO index. 112 The analysis was performed only when MJO events were 113present, thus shrinking the data record to 968 days. Our 114study is focused on the northeast Pacific area, between 11530°N-60°N and 150°W-112.5°W. 116

[6] After removing the linear trend, a combined prin-117 cipal component analysis (PCA) was used to compress 118the meridional and zonal wind anomalies, with the 1198 leading principal components (PC) (accounting for 12095.2% of the variance) retained. For the precipitation 121 anomalies, the 8 leading PCs, accounting for 64.4% of 122the variance, were retained. Analysis using different 123number of PCs showed that our results were not sensitive 124125to the number of modes retained as long as 8 or more PCs were used. 126

[7] The multi-layer perceptron NN model with 1-hidden 127layer used here has a similar structure to the multivariate 128nonlinear regression model used for ENSO prediction by 129our group [Hsieh and Tang, 1998]. Here, the NN model has 130two inputs (predictors) $A \cos \Phi$ and $A \sin \Phi$ (from the MJO 131 index) and 8 output variables (the 8 leading PCs of the 132200-hPa wind anomalies or precipitation anomalies). The 133inputs were first nonlinearly mapped to intermediate vari-134ables h_i (called hidden neurons), which were then linearly 135mapped to the 8 output variables p_k , i.e. 136

$$h_j = \tanh\left(w_j A \cos \Phi + \hat{w}_j A \sin \Phi + b_j\right)$$

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

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where $\hat{w}_i, w_i, \tilde{w}_{ik}, b_i$ and \hat{b}_k are the model parameters. With 140 enough hidden neurons, the NN model is capable of 141 modeling any nonlinear continuous function to arbitrary 142143accuracy. Starting from random initial values, the NN 144model parameters were optimized so that the mean square error (MSE) between the 8 model outputs and the 1458 observed PCs was minimized. To avoid local minima 146 during optimization [Hsieh and Tang, 1998], the NN 147model was trained repeatedly 25 times from random initial 148 parameters and the solution with the smallest MSE was 149chosen. 150

[8] To reduce the possible sampling dependence of 151 a single NN solution, we repeated the above calculation 152100 times with a bootstrap approach. A bootstrap sample 153was obtained by randomly selecting data (with replacement) 154968 times from the original record of 968 days, so that on 155156average about 63% of the original record was chosen in a bootstrap sample [Efron and Tibshirani, 1993]. The ensem-157158ble mean of the resulting 100 NN models was used as the 159final NN solution, found to be insensitive to the number of hidden neurons, which was varied from 2 to 10 in a 160sensitivity test. Results from using 4 hidden neurons are 161

presented. For comparison, the linear regression (LR) model 162 is simply 163

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

3. Results

[9] The output signal from the NN projection is man- 167 ifested by a surface in the 8 dimensional space spanned by 168 the PCs; in contrast, the linear projection from LR is 169 manifested by a plane in the same 8-D space (not shown). 170 The phase of the MJO was binned into eight equal parts as 171 in BV, phase 1 ($-\pi \le \Phi < -3\pi/4$), ..., phase 8 ($3\pi/4 \le 172$ $\Phi < \pi$). of the model outputs were computed for each 173 V_{cdp} phase bin by averaging all data with Φ falling within a given 174 bin. Also by combining the PCs with their corresponding 175 spatial patterns (the empirical orthogonal functions) yielded 176 the spatial anomalies during each phase of the MJO. The 177 composite spatial anomalies of the 200-hPa wind and 178 precipitation are shown during the 8 MJO phases in Figure 1, 179 where the top two rows are the LR results, the middle two 180 rows, the NN results, and the bottom two rows, the nonlin- 181 ear residual (i.e. the NN projection minus the LR projec- 182 tion). The corresponding tropical behaviour of the MJO 183 during the 8 phases are shown in Figure 1 of BV. 184

[10] With the LR projection, the composites for two out- 185 of-phase bins (e.g. bin 1 and 5, 2 and 6, 3 and 7, 4 and 8) 186 gave essentially the same spatial patterns but with oppo-187 sitely signed anomalies (Figure 1), due to the limitations of 188 the LR method. In contrast, for the NN projection, the 189 patterns and the amplitudes of the 200-hPa wind and 190 precipitation anomalies changed as the phase of the MJO 191 varied across the bins, without showing the strict antisym- 192 metry between two out-of-phase bins. For instance, during 193 phase 1 with LR projection, there is a dipole structure in the 194 precipitation anomalies, with negative anomalies along the 195 coast and positive anomalies further west. The superim- 196 posed wind composite shows wind blowing from the land 197 north of 40°N (Figure 1). In the NN projection during phase 198 1, there is no dipole structure in the precipitation anomalies, 199 but only a large tongue of positive anomalies in the open 200 ocean with a maximum value of 0.7 mm day⁻¹, much 201 greater than the maximum of 0.4 mm day⁻¹ found in the LR 202 phase 1 projection. In the NN phase 1, there is an anticy- 203 clonic cell over British Columbia, centered just north of 204 Vancouver Island. Generally, over all 8 phases and for both 205 the NN and LR projections, there is quite good agreement 206 between the wind anomalies and the precipitation anomalies 207 (Figure 1), with wind blowing from the north and from land 208 associated with negative precipitation anomalies, and wind 209 blowing from the south and from the open ocean, with 210 positive precipitation anomalies, as expected. 211

[11] By subtracting the LR projection from the NN 212 projection, the nonlinear residual (bottom two rows of 213 Figure 1) represents the purely nonlinear response after 214 the removal of the linear response. The nonlinear residual 215 for precipitation shows weak nonlinearity during phase 2 216 and 3 (with maximum anomalies about 0.1 mm day⁻¹) and 217 strong nonlinearity during phase 1, 4 and 5, with anomalies 218 reaching about 0.3 mm day⁻¹. The lack of comparable 219 negative anomalies in the nonlinear residual indicates that 220

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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 mm day^{-1} , and the scale for the wind (5 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.

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

[12] We next computed the average of the squared 223precipitation anomalies in each panel in Figure 1, and let 224r be the ratio between this computed value for the nonlinear 225226residual and that for the LR projection during a given phase. 227For phase 1 to phase 8, the values of r are 1.69, 0.25, 0.26, 1.18, 1.79, 0.86, 0.56 and 0.96, respectively, which supports 228our claim that nonlinearity is weak during phase 2 and 3, 229but strong during phase 1, 4 and 5, where r actually exceeds 2301 in all three phases (meaning that the squared anomalies of 231the nonlinear residual averaged over the spatial domain 232exceeds the corresponding value from the linear projection). 233

[13] For the wind speed anomalies, the *r* values are 0.37, 2340.52, 0.69, 0.15, 0.19, 1.74, 0.28 and 0.43 during phase 1 to 235 phase 8, respectively. The nonlinear effect is weakest during 236phase 4 and 5 and strongest during phase 6, where there is a 237strong cyclonic cell on the West Coast. Averaged over all 238 8 phases, r is 0.55, versus an average r of 0.94 for 239precipitation. Thus the overall nonlinear effect is stronger 240in the precipitation than in the wind. We expect precipitation 241242to be more nonlinear than wind, as precipitation depends on temperature and moisture convergence besides wind, and 243244latent heat, which is governed by a step function, introduces

strong nonlinearity into precipitation. 245

4. Conclusion 246

[14] This study has applied a fully nonlinear technique to 247study the nonlinear association between the MJO and the 248northeast Pacific variability of precipitation and 200-hPa 249wind during January-March. By projecting from the MJO 250index to the variables in the northeast Pacific, the linear and 251252nonlinear response to MJO were found. For precipitation, the strength of the nonlinear effect to the linear effect was 2530.94 (in terms of the squared anomalies and averaged over 254all phases of the MJO). This means the nonlinear effect was 255essentially of the same strength as the linear effect. For the 256200-hPa wind, the ratio was 0.55, indicating moderate 257nonlinearity. In general, anomalous winds blowing from 258the north or from land were associated with negative 259precipitation anomalies, while winds from the south or from 260the open ocean, with positive precipitation anomalies. The 261nonlinear effects generally induced positive precipitation 262anomalies during all phases of the MJO. Follow-on work 263could further explore time lags between MJO and variables 264in the northeast Pacific. 265

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