

2 **Hockey sticks, principal components and spurious significance**

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[1] The “hockey stick” shaped temperature reconstruction of *Mann et al.* [1998, 1999] has been widely applied. However it has not been previously noted in print that, prior to their principal components (PCs) analysis on tree ring networks, they carried out an unusual data transformation which strongly affects the resulting PCs. Their method, when tested on persistent red noise, nearly always produces a hockey stick shaped first principal component (PC1) and overstates the first eigenvalue. In the controversial 15th century period, the MBH98 method effectively selects only one species (bristlecone pine) into the critical North American PC1, making it implausible to describe it as the “dominant pattern of variance”. Through Monte Carlo analysis, we show that MBH98 benchmarks for significance of the Reduction of Error (RE) statistic are substantially under-stated and, using a range of cross-validation statistics, we show that the MBH98 15th century reconstruction lacks statistical significance. **Citation:** McIntyre, S., and R. McKittrick (2005), Hockey sticks, principal components and spurious significance, *Geophys. Res. Lett.*, 32, LXXXXX, doi:10.1029/2004GL021750.

31 **1. Introduction**

[2] The term “hockey stick” is often used to describe the shape of the Northern Hemisphere (NH) mean temperature index introduced in *Mann et al.* [1998] (hereinafter referred to as MBH98). For convenience, we define the “hockey stick index” of a series as the difference between the mean of the closing sub-segment (here 1902–1980) and the mean of the entire series (typically 1400–1980 in this discussion) in units of the long-term standard deviation (σ), and a “hockey stick shaped” series is defined as one having a hockey stick index of at least 1σ . Such series may be either upside-up (i.e., the “blade” trends upwards) or upside-down. Our focus here is on the 1400–1450 step (“AD1400 step”) of MBH98, because of controversy over early 15th century temperature reconstructions [*McIntyre and McKittrick*, 2003; *M. E. Mann et al.*, Note on paper by McIntyre and McKittrick in *Energy and Environment*, unpublished manuscript, 2003, available at <ftp://holocene.evsc.virginia.edu/pub/mann/EandEPaperProblem.pdf>, hereinafter referred to as *Mann et al.*, unpublished manuscript, 2003]. Our particular interest in the performance of the Reduction of Error (RE) statistic arises out of that controversy. We also focus on the North American tree ring network (“NOAMER”), because the first principal component (“PC1”) of this

network has been identified as essential for controversial periods of the MBH98 temperature reconstruction [*Mann et al.*, 1999, unpublished manuscript, 2003]. MBH98 has recently been criticized on other grounds in *von Storch et al.* [2004].

[3] MBH98 used principal components (PCs) to reduce the dimensionality of tree ring networks and stated that they used “conventional” PC analysis. A conventional PC algorithm centers the data by subtracting the column means of the underlying series. For the AD1400 step highlighted here, this would be the full 1400–1980 interval. Instead, MBH98 Fortran code (<ftp://holocene.evsc.virginia.edu/pub/MBH98/TREE/ITRDB/NOAMER/pca-noamer>) contains an unusual data transformation prior to PC calculation that has never been reported in print. Each tree ring series was transformed by subtracting the 1902–1980 mean, then dividing by the 1902–1980 standard deviation and dividing again by the standard deviation of the residuals from fitting a linear trend in the 1902–1980 period. The PCs were then computed using singular value decomposition on the transformed data. (The effects reported here would have been partly mitigated if PCs had been calculated using the covariance or correlation matrix.) This previously unreported transformation was recently acknowledged in the Supplementary Information to a Corrigendum to MBH98 [*Mann et al.*, 2004], where they asserted that it has no effect on the results, a claim we refute herein.

[4] PCs can be strongly affected by linear transformations of the raw data. Under the MBH98 method, for those series in which the 1902–1980 mean is close to the 1400–1980 mean, subtraction of the 1902–1980 mean has little impact on weightings for the PC1. But if the 1902–1980 mean is different than the 1400–1980 mean (i.e., a hockey stick shape), the transformation translates the “shaft” off a zero mean; the magnitude of the residuals along the shaft is increased, and the series variance, which grows with the square of each residual, gets inflated. Since PC algorithms choose weights that maximize variance, the method re-allocates variance so that hockey stick shaped series get overweighted. In effect, the MBH98 data transformation results in the PC algorithm mining the data for hockey stick patterns.

[5] In a network of persistent red noise, there will be some series that randomly “trend” up or down during the ending sub-segment of the series (as well as other sub-segments). In the next section, we discuss a Monte Carlo experiment to show that these spurious “trends” in a closing segment are sufficient for the MBH98 method, when applied to a network of red noise, to yield hockey stick PC1s, even though the underlying data gener-

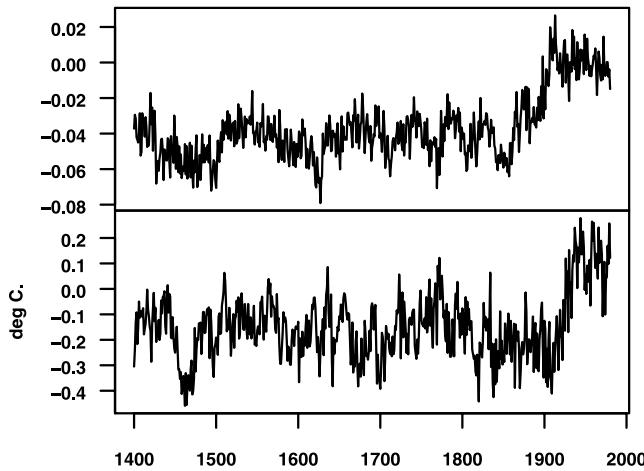


Figure 1. Simulated and MBH98 Hockey Stick Shaped Series. Top: Sample PC1 from Monte Carlo simulation using the procedure described in text applying MBH98 data transformation to persistent trendless red noise; Bottom: MBH98 Northern Hemisphere temperature index re-construction.

105 ating process has no trend component. We then examine
 106 the effect of this procedure on actual MBH98 weights for
 107 the North American PC1. Finally we use the simulated
 108 PC1s to establish benchmarks for the Reduction of
 109 Error (RE) verification statistic used by MBH98, and we
 110 discuss R^2 and other verification statistics for the MBH98
 111 reconstruction.

112 2. Monte Carlo Simulations of Hockey Sticks 113 on Trendless Persistent Series

114 [6] We generated the red noise network for Monte Carlo
 115 simulations as follows. We downloaded and collated the
 116 NOAMER tree ring site chronologies used by MBH98 from
 117 M. Mann's FTP site and selected the 70 sites used in the
 118 AD1400 step. We calculated autocorrelation functions for
 119 all 70 series for the 1400–1980 period. For each simulation,
 120 we applied the algorithm *hosking.sim* from the *waveslim*
 121 package version 1.3 downloaded from www.cran.r-project.org/doc/packages/waveslim.pdf [Gencay *et al.*, 2001],
 122 which applied a method due to *Hosking* [1984] to simulate
 123 trendless red noise based on the complete auto-correlation
 124 function. All simulations and other calculations were done
 125 in R version 1.9 downloaded from www.R-project.org [R Development Core Team, 2003]. Computer scripts used
 126 to generate simulations, figures and statistics, together with
 127 a sample of 100 simulated “hockey sticks” and other
 128 supplementary information, are provided in the auxiliary
 129 material¹. We carried out 10,000 simulations, in each case
 130 obtaining 70 stationary series of length 581 (corresponding
 131 to the 1400–1980 period). By the very nature of the
 132 simulation, there were no 20th century trends, other than
 133 spurious “trends” from persistence. We applied the MBH98
 134 data transformation to each series in the network: the 1902–
 135 1980 mean was subtracted, then the series was divided by
 136 the 1902–1980 standard deviation, then by the 1902–1980
 137 detrended standard deviation. We carried out a singular
 138 value decomposition on the 70 transformed series (follow-
 139 ing MBH98) and saved the PC1 from each calculation.

¹Auxiliary material is available at [ftp://ftp.agu.org/apend/gl/2004GL021750](http://ftp.agu.org/apend/gl/2004GL021750).

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[7] The simulations nearly always yielded PC1s with a
 142 hockey stick shape, some of which bore a quite remarkable
 143 similarity to the actual MBH98 temperature reconstruction –
 144 as shown by the example in Figure 1. A sharp inflection
 145 was regularly observed at the start of the 1902–1980
 146 “calibration period”. Figure 2 shows histograms of the
 147 hockey stick index of the simulated PC1s. Without the
 148 MBH98 transformation (top panel), a 1 σ hockey stick
 149 occurs in the PC1 only 15.3% of the time (1.5 σ – 0.1%).
 150 Using the MBH98 transformation (bottom panel), a 1 σ
 151 hockey stick occurs over 99% of the time, (1.5 σ – 73%;
 152 1.75 σ – 21% and 2 σ – 0.2%).
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[8] The hockey sticks were upside-up about half the
 154 time and upside-down half the time, but the 1902–1980
 155 mean is almost never within one σ of the 1400–1980
 156 mean under the MBH98 method. PC series have no
 157 inherent orientation and, since the MBH98 methodology
 158 uses proxies (including the NOAMER PC1) in a regres-
 159 sion calculation, the fit of the regression is indifferent to
 160 whether the hockey stick is upside-up or upside-down. In
 161 the latter case, the slope coefficient is negative. In fact, the
 162 North American PC1 of *Mann et al.* [1999] is an upside-
 163 down hockey stick, as shown at [ftp://ftp.ngdc.noaa.gov/paleo/contributions_by_author/mann1999/proxies/itrdbrnamer-pc1.dat](http://ftp.ngdc.noaa.gov/paleo/contributions_by_author/mann1999/proxies/itrdbrnamer-pc1.dat).
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[9] The loadings on the first eigenvalues were inflated by
 167 the MBH98 method. Without the transformation, the median
 168 fraction of explained variance of the PC1 was only 4.1%
 169 (99th percentile – 5.5%). Under the MBH98 transformation,
 170 the median fraction of explained variance from PC1 was
 171 13% (99th percentile – 23%), often making the PC1 appear
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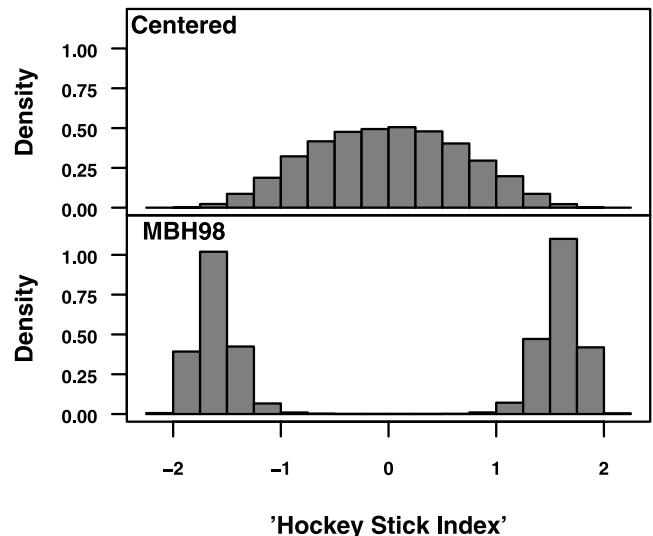


Figure 2. Histogram of ‘Hockey Stick Index’ for PC1s. For the 10,000 simulated PC1s described in text, the histogram shows the distribution of the difference between the 1902–1980 mean and the 1400–1980 mean, divided by the 1400–1980 standard deviation. Top: Conventional (centered) calculation; Bottom: with MBH98 data transformation.

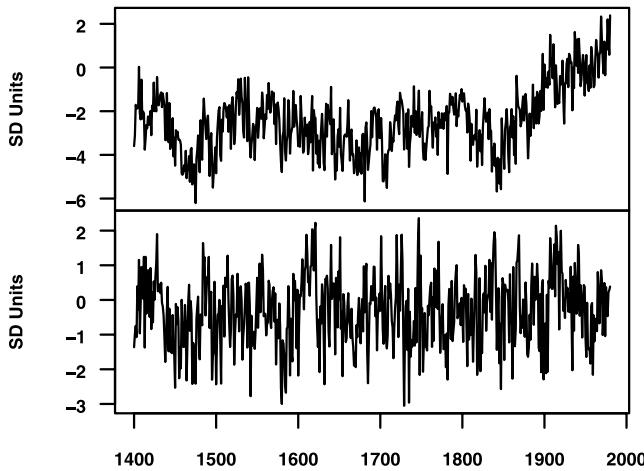


Figure 3. PC1 for AD1400 North American Tree Ring Network. Top: Result with MBH98 data transformation; Bottom: recalculated on the same data without MBH98 data transformation. Both standardized to 1902–1980 period.

173 to be a “dominant” signal, even though the network is only
174 noise.

175 3. The PC1 in the MBH98 North 176 American Network

177 [10] We now show the effect of the MBH98 algorithm
178 on the actual NOAMER network in the controversial
179 AD1400 step.

180 [11] Without the data transformation the PC1 is very
181 similar to the unweighted mean of all the series and, as
182 shown in the top panel of Figure 3, does not have a hockey
183 stick shape. However, under the MBH98 algorithm, the PC1
184 has a marked hockey stick shape, as shown in the bottom
185 panel of Figure 3. The MBH98 method creates a PC1 which
186 is dominated by bristlecone pines and closely related foxtail
187 pines. (Foxtail pines are located in an adjacent mountain
188 range, interbreed with bristlecone pines and are included
189 here with bristlecone pines collectively). Out of 70 sites in
190 the network, 93% of the variance in the MBH98 PC1 is
191 accounted for by only 15 bristlecone and foxtail pine sites

collected by Donald Graybill [*Graybill and Idso, 1993*] (see 192
Table 1). The weights in the MBH98 PC1 have a nearly 193
linear relationship to the hockey stick index. The most 194
heavily weighted site in the MBH98 PC1, Sheep Mountain, 195
is a bristlecone pine site with the most pronounced hockey 196
stick shape (1.6σ) in the network; it receives over 390 times 197
the weight of the least weighted site, Mayberry Slough, 198
whose hockey stick index is near 0. 199

[12] Under the MBH98 data transformation, the distinctive 200
contribution of the bristlecone pines is in the PC1, 201
which has a spuriously high explained variance coefficient 202
of 38% (without the transformation – 18%). Without the 203
data transformation, the distinctive contribution of the 204
bristlecones only appears in the PC4, which accounts for 205
less than 8% of the total explained variance. 206

[13] This substantially reduced share of explained variance, 207
together with the fact that species other than bristle- 208
cone/foxtail pines are effectively omitted from the MBH98 209
PC1, argues strongly against interpreting it as the “dominant 210
component of variance” in the North American network 211
(M. E. Mann et al., Reply to “Global-scale temperature 212
patterns and climate forcings over the past six centuries: 213
A comment” by S. McIntyre and R. McKittrick, unpublished 214
manuscript, 2004, available at http://stephenschneider.stanford.edu/Publications/PDF_Papers/MannEtAl2004.pdf). 215
McIntyre and McKittrick [2005] discuss, *inter alia*, problems 216
relating to the interpretation of bristlecone/foxtail pine 217
growth as a temperature proxy, and we show the impact of 218
using conventional (centered) PC methods on the MBH98 219
northern hemisphere temperature index, which has a signif- 220
icant effect on the relative values in the 15th and 20th 221
centuries. 222

224 4. Benchmarking the Reduction of Error 225 Statistic for the MBH98 Algorithm

[14] In most dendroclimatic studies several verification 226
statistics are used. For example, *Cook et al. [1994]* describe 227
the Reduction of Error (RE), R^2 , Coefficient of Efficiency 228
(CE), sign test and product mean tests as measures of skill. 229
MBH98 only reported RE statistics to demonstrate statisti- 230
cal skill, reporting an RE value for their AD1400 step of 231
0.51. There is no theoretical distribution of the RE statistic 232

t1.1 **Table 1.** 15 Highly Weighted Sites in MGH98 PC1^a

t1.2	ID Code	Name	Species	Elevation (m)	Author	Graybill and Idso [1993] #
t1.3	az510	San Francisco Pks	PIAR	3535	D.A. Graybill	10
t1.4	ca528	Flower Lake	PIBA	3291	D.A. Graybill	13
t1.5	ca529	Timber Gap Upper	PIBA	3261	D.A. Graybill	14
t1.6	ca530	Cirque Peak	PIBA	3505	D.A. Graybill	12
t1.7	ca533	Campito Mountain	PILO	3400	D.A. Graybill and V.C. Lamarche	5
t1.8	ca534	Sheep Mountain	PILO	3475	D.A. Graybill	11
t1.9	co522	Mount Goliath	PIAR	3535	D.A. Graybill	2
t1.10	co523	Windy Ridge	PIAR	3570	D.A. Graybill	4
t1.11	co524	Almagre Mountain	PIAR	3536	D.A. Graybill	1
t1.12	co525	Hermit Lake	PIAR	3660	D.A. Graybill	3
t1.13	nv510	Charleston Peak	PILO	3425	D.A. Graybill	6
t1.14	nv512	Pearl Peak	PILO	3170	D.A. Graybill	9
t1.15	nv513	Mount Washington	PILO	3415	D.A. Graybill	8
t1.16	nv514	Spruce Mountain	PILO	3110	D.A. Graybill	
t1.17	nv516	Hill 10842	PILO	3050	D.A. Graybill	

^a15 high-altitude bristlecone (PILO, PIAR) and foxtail (PIBA) sites dominating MBH98 PC1, constituting 13 of 14 sites listed in Table 1 of *Graybill and Idso [1993]*.

233 and hence no exact or asymptotic tables of significance
 234 levels [Cook *et al.*, 1994]. MBH98 attempted to benchmark
 235 the significance level for the RE statistic using Monte Carlo
 236 simulations based on AR1 red noise with a lag coefficient of
 237 0.2, yielding a 99% significance level of 0.0. However their
 238 simulation under-estimates the actual persistence of tree ring
 239 proxies and ignores the effect of the MBH98 data transforma-
 240 tion in over-weighting hockey stick shaped series.

241 [15] In order to obtain more accurate significance bench-
 242 marks, we regressed each of the 10,000 simulated PC1s
 243 against the MBH98 northern hemisphere temperature series
 244 (the “sparse” subset used by MBH98 for verification [ftp://
 245 ftp.ngdc.noaa.gov/paleo/paleocean/by_contributor/
 246 mann1998/nhem-sparse.dat](ftp://ftp.ngdc.noaa.gov/paleo/paleocean/by_contributor/mann1998/nhem-sparse.dat)) in the 1901–1980 calibration
 247 period – a procedure which more closely emulates actual
 248 MBH98 methods. Since the simulated PC1s are red noise
 249 series containing no information about the climate, they can
 250 be used to establish lower limits for the significance levels
 251 which the actual proxy data must exceed to indicate
 252 reconstructive skill. Since MBH98 used 22 indicators in
 253 their AD1400 step calculation, whereas the Monte Carlo
 254 simulation used only the simulated NOAMER PC1, the
 255 actual RE significance level would be higher than the
 256 benchmark calculated here, which is only a lower limit,
 257 making the arguments herein conservative.

258 [16] For each regression, we calculated the temperature
 259 “reconstruction” from the simulated PC1 in the verification
 260 period (1854–1901), and used the “reconstruction” to
 261 calculate the RE, R², CE, Sign Test and Product Mean Test.
 262 From this data, we determined the 99% significance levels
 263 in the verification period as shown in Table 2. The pattern of
 264 verification statistics was quite consistent: a high RE
 265 statistic, a very low CE statistic and a low R² statistic,
 266 relative to white or weakly red noise values.

267 [17] According to our calculations, the lower-limit critical
 268 value for 99% RE significance is 0.59 (5% – 0.54), values
 269 much higher than the 99% critical value of 0.0 reported by
 270 MBH98. The reported RE value for the AD1400 step of the
 271 MBH98 reconstruction was 0.51 (90th percentile under our
 272 RE distribution). Mann *et al.* have not archived supporting
 273 calculations for the AD1400 step. Accordingly, we emulated
 274 the AD1400 step of MBH98 using their data, obtaining the
 275 verification period statistics shown in Table 3. We were only
 276 able to obtain an RE statistic of 0.46 (80th percentile under
 277 our RE distribution) and an R² statistic of 0.02 (statistically
 278 insignificant). Other verification statistics also lack statistical
 279 significance and the high RE-low R² pattern is obviously
 280 similar to the patterns from comparably treated red noise.

281 5. Discussion and Conclusions

282 [18] PC analyses are sensitive to linear transformations
 283 of data, even if such transformations only appear to be

t2.1 **Table 2.** Statistical Significance Levels^a

Verification Statistic	99% Significance Level (Simulation)	99% Significance Cutoff Used by MBH98
RE (β)	0.59	0.00
R ²	0.15	0.20
CE	0.03	NA
Sign Test	32	NA
Product Mean Test	2.73	NA

t2.2 t2.3 t2.4 t2.5 t2.6 t2.7 t2.8 ^a99% benchmarks from simulations described in text in and as reported by MBH98.

Table 3. Verification Period Statistics for AD1400 Step of t3.1 MBH98 Reconstruction^a

AD1400 Step Results		t3.2	
	Emulation	MBH98 Reported	t3.3
RE (β)	0.46	0.51	t3.4
R ² - verification	0.02	NA	t3.5
Sign Test	22	NA	t3.6
Product Mean Test	1.54	NA	t3.7
CE	-0.26	NA	t3.8

^aFrom emulation and as reported by MBH98.

284 “standardizations”. Here we have shown, in the case of
 285 MBH98, that a “standardization” step (that the authors did
 286 not even consider sufficiently important to disclose at the
 287 time of their study) significantly affected the resulting PC
 288 series. Indeed, the effect of the transformation is so strong
 289 that a hockey-stick shaped PC1 is nearly always generated
 290 from (trendless) red noise with the persistence properties of
 291 the North American tree ring network. This result is
 292 disquieting, given that the NOAMER PC1 has been
 293 reported to be essential to the shape of the MBH98 Northern
 294 Hemisphere temperature reconstruction.

295 [19] For evaluation of statistical skill in paleoclimatic
 296 studies, the Reduction of Error (RE) statistic is widely used,
 297 but lacks a theoretical distribution. Practitioners use Monte
 298 Carlo models to establish significance benchmarks. Here we
 299 have shown that the benchmarks can be dramatically
 300 affected by the Monte Carlo model itself and that the 99%
 301 significance level from a Monte Carlo model more accu-
 302 rately representing actual MBH98 procedures is 0.59, as
 303 compared to the level of 0.0 reported in the original study.
 304 More generally, this example shows that changes in meth-
 305 odology will generally require new Monte Carlo modeling,
 306 that benchmarks carried forward from one methodology
 307 cannot necessarily be applied to a new methodology – even
 308 if the method changes may appear slight, and that great
 309 caution is required prior to concluding statistical signifi-
 310 cance based on RE statistics.

311 [20] An obvious guard against spurious RE significance is
 312 to examine other cross-validation statistics, such as the R²
 313 and CE statistics, as recommended, for example, by Cook *et*
 314 *al.* [1994]. While there are limitations to the R² statistic, the
 315 analysis of statistical “skill” of Murphy [1988] presupposes
 316 that the R² statistic exceeds the skill statistic and cases where
 317 the RE statistic exceeds the R² statistic are of particular
 318 concern [Cook *et al.*, 1994]. In the case of MBH98, unfor-
 319 tunately, neither the R² and other cross-validation statistics
 320 nor the underlying construction step have ever been reported
 321 for the controversial 15th century period. Our calculations
 322 have indicated that they are statistically insignificant. Timely
 323 reporting of these statistics (in the original article) might
 324 have led to an earlier consideration of the discrepancy
 325 between the apparently high RE value and the low values
 326 of other statistics, and thus enabled earlier identification of
 327 the underlying data transformation resulting in this problem.

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