Relative Performance of Empirical Predictors of Daily Precipitation

Tereza Cavazos[1] and **Bruce Hewitson**[2]
[1]*Department of Physical Oceanography, CICESE, Mexico*; [2]*University of Cape Town, South Africa*
(tcavazos@cicese.mx)

Abstract: The urgent need for realistic regional climate change scenarios has led to a plethora of empirical downscaling techniques. In many cases widely differing predictors are used, making comparative evaluation difficult. Additionally, it is not clear that the chosen predictors are always the most important. These limitations and the lack of physics in empirical downscaling highlight the need for a systematic assessment of the performance of physically meaningful predictors and their relevance in surface climate parameters. Accordingly, the objectives of this study are twofold: To examine the skill and errors of 29 individual atmospheric predictors of area-averaged daily precipitation in 15 locations that encompass a wide variety of climate regimes, and to determine the best combination of these to empirically model daily precipitation during the winter and summer seasons. The atmospheric predictors utilized in this study are from the National Center for Environmental Prediction (NCEP) Reanalysis. This work is not concerned with evaluating a particular downscaling methodology, but rather with evaluating the relative skill of physically meaningful predictors that are able to capture different sources of variation. The results indicate that humidity and geopotential heights at mid-tropospheric levels are the two most relevant controls of daily precipitation in all the locations and seasons analyzed. A less ubiquitous role is played by the tropospheric thickness, and the surface meridional and 850-hPa wind components, which appear to be regionally and seasonally dependent. Poor skill is found in the near-equatorial regions and in the Tropics where convective processes dominate and, possibly, where the reanalysis data sets utilized are most deficient. The warm season hemisphere is characterized by the largest errors, likely also due to the enhanced role of convection and sub-grid scale processes during this season. Discrepancies between the performance of the downscaling at grid cell (2^o lat x 2.5^o lon) and local scales further indicate the sensitivity to the spatial resolution of the predictors.

Keywords: Climate downscaling; daily precipitation; skill of predictors; artificial neural networks

1. INTRODUCTION

In recent years, empirical downscaling has gained significant acceptance as a pragmatic and computationally efficient approach to developing regional climate change scenarios. In this approach, reanalysis atmospheric data are used with observed surface records to derive empirical relationships between the larger scale atmospheric forcing and the local climate. These relationships, or transfer functions, can be applied to the same atmospheric fields from general circulation models (GCMs) to determine the local climate response due to changes in the atmospheric forcing. To a large degree the synoptic-scale circulation fields such as mean sea level pressure (SLP) and geopotential heights (Z) have been the most widely used predictors of temperature and precipitation. (See for example Appendix 10.4 in von Storch et al. 2002). This is not only because circulation dynamics accounts for a significant proportion of the local climate variance, but also due to the longer temporal record of these fields, and the relative skill with which GCMs are able to simulate them. Nevertheless, such circulation fields fail to capture key climate processes based on thermodynamics and water vapor content of the atmosphere. Unfortunately, the variety of predictors and methodologies utilized in different studies (von Storch et al. 2002) make comparative evaluation of downscaling investigations difficult. A number of studies (e.g., Zorita et al. 1995, Hewitson and Crane 1996) have pointed out the necessity to include the most physically meaningful predictors into the transfer functions, as this is the first assumption behind the empirical/statistical downscaling approach. The National Centers for Environmental Prediction (NCEP) global reanalysis presents an opportunity to explore a wide number of atmospheric variables at different levels of the atmosphere (Kalnay et al. 1996) as predictors of precipitation, including the most commonly used in the literature (Table 1). The evaluation followed in this study is assessed in 15 locations around the world. The coordinate of these locations, as shown in Table 2, give a general idea of the variety of atmospheric controls that may affect the skill of a regional climate downscaling.

Table 1. NCEP reanalysis list of predictor variables at different levels.

Circulation	Humidity	Thickness
Surface: SLP (slp) U and V winds (u0, v0) Divergence (d0) Vorticity (vo0)	Sp hum (q0) RH (rh0)	500-1000 hPa (th1)
850-hPa: Geop. height (Z8) U and V winds (u8, v8) Divergence (d8) Omega wind (ω8)	Sp hum (q8)	500-850 hPa (th8)
700-hPa: Geop. height (Z7) U and V winds (u7, v7) Divergence (d7)	Sp hum (q7) RH (rh7)	
500-hPa: Geop. height (Z5) U and V winds (u5, v5) Divergence (d5) Vorticity (vo5)	Sp hum (q5)	
200-hPa: Geop. height (Z2) Divergence (d2)		

2. DATA

The observational records consist of 29 twice-daily gridded atmospheric variables from the NCEP reanalysis (Kalnay et al. 1996) with a resolution of 2^{o} lat by 2.5^{o} long. Due to deficiencies in the NCEP precipitation reanalysis data in the Tropics and the warm season extra-tropics (e.g., Janowiak et al. 1998), daily precipitation for this study is from the Goddard Space Flight Center (GSCF) reanalysis (Schubert et al., 1993) that spans from 1980 to 1993 and have the same spatial resolution as the NCEP reanalysis. This resolution allows future comparisons between the performance of GCM outputs and the empirical model developed here. The downscaling is assessed for the December-January-February (DJF) and June-July-August (JJA) seasons on daily timescales. The veracity of the GSFC daily grid cell precipitation was evaluated against data from several meteorological stations falling within grid cells for the 1980-93 period. Comparative results (observed vs downscaled) are shown in Section 5 for a station in Salamanca, Spain (40.94^{o}N, 5.49^{o}W; station id = 2867), which was obtained from the National Institute of Meteorology (INM), Madrid, Spain.

3. DOWNSCALING METHODOLOGY

3.1 Artificial Neural Networks (ANNs)

The general details of this methodology are found in Hewitson and Crane (1996) and Cavazos (1999, 2000), thus only a short description suffices here. The precipitation downscaling is repeated independently for every atmospheric variable in Table 1 and for each target location in Table 2. To determine the relevance of an atmospheric variable as predictor of daily precipitation in a particular location, the following steps are followed: 1) The predictors contain daily data from 9 grid points centered in the target location; b) The predictor variable in each grid point is lagged over 36 hours prior to the day in question to account for antecedent conditions; 3) For every day of the analysis the data from points 1) and 2) are concatened into a single time series. ANNs have shown to be particularly effective in deriving

Table 2. Area-average gridpoint locations used in the analysis. Lat and Lon indicate the center of the gridpoint (2^{o} X 2.5^{o}).

Location	Code	Lat	Lon
Argentina	**Arg**	36S	65W
Australia	**Aus**	34S	150E
Botswana	**Bot**	24S	25E
Zambia	**Zam**	16S	22.5E
Brazil	**Bra**	2S	60W
Pacific Ocean	**Nin3**	Eq	120W
Costa Rica	**Cri**	10N	85W
Bangladesh	**Ban**	24N	90E
Mexico	**Mex**	28N	110W
China	**Chi**	30N	110E
Azores	**Azo**	36N	30W
Spain	**Spa**	40N	7.5W
USA	**Iow**	42N	95W
Germany	**Ger**	50N	10E
Siberia	**Sib**	52N	110E

empirical relationships between the large-scale atmospheric variables and a surface climate parameter (e.g., Hewitson and Crane 1996, Trigo and Palutikof 1999, Cavazos 2000).

3.2 Principal Component Analysis (PCA)

The sources of variance of the top 10 predictors of precipitation are explored with a Rotated Principal Components Analysis (RPCA). These sources help to identify groups of atmospheric variables that are physically linked to different precipitation mechanisms. This is a useful tool that prevents the selection of redundant predictors for the final downscaling model. A single relevant variable from each PC was selected for the final downscaling model for each location.

4. RESULTS

4.1 Best Precipitation Predictors

Results from the ANNs are evaluated based on the performance of each individual suit of predictors in each location. The best performance - based on best correlation and skill and lowest errors (MAE and RMSE) - was averaged overall locations separately for the corresponding winter and summer seasons (Table 3). According to these results, it appears that the moist condition of the mid-tropospheric air is the second most important factor in precipitation processes. This is not surprising, at least for the warm season, since moist mid-tropospheric airmasses are associated with vertical motion and convective processes. In winter the role of Z5 in precipitation is likely related to the equatorward migration of the mid-tropospheric flow and associated changes in the location of jet streams and storm tracks. Surface meridional wind component (v0) appears in the top variables during this season. It seems to plays a significant role in Northern Hemisphere midlatitude locations (not shown), suggesting an influence from surface meridional synoptic systems. The significance of the temperature of the tropospheric layer (th1) is most apparent during the summer (Table 3) when monsoonal circulations are common. During the summer, the poleward retraction of the midtropospheric circulation and warming of the troposphere suggest that precipitation processes may be more directly linked to lower- and upper-tropospheric circulation, as it is common in convective and monsoon regimes. This is reflected in the role of the geopotential heights, with Z7 as the most significant circulation variable (Table 3), in average. Interestingly, SLP, low-level humidities (qo), and low-level divergence (d8) play a minor role in daily precipitation in all the locations analyzed. Possible reasons are explored in Section 4.2. When constructing the final precipitation diagnostic model few questions arise from Table 3: Is it redundant to use both rh7 and q7? Is it useful to include all the geopotential heights? To answer this, it is necessary to quantify and compare the mutual relevance of the predictors to avoid utilizing variables that contribute to common sources of variation. A RPCA was applied to the predictors in Table 3 for winter and summer at each location. One significant variable from each relevant PC was selected to form the final downscaling model. Table 4 shows the suggested precipitation models. SLP is included in the midlatitudes model just because is one of the most commonly used predictor in the literature.

4.2 Missing Predictors

Table 3 indicates that atmospheric variables such as SLP, and low- and upper-level divergence (d8 and d2, respectively) do not appear as key predictors of precipitation. Mean monthly SLP has been one of the most extensively used predictor of precipitation in downscaling studies. The Iberian Peninsula, in particular, has been the target of several downscaling studies that have used mean monthly SLP (e.g., von Storch et al. 1993, Corte-Real et al. 1995, 1998) and daily SLP (e.g., Goodess and Palutikof 1998, Zhang et al. 1997) as predictors of precipitation. The planetary scale flow varies from day to day due to interactions.

Table 3. Top 10 predictors of daily precipitation averaged overall all locations in Table 2 for the corresponding winter (W) and summer (S) seasons.

	1	2	3	4	5	6	7	8	9	10
W	Z5	rh7	q7	Z7	q5	v0	th1	Z2	Z8	th8
S	rh7	q7	q5	th1	Z7	Z2	Z5	Z8	v0	th8

Table 4. Precipitation (P) functions for the ANN downscaling according to most relevant predictor variables from a RPCA. Top predictors were averaged overall tropical (T) and midlatitude (M) locations in Table 2.

	Winter (W)	Summer (S)
T	P = *f* (th1, q7, z7, v0)	P = *f* (z7, q7, th1, u8)
M	P = *f* (z5, q7, slp); P = *f* (z7, q7, slp)	P = *f* (z7, q7, u8); P = *f* (z7, q7, v8)

with transient synoptic scale disturbances. As a result, monthly mean values tend to smooth out the actual structure of the atmospheric flow and, thus, the climate response. This may explain the discrepancy between past studies based on mean monthly SLP data and the present analysis. Although some studies (e.g., Zhang et al. 1997) have used daily SLP to classify weather events, the circulation patterns were used to downscale monthly precipitation, as opposed to daily. Generally, in tropical convective regions low-level convergence is accompanied by upper-level divergence (Webster et al. 1998). The summer results from the RPCA in Table 4 are partially consistent with this premise, as the low-level wind component (u8) appears as an independent factor for the Tropics and extratropics. We believe that the low role of divergence (d8 and d2) in this analysis may have been due to an amplification of errors of the differential calculations from which the divergence fields were obtained. This problem may also apply to the poor role of vorticity (vo0 and vo5) in the current analysis. Some studies (e.g., Wilby et al. 1998) have found that vorticity is a good predictor of precipitation. Unfortunately, the accuracy of tropical divergence derived from global analyses has been suspect (e.g., Trenberth and Olson 1988; Liebmann et al. 1998) due in part to the sparse number of upper-air stations in the Tropics.

5. Final Diagnostic Model

The performance of the final models (Table 4) is illustrated in Fig. 1 through different measures of accuracy. During DJF, with the exception of Costa Rica (Cri), the correlation and skill of the models increase poleward from the equator, while the errors are worst during the wet season. Wet and dry seasons are clearly marked in the error distribution of DJF in Fig. 1a, with the MAE and RMSE being larger in the austral summer than in the northern winter. The JJA error distribution is not as distinctive as the one in DJF because of the large errors obtained in Brazil (Bra) and Australia (Aus), and small errors in two dry Mediterranean climate locations (Azo and Spa). In average, the correlation varies from 0.3 in the near-equatorial locations to 0.77 in the midlatitudes. The best results are obtained in the grid point in Spain (Spa) for both winter and summer. Large errors in tropical locations and during the wet season may be due to (1) enhanced sub-grid scale processes, such as convection, not captured by the predictors and (2) deficiencies of the reanalysis data, especially in the Tropics. Table 5 shows the contribution (%) of the atmospheric predictors to the daily precipitation variance averaged over all locations of the mid-latitudes and the Tropics. In the former locations, the mid-tropospheric circulation (Z5 or Z7) accounts for the largest amount of explained variance of precipitation followed by the midtropospheric moisture (q7). In the Tropics, the role of the circulation, moisture availability, and temperature thickness seem to be equally important. The daily performance of the downscaling model is further illustrated in Fig. 2 for two winters in Salamanca (wettest and driest of the 1980-1993 period) and its nearest GSFC grid cell. The synoptic events in Salamanca (Fig. 2a) are well captured in the nearest grid cell (Fig. 2a), but in a lesser magnitude. The observed seasonal precipitation (Pot) is comparable at both scales. The downscaling model captures well the phase of daily episodes, but tends to underestimate (overestimate) large (small) events.

Table 5. Contribution (%) of the atmospheric predictors to the daily precipition variance using the best downscaling models shown in Table 4 for winter (W) and summer (S).

(a) Tropics/Subtropics				
	q7	**th1**	**Z7**	**v0**
W	**29.0**	**19.2**	**22.3**	**20.7**
	q7	**Z7**	**th1**	**u8**
S	**38.9**	**33.0**	**23.6**	**3.71**

(b) Midlatitudes			
	Z5	**q7**	**SLP**
W	**66.5**	**29.0**	**2.04**
	Z7	**q7**	**u8**
S	**50.3**	**39.1**	**7.2**

6. Summary and Conclusions

The motivation of this study is the need to derive more realistic regional climate change scenarios. There is a lack of a systematic study that explores the relevance of a large number of atmospheric variables as predictors of daily precipitation on a variety of climate regimes. This study clarifies these issues by evaluating the relative performance of 29 individual NCEP-NCAR atmospheric variables as predictors of daily precipitation in 15 locations of the globe. The assessment focuses on the skill and errors of individual predictors and the physical linkages with precipitation. The final objective is to find the most relevant set of predictors of precipitation under different climate

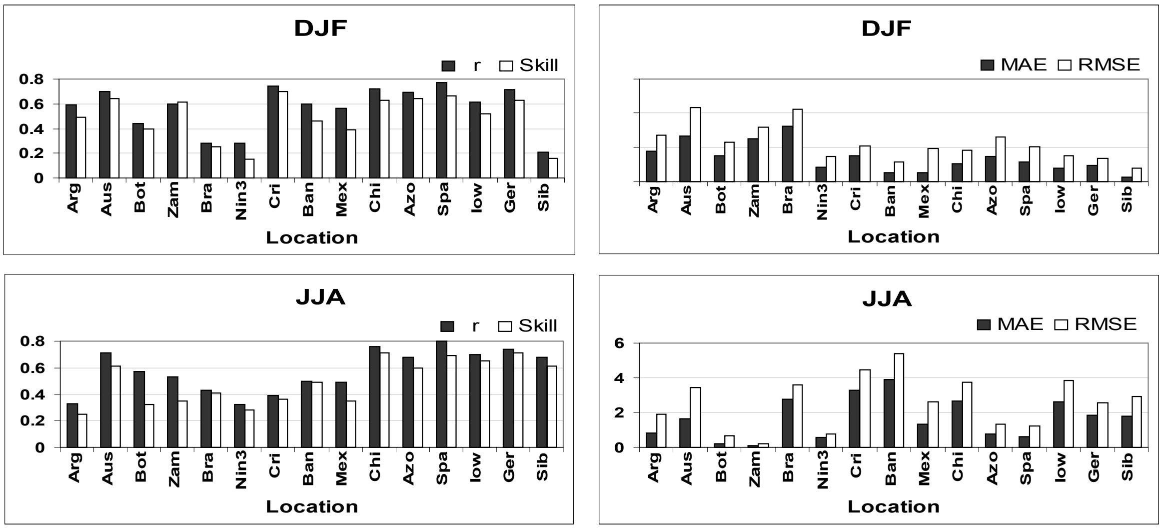

Figure 1. Final downscaling results based on the daily precipitation functions shown in Table 4 for each location in Table 2 for DJF and JJA. Measures of performance as described at the end of Section 3.1. Locations are displayed from the southernmost (Arg) to the northernmost (Sib) gridpoint. The equator is at Nin3.

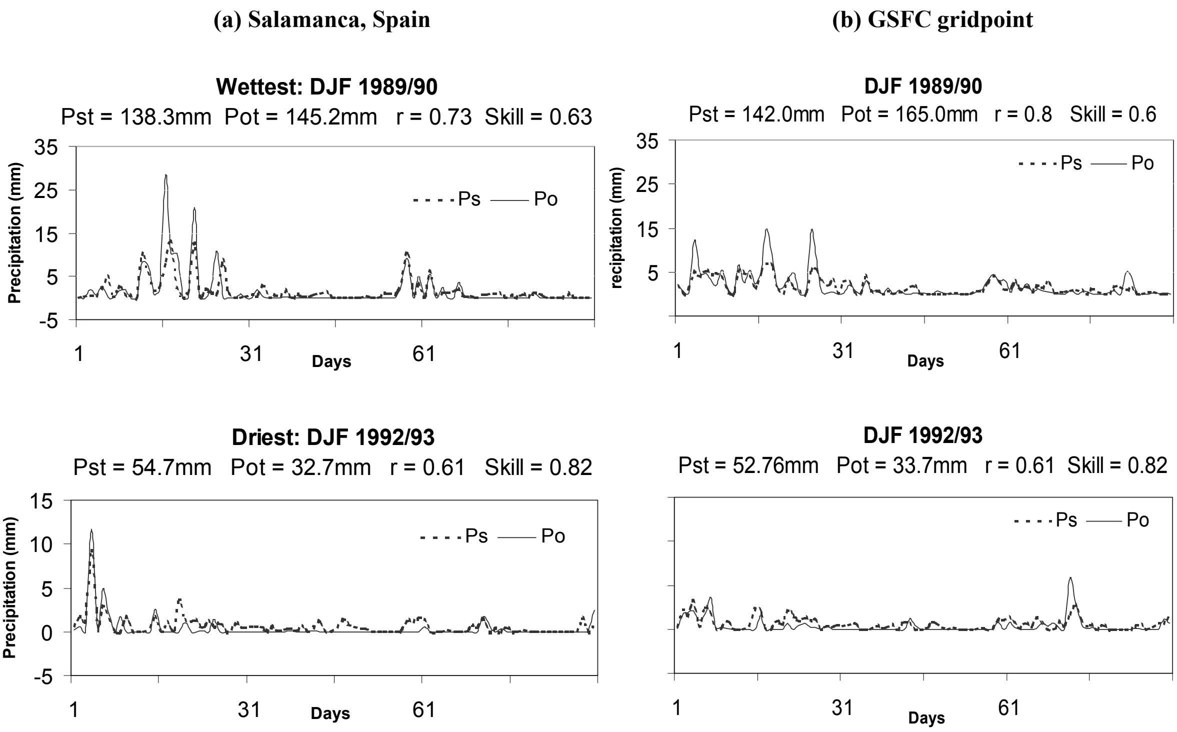

Figure 2. Daily performance of the final downscaling precipitation model for the wet season at (a) Salamanca and (b) the nearest GSFC gridpoint centered at 40°N and 7.5°W for the wettest and driest winters of the 1980-1993 period. Po and Pot are daily and seasonal observed precipitation, respectively; Ps and Pst are daily and seasonal downscaled precipitation, respectively; r and skill as described at the end of Section 3.1.

regimes. A downscaling technique based on artificial neural networks (ANNs) is used as a diagnostic tool to evaluate the role of each individual predictor at each target location.

The best performance and the largest number of potentially skillful predictors were obtained outside of the Tropics and for the dry/cool season. Mid-tropospheric circulation (Z7, Z5) and the mid-tropospheric specific humidity (q7) are the most relevant predictors of daily precipitation at any location and season. This contrasts with most downscaling studies which are mainly based on circulation predictors. The final downscaling models produce large errors during the wet season; this indicates that sub-grid scale precipitation processes such as convection are not well captured by the model. Hence, to derive realistic climate scenarios, the residual variance needs to be parameterized and incorporated into the downscaling model in some manner (e.g., using stochastic methods). Large errors in tropical regions may be also linked to inconsistencies between predictors and predictand data used as the "observed data", suggesting the need for improving observed records and reanalysis data sets in the Tropics.

REFERENCES

Cavazos, T., Large-scale circulation anomalies conducive to extreme events and simulation of daily rainfall in northeastern Mexico and southeastern Texas, *J. Climate*, **12**, 1506-1523, 1999.

Cavazos, T., Using self-organizing maps to investigate extreme climate events: An application to wintertime precipitation in the Balkans, *J. Climate*, **13**, 1718-1732, 2000.

Corte-Real, J., B. Qian, and H. Xu, Regional climate change in Portugal: Precipitation variability associated with laarge-scale atmospheric circulation, *Int. J. Climatol.*, **18**, 619-635, 1998.

Goodess, C. M. and J. P. Palutikof, Development of daily rainfall scenarios for southeast Spain using a circulation-type approach to downscaling, *Int. J. Climatol.*, **10**, 1051-1083, 1998.

Goodman, P. H., NevProp software, version 3. University of Nevada, 1996.

Hewitson, B. C. and R.G. Crane, Climate downscaling: techniques and applications, *Clim. Res.*, **7**, 85-95, 1996.

Kalnay, E. and Co-authors, The NCEP/NCAR 40-year reanalysis project, *Bull. Amer. Meteor. Soc.*, **77**, 437-471, 1996.

Janowiak, J., A. Gruber, C. Kondragunta, R. Livezey, G. Huffman, A comparison of NCEP- NCAR reanalysis precipitation and the GPCP rain gauge-satellite combined data set with observational error considerations, *J. Climate*, **11**, 2960-2979, 1998.

Liebmann, B., J. A. Marengo, and J. D. Glick, A comparison of rainfall, outgoing long-wave radiation, and divergence over the Amazon Basin, *J. Climate*, **11**, 2898-2909, 1998.

Schubert, S.D., Rood, R.B., Pfaendtner, J., An assimilated data set for earth science applications, *Bull. Amer. Meteor. Soc.*, 74, 2331-2342, 1993.

Trenberth, K. E. and J. G. Olson, An evaluation and intercomparison of global analyses from the National Meteorological Center and the European Centre for Medium-Range Weather Forecasts, *Bull. Amer. Meteor. Soc.*, **69**, 1047-1057, 1988.

Trigo, R.M. and J.P. Palutikof, Simulation of daily temperatures for climate change scenarios over Portugal: a neural network model approach, Clim. Res. 13, 61-75, 1999.

von Storch, H., E. Zorita, and U. Cubasch, Downscaling of global climate change to regional scales: An application to Iberian rainfall in wintertime, *J. Climate*, **6**, 1161-1171, 1993.

von Storch, H., B. Hewitson, and L. Mearns, Regional Climate Information – Evaluations and Projetcions (Chapter 10), In *Climate Change 2001: The Scientific Basis*, Report of the IPCC, 2002.

Webster, P. J., V. O. Magaña, T. N. Palmer, J. Shukla, R. A. Tomas, M. Yanai, and T. Yasunari, Monsoons: Processes, predictability, and the prospects for prediction, *J. Geophys. Res.*, **103** (C7), 14451-14510, 1998.

Wilby, R.L., T.M.L. Wigley, D. Conway, P.D. Jones, B.C. Hewitson, J. Main and D.S.Wilks, Statistical downscaling of general circulation model output: A comparison of methods, *Water Resources. Res.*, **34**, 2995–3008, 1998b.

Zhang, X., X. L. Wang, and J. Corte Real, On the relationships between daily circulation patterns and precipitation in Portugal, *J. Geophys. Res.*, **102**, 13495-13507, 1997.

Zorita, E., J. P. Hughes, D. P. Lettenmaier, H. von Storch, Stochastic characterization of regional circulation patterns for climate model diagnosis and estimation, *J. Climate*, **8**, 1023-1042, 1995.