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TEMPORAL DISAGGREGATION OF PROBABILISTIC SEASONAL CLIMATE FORECASTS

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1. INTRODUCTION

Seasonal climate forecasts are issued by NOAA's Climate Prediction Center for average temperature and total precipitation over 3-month overlapping periods covering the coming year. In particular, the Probability of Exceedance forecasts appear to offer useful information for many practical applications (Barnston et al. 2000). However, many crop and hydrologic models employ weather generators based on monthly statistics (mean, variance, conditional probabilities of precipitation) to produce stochastic realizations of daily weather (e.g., air temperature, precipitation, solar radiation). To make the forecasts immediately useful for applications employing weather generators, the forecasts for 3-month periods need to be disaggregated into 1-month, non-overlapping increments. The disaggregation problem is identical for both mean temperature and total precipitation forecasts, and has been addressed in previous work by Wilks (2000), which revealed characteristics of the disaggregated 1-month forecast that are unacceptable for practical applications.

The algebraic inversion approach to disaggregation used by Wilks (2000) is mathematically proper and intuitively correct. A forecast cycle covers 15 consecutive months. Since a forecast for the first month is also issued (i.e., the first month is defined), this gives 13 equations with 14 unknowns. This linear system of equations can be closed by assuming that the 15th month's forecast anomaly equals zero, and the system can then be solved for the individual 1-month forecast anomalies. Unfortunately, these assumptions place strong constraints on the linear system, such that the resulting sequences of 1-month forecasts often bounce month-to-month between positive and negative extremes (see Figure 2 in Wilks 2000). Two examples of this "ringing" behavior will be shown later in this paper. The solution sequence is mathematically correct but seriously implausible in a physical sense: smooth increases or decreases in the 3-month forecast sequence disaggregate into unreasonably oscillating 1-month forecast sequences. As recognized by Wilks, the 3-month forecasts are clearly not being created with an underlying requirement that they disaggregate into a physically reasonable sequence of monthly forecasts. This is a significant problem for applications that require monthly forecasts.

The lack of self-consistency inherent in the overlapping 3-month forecasts is also revealed by inspection of precipitation anomalies summed from non-overlapping 3-month forecasts over a forecast cycle. Forecast users intuitively expect that a sequence of overlapping 3-month forecasts implies a unique sequence of 1-month forecasts, with an associated forecast-cycle-total anomaly. This is frequently not the case, a fact which further complicates the development of disaggregation methods. To illustrate, consider a hypothetical sequence of 1-month forecast anomalies over a forecast cycle of 13 months (Table 1). These anomalies have a specific cycle-total sum (bottom line of table) that is replicated by any group of non-overlapping consecutive 3-month forecasts (Sets 1, 2, 3).

Table 1. Illustration of a self-consistent sequence of overlapping 3-month forecast anomalies. The monthly ("1-Mon") and 3-month anomalies ("3-Mon") are in inches of precipitation. "JAS" refers to July-August-September. Each "Set" is composed of consecutive non-overlapping 3-month periods.

	1-Mon		**3-Mon**	**Set 1**	**Set 2**	**Set 3**
July	0.0					
Aug	0.0	JAS	0.0			
Sep	0.0	ASO	0.0			
Oct	0.0	SON	0.22	0.22		
Nov	0.22	OND	0.51		0.51	
Dec	0.29	NDJ	0.68			0.68
Jan	0.17	DJF	0.51	0.51		
Feb	0.05	JFM	0.24		0.24	
Mar	0.02	FMA	0.11			0.11
Apr	0.04	MAM	0.06	0.06		
May	0.0	AMJ	0.04		0.04	
Jun	0.0	MJJ	0.0			
Jul	0.0	JJA	0.0			
Aug	0.0	JAS	0.0			
Sep	0.0					
sum	**0.79**			**0.79**	**0.79**	**0.79**

As an example of the lack of self-consistency in the forecasts, the 3-month forecast cycle for Forecast Division 61 (Dallas Region, Texas) issued in June 2002 has been simplified into a sequence of 3-month precipitation anomalies, defined as the difference between the forecast mean and 30-year mean. These

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forecasts are listed in Table 2. Note that the cycle-total anomaly depends on which group of consecutive non-overlapping forecasts is considered. This lack of uniformity is indicative of inconsistency in the 3-month forecasts. In summary, current overlapping 3-month forecast sequences of precipitation anomalies do not imply a physically plausible set of underlying monthly anomalies.

Table 2. Illustration of an actual forecast sequence with ambiguous cycle-total anomaly; notation as in Table 1, except that "Frcst" represents the 3-month forecast anomalies.

Mon	**Anom**	**3Mon**	**Frcst**	**Set 1**	**Set 2**	**Set 3**
Jul	?					
Aug		JAS	0.0			
Sep		ASO	0.0			
Oct		SON	0.0			
Nov		OND	0.61	0.61		
Dec		NDJ	0.82		0.82	
Jan		DJF	0.50			0.50
Feb		JFM	0.14	0.14		
Mar		FMA	0.06		0.06	
Apr		MAM	0.12			0.12
May		AMJ	0.0			
Jun		MJJ	0.0			
Jul		JJA	0.0			
Aug		JAS	0.0			
Sep						
sum	**?**			**0.75**	**0.88**	**0.62**

Given these self-consistency problems with the 3-month forecasts, our goal was to find one or more methods to develop a sequence of 1-month forecast anomalies that is physically plausible and internally consistent; within the implied range of cycle-total precipitation anomaly indicated by the 3-month forecast cycle; and which re-sums to a good approximation of the original forecast sequence. We believe these criteria will help to select a method that produces self-consistent sets of 1-month forecasts while maintaining as much of the original 3-month forecast sequence as possible. We explored dozens of possible methods, and present two that are relatively effective and simple to apply. In general, we found that the simpler approaches tended to produce more consistent and repeatable results.

2. METHODS

Our development begins with the recognition of two forecast properties: each 3-month forecast is developed without regard to the forecasts immediately adjacent in time; and there is no information available concerning the distribution of the 3-month anomaly over the constituent individual months. For simplicity, we also restrict ourselves to a single cycle of 13 forecasts (lead times from 0.5 months to 12.5 months).

For the first method, we assume that the signal in the 3-month anomaly is evenly distributed across the 3 months (i.e., divided into thirds) and that all 3-month forecasts are of equal validity. This gives 1 to 3 estimates for each month in the forecast cycle (1 for the first and last month, 2 for the 2nd and 14th month of the sequence, 3 for all others). We then average the estimates for each month to produce a monthly value, ignoring the first and last months since we only have a single estimate for each. For example, given the forecasts for September-October-November (SON), October-November-December (OND), and November-December-January (NDJ), then the 1-month anomaly for November is calculated as:

$$F_{Nov} = \frac{1}{3}\left(\frac{F_{SON}}{3} + \frac{F_{OND}}{3} + \frac{F_{NDJ}}{3}\right) \qquad (1)$$

The 1-month anomaly for the 2nd and 14th months (August 2002 and August 2003 in this example) is calculated as the average of two estimates rather than three, as indicated in Table 3. A subset of the results of this "Average" method applied to the forecasts in Table 2 is shown in Table 3. This is a relatively simple problem in disaggregation, with a persistent positive anomaly bracketed by zero anomalies.

Table 3. Illustration of the "Average" method for the first seven 3-month forecast anomalies from the forecast cycle issued in June 2002 for forecast division 61 (Dallas Region, Texas).

3Mon	**Frcst Anom**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**
JAS	0.0	0.0	0.0	0.0				
ASO	0.0		0.0	0.0	0.0			
SON	0.0			0.0	0.0	0.0		
OND	0.61				.203	.203	.203	
NDJ	0.82					.273	.273	.273
DJF	0.50						.167	.167
JFM	0.14							.047
...	...							...
avg		**-**	**0.0**	**0.0**	**.068**	**.159**	**.214**	**.162**

For the second method, we assume that the signal in the 3-month anomaly is centered on the middle month. Such a direct assignment of the 3-month anomaly to the mid-month produces a first-guess estimate that is too large, so we adjust the magnitude in the following manner. For each month, the magnitude of the first-guess is multiplied by the ratio of the first-guess to the sum of the 3 centered first-guesses. If the denominator (sum of 3 first-guess months) is zero, the ratio is set to zero. For example, the 1-month anomaly for November is calculated as:

$$F_{Nov} = F_{OND} \times \frac{F_{OND}}{\left[F_{SON} + F_{OND} + F_{NDJ}\right]} \qquad (2)$$

The 2nd and 14th month in the 1-month sequence are calculated using just two first-guesses in the denominator (F_{JAS} and F_{ASO} for August 2002, F_{JJA} and F_{JAS} for August 2003 in this example). This method is demonstrated in Table 4 for the same set of forecast anomalies from Tables 2 and 3.

Table 4. Illustration of the "Middle" method, using the same forecasts as in Tables 2 and 3.

3Mon	Frcst Anom	Mon	First Guess	Ratio	1-Mon Anom
JAS	0.0	Aug	0.0	0 / 0 -> 0	0.0
ASO	0.0	Sep	0.0	0 / 0 -> 0	0.0
SON	0.0	Oct	0.0	0 / 0.61 = 0	0.0
OND	0.61	Nov	0.61	0.61 / 1.43	0.26
NDJ	0.82	Dec	0.82	0.82 / 1.93	0.35
DJF	0.50	Jan	0.50	0.5 / 1.46	0.17
JFM	0.14	Feb	0.14	0.14 / 0.7	0.03
FMA	0.06	Mar	0.06	0.06 / 0.32	0.01
MAM	0.12	Apr	0.12	0.12 / 0.18	0.08
AMJ	0.0	May	0.0	0 / 0.12 = 0	0.0
MJJ	0.0	Jun	0.0	0 / 0 -> 0	0.0
JJA	0.0	Jul	0.0	0 / 0 -> 0	0.0
JAS	0.0	Aug	0.0	0 / 0 -> 0	0.0

The sequences of 1-month forecast anomalies from these two methods, as well as the algebraic method used by Wilks, are shown in Figure 1. (The July forecast needed by the Algebraic method was 0.0 inches.) The numbers on the abscissa represent the forecast lead time, rounded up (i.e., 0.5 months becomes 1, 1.5 months becomes 2, etc.). The unacceptable "ringing" solution of the algebraic disaggregation is apparent, occurring in response to the zero anomalies in the forecast sequence. Both the Average and Middle 1-month sequences are physically plausible, in the sense that they follow the sign of the 3-month anomaly sequence (all positive anomalies). They are both internally consistent as well (all consecutive non-overlapping 3-month sums produce the same cycle-total anomaly as the sum of the 1-month anomalies). The Average method produces a smoother and less amplified sequence of 1-month anomalies compared to the Middle method.

The cycle-total anomaly summed from the 1-month anomalies is 0.74 for the Average method, and 0.9 for the Middle method, compared to the three possible totals summed in Table 2 (0.75, 0.88, 0.62). By this measure, the Average method is within the range of year-total precipitation anomaly indicated by the 3-month forecast cycle, while the Middle method is near the high end of the range.

The re-summed 3-month sequences are used to check the requirement that the methods reproduce a good approximation of the original forecast sequence, and are shown in Figure 2. The Average method acts as a low-pass filter on the forecast anomaly sequence, damping short-duration variations and extreme magnitudes, and displacing the initiation of the non-zero anomaly (lead time 4) earlier by two months. The Middle method also displaces the initiation, but only by one month, while preserving more of the amplitude of the variations. By this measure, the Middle method appears to be the better fit.

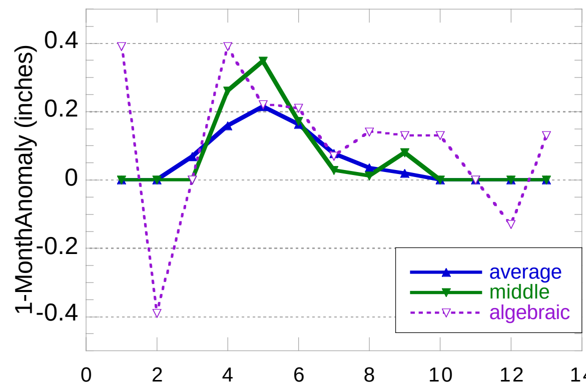

Figure 1. Results of three methods to disaggregate the 3-month forecast anomalies issued June 2002 for forecast division 61.

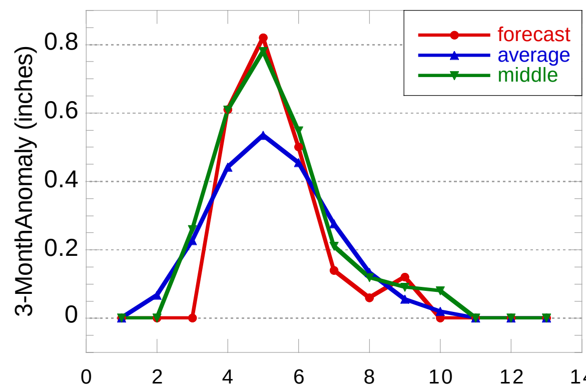

Figure 2. Original sequence of 3-month forecast anomalies, with re-summed sequences from 1-month anomalies from Average and Middle methods.

To further illustrate the strengths and weaknesses of the two methods, we use a more difficult test, derived from the forecast cycle issued in June 2000 for forecast division 102 (Southern New Mexico). This sequence begins with a large positive anomaly, drops to zero, and then oscillates around zero (Table 5). Summing over non-overlapping 3-month periods, the cycle-total anomaly ranges from 0.49 to -0.12 inches, which is a confusing range of values given the predominantly positive sequence. The 1-month sequences are presented in Figure 3, with the 3-month re-sums in Figure 4.

This test clearly illustrates the implausible "ringing" solution of the Algebraic method (the July forecast needed by the Algebraic method was estimated to be 0.2 inches). Again, both 1-month anomaly sequences are physically plausible in the sense that they follow the sign of the 3-month forecast sequence. Also, both the

Average and Middle methods produce internally consistent cycle-total anomalies. The cycle-total anomaly for the Average method is 0.204 inches, and 0.487 inches for the Middle method, both within the range of the implied forecast anomalies, with the Middle method again close to the upper end.

Table 5. Forecast sequence used for second test of methods; anomalies are in inches of precipitation.

3-Month Period	Forecast Anomaly
JAS	0.46
ASO	0.0
SON	0.0
OND	-0.15
NDJ	-0.12
DJF	0.0
JFM	0.04
FMA	0.0
MAM	0.10
AMJ	0.14
MJJ	0.0
JJA	0.0
JAS	0.0

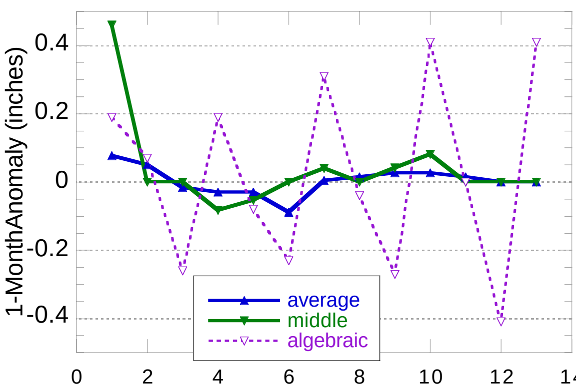

Figure 3. Results of three methods to disaggregate the 3-month forecast anomalies issued June 2000 for forecast division 102.

The re-summed sequences show that the Average method is again acting as a low-pass filter, damping the short-term variations and the extreme magnitudes of the original forecast sequence, while reproducing sustained anomalies. The Middle method again does some damping, but less than the Average method, and more closely follows the oscillations around zero. However, the Middle method has difficulty with the initial high positive anomaly (lead time 1) followed by a zero anomaly, duplicating that large anomaly for lead time 2. This odd result can be ameliorated by the addition of two forecasts to the beginning of the cycle, for example, the first lead time forecasts issued during the previous two months (MJJ and JJA). Such an addition modifies the denominator of the ratio, improving the match of the anomaly for lead time 2.

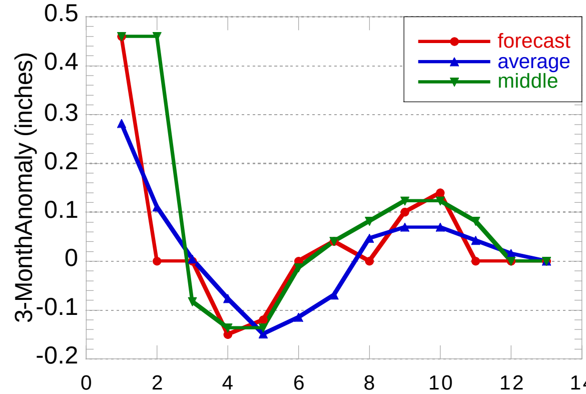

Figure 4. Forecast sequence of 3-month anomalies, with re-summed sequences from 1-month anomalies from Average and Middle methods.

3. CONCLUSIONS

No heuristic approach can resolve the underlying problem of inconsistent 3-month overlapping forecasts. That can only be addressed by the issuance of 1-month forecasts by NOAA/CPC, rather than the current 3-month format. Until such forecasts are available, heuristic approaches to disaggregation similar to those presented here offer an opportunity to begin to interpret and apply the forecasts in situations that require monthly forecasts. The two methods presented here are both simple and uniformly applicable without preliminary assessment of the forecast anomaly sequence. Both methods produce internally consistent results. Both methods also damp short-term oscillatory behavior in the forecast sequence, the Average method more so than the Middle method. This is probably a desirable property, since such short-term oscillations reflect internal inconsistency in the overlapping forecasts. But the filtering effect also broadens the signal, especially forward in time, which is not a desirable characteristic if one has more confidence in the shorter lead time forecasts. Given this consideration, the Middle method does less damage to the initiation of a persistent anomaly. Both methods also do a good job of replicating the longer-scale pattern of the forecast anomaly sequence, but the Middle method does a better job of matching the maxima and minima. All considered, the Middle method appears to be the best current approach to the disaggregation problem.

4. REFERENCES

Barnston, A. G., Y. He, and D. A. Unger, 2000: A forecast product that maximizes utility for state-of-the-art seasonal climate prediction. *Bull. Amer. Meteor. Soc.*, **81**, 1271-1279.

Wilks, D. S., 2000, On interpretation of probabilistic climate forecasts. *J. Climate*, 13, 1965-1971.