Empirical Indicators of Crisis Phase in the Middle East, 1979-1995

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ABSTRACT

A number of studies of crisis behavior—for example, the Butterworth, SHERFACS, and CASCON data sets—have assumed that political behavior goes through a series of clear "phases" characterized by distinct patterns of interactions. To date, these phases have been identified contextually by human coders rather than through any systematic procedures.

This paper uses event data to analyze phases in the political behavior between eight Middle Eastern actors—Egypt, Israel, Jordan, Lebanon, the Palestinians, Syria, the United States and USSR/Russia—for the period July 1979 to June 1995. The event data are generated from the Reuters news service using the KEDS machine-coding system, then converted to monthly time-series using the Goldstein (1992) scaling. The system is then analyzed in SPSS using three data-reduction methods:

- factor analysis of the multiple time series to identify the underlying patterns of behavior found in the system;
- discriminant analysis to determine whether the dyadic time-series can predict the phases assigned by a human coder;
- cluster analysis of behavior vectors over time to identify inductively the phases.

As we expected, the factor analysis identifies the Israeli-Palestinian conflict and the war in Lebanon as the two most important features of the data; other factors reflect inter-Arab and major-power relationships. The factor scores do not, however, prove very useful in either the discriminant or cluster analysis. The discriminant analysis identified the human-coded phases with about 90% accuracy; a stepwise discriminant did this with 70% accuracy using only 12 of the 54 dyads. Finally, the cluster analysis identified five distinct phases that align fairly well with the human-coded phases, particularly in the first half of the time period. The overall results of

the analysis correspond fairly well with our contextual understanding of the political situation in the Middle East and show considerable promise in providing a means of studying the behavior of a complex N-actor system systematically, rather than focusing on a small number of dyads. The paper concludes with observations on how these methods might be applied to the problems of early warning.

Introduction

A number of contemporary studies of crises assume that political behaviors go through a series of phases that are delineated by an emphasis on different sets of behavior. In the empirical literature, crisis "phase" has been explicitly coded in data sets such as the Butterworth international dispute resolution dataset (Butterworth 1976), CASCON (Bloomfield and Moulton 1989) and SHERFACS (Sherman and Neack 1993).[1] Describing the early CASCON work, Sherman and Neack explain that:

> ...conflict is seen "as a sequence of phases". Movement from phase to phase in a conflict occurs as "the factors interact in such a way as to push the conflict ultimately across a series of *thresholds* toward or away from violence (Bloomfield and Leiss 1969). Characteristics of disputes can be visualized as the timing and sequencing of movement between and among phases. Processes of escalation of violence, resolution or amelioration of the seriousness (threat of violence-hostilities) and settlement are identifiable through the use of phrase structures. (Sherman and Neack 1993:90)

SHERFACS, for example, codes six phases: "dispute phase," "conflict phase," "hostilities phase," "post-hostilities conflict phase," post-hostilities dispute phase," and "settlement phase".

In the policy literature, crisis phase has emerged as a key part of the "preventive diplomacy" concept, because of the assumption that diplomacy can be more effective in the early stages of a crisis (e.g., before the outbreak of military hostility) than in later periods. In situations where preventive diplomacy is not an option, crisis phase may still be of utility in providing an early warning of, for example, large-scale refugee movements. Depending on the phase of a crisis, a localized outbreak of military action may be contained without generating large numbers of refugees, or it might rapidly spread, requiring the need for an international response. Much of the literature on ethnic conflict assumes that militarized ethnic disputes such as those found in the former Yugoslavia, the former Soviet Union, Rwanda, Sri Lanka and other locations go through a series of relatively predictable phases (see Alker, Gurr, and Rupesinghe 1995).

The phases identified in the Butterworth, CASCON and SHERFACS datasets have all been assigned by human coders. While human-coding is obviously necessary in the early stages of the development of a new concept, it presents three problems. First, when the coding of a phase is

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[1] Sherman and Neack (1993) provide a review of the evolution of these data sets.

dependent on human judgment, the *de facto* definition of the phase is likely to drift over time. This can occur as a single coder becomes more experienced with the data, and is very likely to occur during attempts to transfer the definitions across projects. Consequently, a phase variable measured across data sets may have significant measurement error, and phases in one data set may seem to have different implications than phases in another because the coders were, in fact, working with disparate definitions. In contrast, the statistical identification of phases—combined with the machine-coding of event data (Gerner et al. 1994)—should make it possible to code crisis phase consistently and efficiently in a variety of contexts and from an assortment of different sources.

Second, in the earlier research, phases were coded retrospectively. While this may be useful from the standpoint of validity, it is likely to exaggerate the effectiveness of phase as an early warning indicator, as well as overestimating the ability of a policy analyst to assess the current phase of a crisis while experiencing it. If phase structure is going to be developed as an effective tool, it must be able to work in real time rather than with "20-20 hindsight."

Third, the tendency of human analysts to impose order on episodes of political events means that in some instances human coders may see phases that are not actually present in the data. This is a problem for the development of statistical early warning indicators because either (a) the human coder is correctly identifying the phase, but is making the assessment based on additional information that must be provided to the statistical early warning system (i.e., any model using phase variables coded differently will have a specification error) or (b) the human coder is incorrectly identifying the phase, which will bias any statistical estimates made with the data. We suspect that human-coded phase identification contains both types of error.

This paper analyses the phase structure of political events in the Levant—Egypt, Israel, Jordan, Lebanon, the Palestinians, Syria—for the period 1979-1995 using event data.[2] This region exhibits some of the most complicated political behavior in the world, with a variety of state and non-state actors vying for influence in the context of the ongoing Arab-Israeli conflict and, until 1990, USA-Soviet competition. Unlike most of the human-coded work on crisis phase, this region—and the event data describing it—involves not a single crisis but several inter-linked disputes. The two dominant political themes have been the Israeli-Palestinian conflict and the Lebanese civil war—both going through phases of hostility and mediation

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[2] The advantages and disadvantages of event data are discussed by Azar, Brody and McClelland (1972), Burgess and Lawton (1972), Azar and Ben Dak (1975), Daly and Andriole (1980), Doran, Pendley, and Antunes (1973), Azar and Ben-Dak (1975), Peterson (1975), Munton (1978), Goldstein and Freeman (1990), Merritt, Muncaster, and Zinnes (1993), Gerner et al. (1994), and Schrodt (1995). Marlin-Bennet and Roberts (1993) provide a recent discussion of event data from a research perspective.

during this period—but there were also other key focal points, such as US efforts on the resolution of the larger Arab-Israeli dispute and spin-off interactions from the Iran-Iraq War and the Iraq's invasion of Kuwait. This extensive foreign policy activity presents a realistic challenge to any effort to identify crisis phase through statistical indicators because of the quantity and variety of material.

Methodology

One of the most substantial challenges in using event data to analyze behavior in an international subsystem is the sheer quantity of information available. An eight-actor system such as the one we are analyzing—the six Levantine actors plus the two superpowers—has event measures for 56 directed dyads, each contributing something to the overall behavior of the system as a whole. However, much of this behavior is inter-correlated because it is generated by a small set of political issues. In order to characterize the behavior of the system, we therefore need to do two things:

1. Ascertain the underlying issues that are generating the observed behaviors;
2. Identify the contributions of various dyads to determining those behaviors.

If the concept of crisis phase is correct, we would expect that the observed behaviors would fall into distinct patterns over time and that we could determine the event behaviors that are characteristic of any phase. Finally, if the behaviors determining a phase are distinct and reflected in event data, it should also be possible to determine those phases inductively by looking at the data itself, without prior knowledge of the phases.

The approach we will use to analyze the system is to look at the behavior of the vector

$$[AB, AC, AD, \ldots, AH, BA, BC, \ldots, BH, CA, \ldots, HF, HG]_t$$

where A,B,...,H are the actors in the system and XY_t is the total Goldstein-scaled events directed from X to Y aggregated over a month.[3] Conceptually, the behavior of the system is simply the path that this vector traces over time in a 54-dimensional space.[4]

The high dimensionality of that space makes this path somewhat difficult to visualize. This is not a new problem in event data analysis: The response of most of the earlier event data

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[3] In other words, we converted each X∅Y event to its numerical score on the Goldstein scale, then totaled these numerical scores by month. Schrodt and Gerner (1994) gives a number of time series plots of the data for the 1982-1993 period.

[4] We have excluded the USA->USR and USR->USA dyads from our analysis since most of their interactions did not deal with the Middle East.

studies was to ignore N-actor systems and instead focus either on a small number of dyads (e.g., Ward 1982, Dixon 1986, Goldstein and Freeman 1990), or look at the interactions of one actor with a number of states (e.g., Howell and Barnes 1993). In situations where there are a small number of clearly dominant dyads—for example the USA/USSR/PRC triad of the Cold War—this is effective, but it is clearly not sufficient in a complex system such as the Middle East.

The first objective of our analysis, therefore, is to see whether we can substantially decrease the dimensions of the behavior. Reducing the dimensionality will be possible provided there are consistent correlations between some of the dyadic behaviors in the system. There are at least three substantive reasons that we can expect this to be the case.

First, there is considerable policy coordination between some of the states. In the extreme case, Lebanon's foreign policy has largely been run by Syria since the late 1980s. Lebanon's reported behaviors can be expected largely to mirror those of Syria, so knowledge of Syria's position may by itself provide sufficient information to predict Lebanon's position. The less extreme example of this would be simple policy coordination: For instance, during the Reagan years US and Israeli policies closely paralleled each other on most issues, as did those of Syria and the USSR.

Second, all of the states in the system are reacting to the same set of events: Israel's invasion of Lebanon, Syria's eventual establishment of military hegemony in Lebanon, the Palestinian *intifada*, the Madrid peace process and so forth. To the extent that states share similar policy positions, they will react to these events in comparable ways. Furthermore, to the extent that certain issues receive greater emphasis in the Reuters reports—the source of our event data—we should expect to see correlated behavior related to those events.

Finally, it is likely that some of the actors in the system have very little influence on the overall events. In our data set, two likely candidates are Egypt—which was diplomatically isolated during most of the period due to the Camp David agreements—and Jordan, which is comparatively small and neither initiates nor receives many events. A model of the behavior of the system could therefore ignore these (or other) actors.

While there are a variety of different methods that could be used to reduce dimensionality through correlation, we will focus on the oldest and most well-understood: factor analysis (Kim and Mueller 1978). Factor analysis—which clusters variables based on their mutual correlations—allows us to answer both of the questions presented above. First, if foreign policies are primarily being determined by some exogenous events—whether the foreign policy of another actor or the interactions of another dyads (e.g., the Israeli-Palestinian conflict)—then these should show up as a distinct factor; further, the nature of that factor should be apparent from the dyads with which it is most strongly correlated. Second, if a state is not actively involved in the system (or is uninvolved with some subset of issues), this will be evident from an absence of correlation between its behavior and those factors. Finally, if a small number of factors explain a large amount of the variance in the system, models dealing with the systemic behavior can use those factors rather than the larger number of dyadic behaviors; the factors have the additional advantage of being uncorrelated (orthogonal).

Conceptualizing the system as moving in a high-dimensional vector space also allows us to deal formally with the issue of crisis phase. In the vector terminology, a "phase" is characterized by a region in the vector space where points cluster over time. Empirically, a phase typology would be evident by the system spending most of its time inside the distinct clusters of behaviors that characterize the phase, with brief transitions between these clusters.

Figure 1 illustrates this process informally for the World War II period, using the two dimensions of "talking versus fighting" and "local versus global involvement." The years prior to 1936 involved little violent conflict. The system then shifted to a series of militarized crises during the period 1936-38, and erupted into a full-scale European war in 1939-40. After a lull in the early part of 1941, the war spread first to the USSR, and then to the Pacific, and the 1942-1944 was characterized by a global war. In 1945, this war ended, first in Europe and then in the Pacific, but the post-war politics, rather than returning to the unilateralism/isolationism of the pre-war period, remained global. The 1946-47 cluster continues to characterize the system for most of the Cold War, with occasional departures from this cluster to take in Korea, Suez, the Cuban Missile Crisis and so forth.

Figure 1
Schematic Representation of Phases during the WWII Period

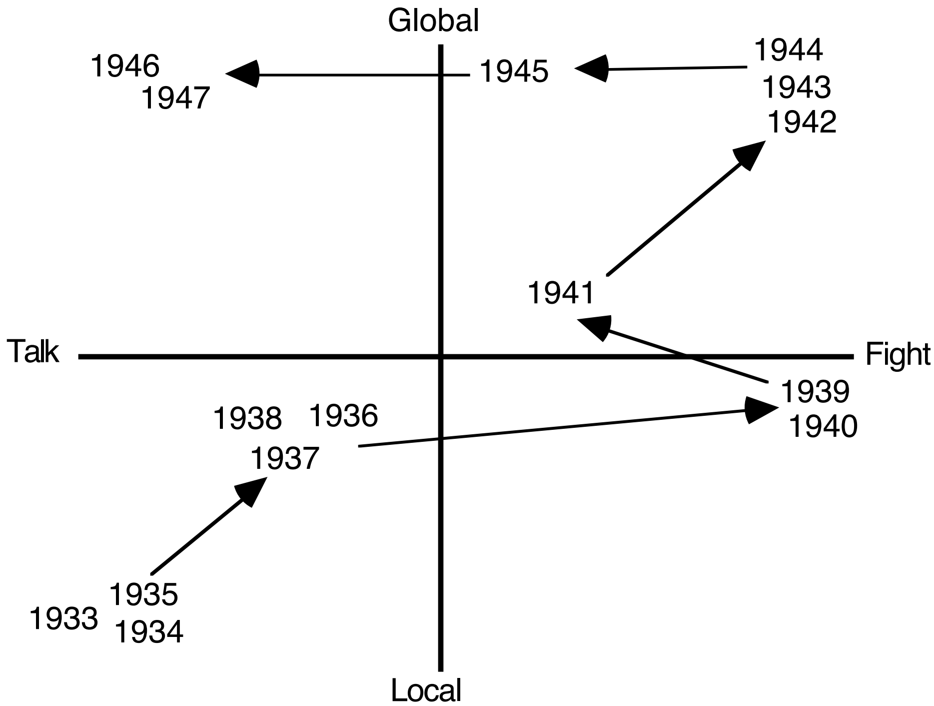

Figure 1 is idealized and an analysis using event data will be complicated by the problem of aggregating dyadic behaviors, the existence of multiple issues determining those behaviors, and the fact that actual political behavior is considerably noisier than the short-answer-exam summary of international politics in the 1930s and 1940s presented above. Nevertheless, if behavior in a system can be characterized by a phase typology and if the behaviors defining those phases are captured by event data, it should be possible to determine those phases using clustering.

In this paper, we will look at the clustering problem both deductively and inductively. In the deductive analysis, we start by positing, based on our contextual knowledge of the politics of the region, a set of behavioral phases in the political events in the Middle East during the 1979-1995 period. Using discriminant analysis (Klecka 1980), we will ascertain the extent to which these phases can be predicted by the dyadic behaviors measured by event data. Examination of the discriminant space will also provide some insight into what types of behaviors are most important in determining the phase.

The inductive study will not set the phases *a priori*, but instead try to discern the phases directly from the observed data by using cluster analysis (Aldenderfer and Blashfield 1984, Bailey 1994). In other words, we will look for clustering in the data itself rather than externally imposing any order upon it. Once these clusters have been determined, we will look at whether the system tends to remain in a cluster for a period of time, as postulated by the phase model, then try to interpret the political meaning of the clusters based on our contextual knowledge of the situation. We will also briefly consider the issue of whether there are early warning indicators that show when the system is ready to shift from one cluster to another.

Data

The data used in this study were machine-coded from Reuters lead sentences downloaded from the REUTNA file of the Nexis data service for the period July 1979 to June 1995; this generates about 100,000 events.[5] We coded these data using the Kansas Event Data System (KEDS), a Macintosh program that generates event data from machine-readable reports; the program is described in Gerner et al. (1994), and Schrodt, Davis and Weddle (1995). KEDS does some simple linguistic parsing of the news reports—for example, it identifies the political actors, recognizes compound nouns and compound verb phrases, and determines the references of pronouns—and then employs a large set of verb patterns to determine the appropriate event code. KEDS has an accuracy in excess of 85% when coding WEIS events for the Middle East; we discuss the validity of these data extensively in Schrodt and Gerner (1994).

The individual WEIS events were converted to a monthly net cooperation score using the numerical scale in Goldstein (1992) and totaling these numerical values for each of the directed dyads of each month. The dyads considered were all interactions among Egypt, Israel, Jordan, Lebanon, the Palestinians, Syria, United States and Soviet Union/Russia except for the USA>USR and USR>USA dyads; this gives a total of 54 directed dyads with 192 monthly totals in each dyad.

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[5] NEXIS is searched using keywords that can be arranged into Boolean statements. To create this data set, the search command was HEADLINE(ISRAEL! OR JORDAN! OR EGYPT! OR LEBAN! OR SYRIA! OR PLO OR PALEST! OR KUWAIT! OR IRAQ!). This retrieved only a small number of totally irrelevant stories, primarily reports on international athletic competitions. (KEDS eliminates such stories with a high degree of accuracy.) The "!" is a wild card character that matches any word beginning with the preceding letters; so "PALEST!" picks up not only "Palestinian", for example, but "Palestinians" and "Palestine". The text downloaded from NEXIS must be reformatted to eliminate headers, keywords and other extraneous material; this is done using a custom program and requires relatively little time. Many of these events are outside the 54 directed dyads considered in this study; those probably contain about 50,000 events. The coded data, as well as the KEDS program and its dictionaries, are available from the authors and will be posted to the csf.colorado.edu/isafp/data FTP site. The 1982-1993 part of the data, used in Schrodt and Gerner (1994), is available through the ICPSR's "Publications-Related Archive".

Prior to doing the analysis, we assigned the following phase identifications to various periods:

Label	Dates	Months	Defining Characteristic
Camp David	Jun.79-May.82	35	Before Israel's 1982 invasion of Lebanon
Lebanon	Jun.82-May.85	36	Israeli troops in Lebanon
Taba	Jun.85-Nov.87	30	Israeli withdrawal from Lebanon until *intifada*
Intifada	Dec.87-Jul.90	32	Palestinian intifada
Kuwait	Aug.90-Oct.91	15	Iraq's invasion of Kuwait until start of Madrid talks
Madrid	Nov.91-Aug.93	22	Bilateral and multilateral peace talks
Oslo	Sept.93-Jun.95	22	Oslo peace process

These phases reflect the dominant issues and activities affecting the region and are not intended to exactly parallel the crisis phases of the CASCON and SHERFACS data sets. They do, however, mirror many of the characteristics of the CASCON and SHERFACS phase structures, notably the movement between periods of violent conflict and periods of dispute resolution.

Factor Analysis

We factor analyzed the 54 directed dyads using principal components; the original factors were then rotated using the varimax criterion, which minimizes the number of variables that have high loadings on any given factor.[6] The results of the factor analysis are presented in Table 1 and in Figures 2 and 3.

Table 1 shows the factors having the five highest eigenvalues and the variables with which they are most strongly correlated. As expected, the two factors explaining the highest amount of variance are those associated with the Israeli and Syrian involvement in Lebanon, and the Israeli-Palestinian dispute. The third factor appears to emphasize the dyads involved in the Camp David peace process, while the fourth and fifth factors emphasize the US involvement in the Lebanon dispute and Jordan's interactions with Syria and Lebanon respectively. This last factor was contrary to our expectation that Jordan would be relatively unimportant in the region. Thirteen dyads have no correlations of 0.20 or higher with the first five factors: all of these involve either the Soviet Union, which has been a relatively minor actor in the region, or Egypt, which until

[6] In other words, it tends to associate each variable with one and only one factor. In the unrotated solution, the first two factors also emphasize the Lebanon and Israeli-Palestinian disputes but with less separation of the variables. All analyses were done using SPSS 6.1 for the Macintosh Power PC.

recently was politically isolated from most of the Arab world due to its signing of the Camp David agreements with Israel. In the varimax rotation, most of the dyads correlate strongly with only a single factor; the exceptions are ISR>USA and ISR>PAL (correlating with factors 2 and 3), and LEB>USR (correlating with factors 3 and 4).

The first five factors explain only 27.8% of the variance; by the usual standards of factor analysis, this is quite small. As shown in the scree plot in Figure 3, there are 21 factors with eigenvalues greater than 1.0 (the usual rule-of-thumb for significant factors) and the factors above five show a long and very gradual decline in the variance explained. Most of those smaller factors appear to be picking up the idiosyncratic behavior of one or two dyads. Contrary to our expectations, it is not possible to reduce the behavior system to a small number of factors.[7]

Figure 2 shows (sort of...the distribution is a lot clearer when viewed in a continuous rotation) the distribution of the variables in the factor space defined by the first three unrotated factors.[8] The blob near the origin contains the large number of dyads that do not highly correlate with any of the three factors. The dyads dealing with regional interactions in the Lebanon conflict are located above this, with high scores on factor 1. The Israeli-Palestinian dispute has high scores on factor 2, although in this rotation only the PAL□USA and ISR>PAL dyads are evident. The USA□Lebanon interactions show up as unrotated factor 3, which is similar to factor 4 in the rotated solution.

Discriminant Analysis

In the discriminant analysis we attempted to use the dyadic behaviors and the factor scores to classify the months of the data set into the phases we had previously assigned. We first ran the discriminant analysis with all of the behavioral variables and with the 21 factors having eigenvalues greater than one; we then did a stepwise analysis to determine whether the phases could be identified by looking at only a small number of dyads. The results of this analysis are presented in Tables 2 and 3; Figures 4 and 5 show the first two dimensions of the discriminant space.

As Table 2 indicates, when all of the behavioral variables are used, the discriminant analysis differentiates the phases with a high degree of accuracy: 90% of the months are classified

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[7] This may be due in part to the wide variety of behaviors shown in this long time series and the diversity of dyads. In some earlier experiments where we looked at only the dyads involving Israel and the Palestinians as sources of behavior, plus LEB>SYR, LEB>PAL, SYR>ISR and SYR>LEB and used data from 1982 to 1993, we found that four factors explained about 70% of the variance. Factor analysis may therefore be useful as a data reduction technique in systems less diverse than the one we've considered here.

[8] Why unrotated?: because this is the only option SPSS provides and we couldn't eyeball the varimax rotation...

correctly, and most of the errors are plausible (e.g. *Oslo* for *Madrid*; *Madrid* for *Taba*). When we use stepwise selection, the discriminant analysis chooses the following 12 variables (in order of selection; number in parentheses is the Wilks' lambda)

ISR>PAL (.636)	LEB>ISR (.427)	PAL>UAR (.324)
ISR>JOR (.250)	UAR>USA (.203)	PAL>LEB (.173)
JOR>ISR (.146)	UAR>ISR (.127)	SYR>LEB (.110)
UAR>JOR (.094)	ISR>LEB(.081)	JOR>USA (.071)

With 70% of the cases classified correctly, the stepwise discriminant is considerably less accurate than the system using all of the variables, although incorrect classification is still most likely to occur into phases immediately before and after the correct phase. The stepwise selection appears to select a single dyad to represent each type of dominant behavior in the system, and eliminates dyads correlated with those selections. Unsurprisingly, most of the chosen dyads involve either Israel, Lebanon or the Palestinians as an actor.

The use of factors in the discriminant analysis substantially reduces the classification accuracy. When all 21 factors with eigenvalues greater than 1.0 are used, the classification accuracy is 70%. In the stepwise analysis, only six factors are used —17 (!), 1, 2, 4, 6, 8, and 9—and the classification accuracy is only about 59%. The factors seem to be missing important classification information, which we would expect given the shallow slope of the scree curve.

Figures 4 and 5 show the first two dimensions of the discriminant space; in both cases, the diagrams are based on the analysis of all of the variables rather than the stepwise analysis. If the factor discriminant plot in Figure 5 is rotated clockwise by 90° (i.e. the X and Y discriminant dimensions are swapped), it is quite similar to the behavior discriminant plot in Figure 4. Unlike the factor analysis, the discriminant analysis concentrates most of the explanatory power in the first three dimensions: In the behavior space these three dimensions explain about 75% of the variance; in the factor space about 85%.

In the behavior discriminant space, the first (horizontal) dimension discriminates the phases chronologically: the centroids are in almost perfect temporal order from left to right except for the swapping of *Camp David-Lebanon* and *Intifada-Kuwait*. This is particularly interesting given that none of the variables contain explicit chronological information; the discriminant analysis is instead picking up the changes in behavior over time. The interpretation of the second (vertical) dimension is less clear; it may serve primarily to differentiate the *Camp David* and *Lebanon* phases, which strongly overlap in the first dimension.

Because the *intifada* is one of the most conspicuous features of the data set, a puzzling aspect in the two-dimensional diagrams is the location of the *Intifada* cluster, which is thoroughly intermixed with the *Madrid* and *Oslo* clusters. As Figure 6 shows, this is an effect of the projection: the third dimension clearly separates the *Intifada*, *Madrid*, and *Oslo* phases and generally seems to reflect a violent conflict/conflict resolution dimension.

Cluster Analysis

The discriminant analysis demonstrates that political phases that have been identified *a priori* can be differentiated with a high degree of accuracy using information about the dyadic behaviors in the system. This means that the phases are statistically distinct and their identification does not require additional information (e.g., hindsight bias) available only to the human coder. However, the discriminant results do not necessarily mean that the phases we have identified are the same as those that would arise naturally from clusters of data points in the 54-dimensional space.

In order to determine the clusters actually present in the data, we used the SPSS K-Means agglomerative clustering algorithm, with the Euclidean metric—\I\SU(i=1,54,(x_i - y_i)^2)—as the distance between points. The K-Means algorithm starts by finding K cases that are widely separated in the vector space; these are used as the initial cluster centers. It then assigns each of the remaining N-K cases to the cluster whose center is closest to the case. When this is completed, the center of each of the K clusters is recomputed, and the process of assigning each case to the cluster whose center it is closest to is repeated. Because the centers being used in the computation are now the true cluster centers rather than the location of the initial center, this will cause some of the points to change clusters. This process is repeated until the cluster membership no longer changes.

Because K-Mean starts with cluster centers that are widely separated, some of the initial centers will be outliers and their clusters will contain only one or two points when the iterations have been completed. Consequently, we used a two-stage process: In the initial iteration we used a relatively high (16) number of centers, then identified the centers of the large clusters. These large clusters were quite distinct: in the complete data set, the large clusters contained 20 to 50 points, whereas the remaining clusters contained fewer than five points. The centers of the large clusters were then used as the starting points for a new clustering that assigned the outlying points to the large clusters.[9]

The results of the clustering using the 54 directed dyads are shown in the left two bars in Figure 7. The shading or color of each bar shows the cluster membership; time is indicated by

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[9] We also allowed this assignment process to iterate but this had little effect on the final cluster centers.

the vertical direction, and the horizontal lines show the phase divisions that we had originally defined. The second bar shows the original clustering assignment; the first bar has attempted to smooth this by using a four-month moving mode.[10] Note that because of the modal smoothing, an abrupt change of the form XXXYYYY (e.g., the *Camp David-Lebanon* transition and the *Taba-Intifada* transition) shows up in the smoothed data one month before the actual transition.

The 54-dyad analysis identified five behavior clusters; three of these correspond closely to the phases we had earlier identified. The *Camp David* cluster is quite uniform, although it shifts into a new phase several months before Israel's invasion of Lebanon. This is followed by a short phase that corresponds to Israel's initial invasion of south Lebanon and the siege of Beirut; in the smoothed data this phase is found at only one other point, near the end of Israel's withdrawal. The system settles back into the *Camp David* pattern for most of the period of that the US-led multinational force was in Beirut, then shifts into a *Lebanon* mode that is maintained until almost exactly the end of period. In the smoothed data, the *Lebanon* phase is followed by a relatively consistent *Taba* pattern, although in the unsmoothed data it periodically jumps between this pattern and the *Camp David* and *Lebanon* occupation patterns. The *Taba* phase ends abruptly at the expected transition point to the outbreak of the *intifada*.

At this point, our phases and those identified by the clustering algorithm part company. The *Intifada* phase is much shorter than what we had identified; after this the system shifts back to the *Taba* pattern. In the unsmoothed data, there are short-term changes around the remaining transition points we'd identified, but these periods do not form distinct clusters. The system returns to the *Intifada* pattern near the end of the *Madrid* period—this is consistent with an upsurge of violent incidents between Israelis and Palestinians during this time—and the *Oslo* period is characterized by an unusually frequent pattern of cluster transitions, but it does not get its own cluster.

We were puzzled by the inability of the system to identify the Madrid and Oslo peace processes as distinct periods, and speculated that this might be due to the fact that we'd defined our phases primarily with respect to the Israeli-Palestinian conflict. We therefore did an additional analysis looking only at the dyads that involved Israel or the Palestinians as a source or target. These results are shown in the second two bars; the shadings/colors were chosen to be

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[10] $MM_t = \text{Mode}(X_t, X_{t+1}, X_{t+2}, X_{t+3})$ Ties were resolved in favor of the most recent value if the tie had the pattern XXYY and to the modal value on either side of the value for any other pattern. A white space indicates either that no mode could be computed because the 4-month interval contained four different clusters, or that the mode occurred in the pattern YZXX, i.e. the actual transition did not occur until t+3. None of these assumptions are critical to the smoothing, and if anyone has a better idea of how to smooth a nominal time series, we're open to suggestions.

similar to those in the original analysis though the actual cluster centers differ because we are looking at only 30 dyads.

The Israeli-Palestinian analysis found seven clusters, although neither of the two new clusters correspond to the *Madrid* and *Oslo* phases. The *Camp David*, Lebanon invasion, and Lebanon occupation clusters are almost the same as in the earlier analysis, as is the single cluster extending from the Spring, 1989 to Fall, 1992. The two new clusters correspond to periods of high—but below *intifada*-level—Israeli-Palestinian violence before and after the *Intifada* cluster (and replacing that assignment in the second period of violence in early 1993), and a small cluster in the unsmoothed *Taba* period that probably corresponds to the Taba negotiations themselves. Curiously, while the *Madrid* and *Oslo* periods still do not receive separate cluster assignments, the umsmoothed behavior into these two phases jumps around between all of the other clusters rather than settling into a single pattern.[11]

The only analysis we have done that successfully finds a "peace process" cluster was an analysis using the 21 factor scores. In this experiment, the *Camp David* period and the *Madrid-Oslo* period were each in distinct clusters (without a transition between *Madrid* and *Oslo*), but the intervening period did not show distinct patterns—in fact the factor score clustering was the only analysis not to show any part of the *intifada* as a distinct phase. We examined time series plots of various factors and it appears that Factor 4 (see Figure 8) may account for this successful identification of the peace process. On the basis of the variable loadings, we had initially identified that Factor 4 as related to US involvement in Lebanon, but it has consistently high values during the Madrid-Oslo period and was the only factor we looked at that showed this pattern.[12]

Analysis and Conclusion

The results of this analysis are generally quite encouraging for the prospects of systematically studying phase structures using conventional statistical methods. In this section we will briefly assess where we expect to take each of these as we move toward early-warning and phase-assessment models using these techniques.

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[11] This is also true during the *Taba* phase; in fact the cluster we've called *Taba* is probably a post-*intifada* phase that also is used to characterize the *Taba* period in the original analysis.

[12] The time series plots of the factors are generally not very informative. Part of the problem may be that the factors are orthogonal: This is useful for statistical purposes such as regression but makes the factors very difficult to interpret politically because political interactions are not orthogonal—events in Lebanon continually affected Israeli-Palestinian interactions and vice versa.

The factor analysis appears to be the least useful technique, at least in this region of the world. The clusters of variables identified by the varimax rotation are politically plausible and correctly identified what we viewed to be the two dominant political features of the data set, as well as identifying a politically-plausible set of less-important dyads. However, the first five factors explain only about one-quarter of the variance in the data, and the slope of the scree plot after those five factors is very shallow, so a large number of additional factors would be required to obtain additional variance. Consequently, factor analysis does not appear very promising as a data reduction method; one should instead use the original behavioral variables. With the exception of the identification of the *Madrid-Oslo* cluster, he discriminant and cluster analysis also bear out this expectation.

The results of the discriminant analysis, on the other hand, were very reassuring—the event data were sufficient to distinguish our *a priori* phase assignments with a high degree of accuracy and, furthermore, identified plausible dimensions. The information required to identify these phases is, in fact, present in the data. Unlike the factor analysis, the discriminant analysis quite substantially reduced the dimensionality of the behavior, focusing about three-quarters of the discriminating power into three dimensions having roughly equal importance. *If used judiciously*, stepwise discriminant might be helpful as a technique for reducing the number of variables that need to be monitored in the system in order to assess its phase and provide warning of phase transitions. Because any stepwise procedure is highly affected—aye, thrives on—collinearity, we do not suggest simply accepting the stepwise results as given, but if combined with additional information (for example on the consistency and reliability of the newswire reports used to generate the event data for the various dyads) stepwise discriminant analysis might provide useful guidance in simplifying the requirements of a monitoring system.

Finally, the clustering method worked surprising well in two respects. First, in a number of instances, it either identified the same phases we had assigned, or else identified plausible alternative phase transitions (e.g. an earlier end of the *Intifada* phase than we'd identified and the "sub-*intifada*" (*intifada-saghir*?) phase in the Israel-Palestinian analysis). Given that the cluster analysis was completely inductive, was working only with the aggregated dyadic behaviors, and had no indication of the overall structure of the political behavior, the clustering worked quite well.

Many of the clustering results also appear to be consistent with our assumption that a system will begin to show instability in the behavior space prior to experiencing a phase shift. In the analysis of the 54-dyads, only the *Intifada-Kuwait* transition—which was completely exogenous to the Levant—does not show some fluctuation in phase assignments prior to the transitions. These changes are only necessary, not sufficient, but they offer the possibility of some form of early warning. The *Madrid-Oslo* period in the Israeli-Palestinian test is characterized by almost continuous changes between clusters, and it may be possible to use this information to characterize that phase. To date we have looked only at the assignment of points to the nearest cluster center, and by using more sensitive numerical measures—the obvious being a point's distance to various cluster centers—it may be possible to derive some useful early-warning measures.

Additional Approaches

Use of event counts rather than scaled data

The analysis presented here works in a continuous variable space by aggregating events using the Goldstein scale. Our earlier work (Schrodt and Gerner 1994) shows that the Goldstein-scaled values reflect events on the ground fairly well, but at the same time it is unlikely that this scaling is optimal for the various purposes we are studying here, such as deriving factors or clustering.

The obvious alternative to using the Goldstein scale would be to use the counts of the nominally-coded events themselves. These could be used in a factor analysis to empirically determine weights for the various types of events (i.e. similar to the Goldstein scale weights), and then those factors could be used for the clustering studies. An additional advantage of this approach is that the scales would not need to be the same for each actor: for example it is quite likely that a threat of military action from Israel or Syria carries considerably more weight than a threat from Jordan or Lebanon.

The reason we have not done this yet is that it expands the dimensionality of the behavior of the system by a factor of 22 if one aggregates to the level of 2-digit WEIS scores and by a factor of 66 if one goes to 3-digit WEIS scores. This would produce a factor analysis where the number of variables is considerably larger than the number of data points, not to mention the computational nightmare of dealing with a 1188- or 3564-dimensional matrix, most of whose entries are zero. It might, however, be feasible to do this in a subsystem (e.g. Israel, Lebanon, Palestinians, Syria) to get some indication of how the various nominal categories should be weighted.

Clustering using time as a variable

While the discriminant analysis actually found that chronological time was the single best discriminating factor, we have yet to include time as a variable in any of our analyses. Time is probably more important as a surrogate for exogenous events in the system—for example the end of the Cold War—than as an actual variable, but adding time to the cluster analysis might eliminate some of the instability seen in the existing phase assignments and could provide a more systematic method of smoothing than is provided by the moving mode we used here. Because time is a continuous variable, it can be readily incorporated into the distance calculations of the clustering algorithm and the weight given to temporal proximity in determining clusters could be adjusted as a parameter. It is not possible to do this inside the SPSS K-Means algorithm, but writing the appropriate computer code would be easy and the computations are straightforward.

Clustering using alternative metrics

The Euclidean metric used in this analysis is only one of many metrics that could be used for clustering. One obvious alternative approach would be to assign different weights to the various dyads. This weighting could be based on the total number of reported interactions or, conversely, adjust the interactions based on the overall level of reports in Reuters, on the assumption that a single reported interaction in a poorly-covered dyad such as Syria-Jordan is worth more than a number of interactions in a well-covered dyad such as Israel-USA. The Euclidean measure itself seems to be working fairly well, though we may experiment with a couple of additional alternatives—for example the correlation distance—that can be computed using SPSS.

Implications for Early Warning

To the extent that the Middle East is typical, this analysis has three implications for the use of event data for early warning purposes. First, it is clearly possible to analyze the behavior of an N-actor system taken as a whole, rather than looking at individual dyads or small sets of dyads. In addition, this can be done using readily-available and well-understood statistical techniques, though we suspect that in the long run specialized methods also will be useful. The ability to analyze N-actor systems is particularly important once one begins to consider sub-state actors such as political factions and ethnic groups. We have yet to do this, but coding sub-state actors is relatively straightforward with automated coding, and the techniques presented here should work as well with sub-state actors as they have with international actors. It would be interesting, for example, to look for phase shifts in the Lebanon conflict using data that differentiated the activities of the various ethnic and political groups within Lebanon.

Second, as we noted above, the behaviors recorded in event data—at least in a well-covered area such as the Levant—are sufficient to correctly discriminate periods of time into the phases assigned by human coders, even when those phase assignments do not correspond exactly to the phases generated by clustering. Given the validity and reliability problems of event data, and the coding ambiguities and hindsight bias that affect human coding of phases, this conclusion was by no means guaranteed. Because of this, we suspect that other studies using phase (whether human or machine coded) as an independent variable—for example in assessing the effects of multilateral intervention on crisis outcome—will not be severely affected by specification error, as would be the case if phase assignments required information beyond that present in the behaviors of the dyads.

Finally, the next step in this analysis should be a study of the continuous movement of the behaviors with respect to the clusters, rather than the simple assignment of months to clusters. While the system is clearly not going to operate with the simplicity of that shown in Figure 1, eyeballing the cluster assignments in Figure 7 shows two behaviors that need to be further explored: (a) fluctuation in the cluster assignment prior to a phase transition; (b) human-assigned phases that are characterized by rapid shifts between the machine-assigned clusters. By focusing our analysis on the measurement of distances rather than the nominal assignment of phases, we may find some useful early warning indicators.

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Table 1. Factor analysis of behaviors

	F1 (7.7%)	F2 (6.3%)	F3 (4.9%)	F4 (4.6%)	F5 (4.3%)
FACTOR 1					
Lebanon Conflict: Regional					
ISR_SYR	.77063	-.03720	.11422	-.02361	.07655
ISR_LEB	.68424	-.19475	.27245	-.10951	-.09765
LEB_ISR	.62104	-.24898	.24919	.05920	-.06969
SYR_ISR	.61084	.07267	-.11728	.07409	.00749
SYR_LEB	.60889	.11476	.04020	-.05356	.02015
LEB_PAL	.57580	-.01108	-.07544	.21770	-.10324
LEB_SYR	.46670	.11858	.04985	.06833	.31355
PAL_LEB	.44162	.19937	-.10359	.21732	-.20491
USR_ISR	.42010	.02499	-.08466	.08717	-.01734
SYR_PAL	.22236	.12262	-.01088	.02583	-.20527
USR_UAR	-.20941	-.07410	.04204	.11440	-.04012
FACTOR 2					
Israeli-Palestinian Conflict					
PAL_USA	-.01140	.67335	.16935	.05846	.02171
USA_PAL	-.07209	.67097	.40013	.10936	-.01038
PAL_ISR	.17422	.62088	.32562	-.21247	-.02340
JOR_ISR	-.02782	.53735	.00195	.00048	-.03524
ISR_JOR	.07398	.47184	-.23271	-.00117	.07636
USA_ISR	.07911	.45914	.24348	.09691	-.05160
USA_JOR	.05478	.44701	.07666	.03048	-.00098
ISR_PAL	.14883	.43142	.44274	-.19908	-.17906
PAL_JOR	.08964	.28951	-.13685	-.03585	.02426
JOR_USA	-.12043	.28389	-.17349	.03143	-.18260
ISR_USA	.01100	.27068	.30519	.01339	-.04944
FACTOR 3					
Camp David					
USA_UAR	.02558	.00486	.66380	-.06710	-.02713
UAR_ISR	-.00127	.06118	.52263	-.08769	-.00699
UAR_USA	-.23293	-.04316	.51401	.01873	-.18212
USR_LEB	.13009	.13405	.50231	.07938	.08913
ISR_PAL	.14883	.43142	.44274	-.19908	-.17906
LEB_USR	-.07693	.05194	.40661	.40874	.08390
ISR_UAR	-.00881	.12267	.36692	.05849	.08068
ISR_USA	.01100	.27068	.30519	.01339	-.04944
JOR_PAL	-.02718	.15418	-.22082	-.06511	.07733
FACTOR 4					
Lebanon: USA					
USA_LEB	.08833	-.18332	.12994	.76498	.10621
LEB_USA	.05307	-.18532	.18739	.64917	.07936
USA_SYR	.09892	.18497	-.11931	.63707	.03229
SYR_USA	.24475	.21204	-.26704	.55962	-.00572
PAL_SYR	.03789	.20720	-.01864	.41491	-.01741
LEB_USR	-.07693	.05194	.40661	.40874	.08390
UAR_JOR	.06964	.09702	-.17668	-.39245	.06674
USR_SYR	.06621	.04058	.09849	-.25670	.22495

FACTOR 5					
Lebanon: Jordan					
LEB_JOR	-.00552	-.03504	.07876	.06993	.71868
SYR_JOR	-.03992	-.03719	.01751	-.05237	.63703
JOR_LEB	-.02787	-.21985	-.01113	.11656	.63112
JOR_SYR	-.01605	.06181	-.13909	-.06578	.59969
UAR_LEB	.02816	-.07193	.18916	.00761	-.45215
NO LOADING ABOVE 0.20					
USR_PAL	-.01669	-.07878	.10301	-.01354	.02777
ISR_USR	.17039	.07589	-.04179	.12619	.11579
JOR_UAR	.01317	.08728	-.15176	-.09154	-.00567
JOR_USR	-.18509	-.10403	-.01510	.13735	.06898
LEB_UAR	-.03002	-.00800	-.05067	-.04281	-.09013
PAL_UAR	.04259	.19829	-.03830	.06054	.06002
PAL_USR	.14461	-.11372	.07763	.03280	.12822
SYR_UAR	.12219	-.02485	-.01058	.06838	-.00954
SYR_USR	-.05312	-.00329	.11365	-.03779	.00136
UAR_PAL	-.00749	.15084	.19741	-.11524	.03150
UAR_SYR	.02537	-.14900	-.06708	-.03898	-.04597
UAR_USR	-.15024	-.07283	.05017	.13420	-.14650
USR_JOR	-.00721	-.13682	.06754	.09339	.02446

SOURCE: Factor analysis of all directed dyads; varimax rotation. Variables are sorted by maximum loading; they are included in two factors if the difference between the two highest loadings is <0.05. Variables are included in a factor if the loading is >0.20 in absolute value. Figures in () in first line show variance explained by each factor.

Table 2. Discriminant analysis of behavior

Behavior, All Variables

Predicted

Actual	Camp David	Lebanon	Taba	Intifada	Kuwait	Madrid	Oslo	N
Camp David	**100.0%**	0%	0%	0%	.0%	0%	0%	35
Lebanon	2.8%	**86.1%**	5.6%	2.8%	0%	2.8%	0%	36
Taba	0%	0%	**86.7%**	0%	3.3%	10.0%	0%	30
Intifada	3.1%	0%	3.1%	**90.6%**	0%	3.1%	0%	32
Kuwait	0%	0%	0%	0%	**100.0%**	0%	0%	15
Madrid	4.5%	0%	4.5%	0%	.0%	**77.3%**	13.6%	22
Oslo	0%	0%	0%	0%	0%	9.1%	**90.9%**	22

Percent of cases correctly classified: 90.10%

Function	Var Explained	Cumulative Pct	Wilks's Lambda	Signif
1	28.74	28.74	.023784	.0000
2	24.44	53.18	.072227	.0000
3	20.62	73.80	.196315	.0000
4	11.12	84.92	.378201	.0003
5	8.61	93.53	.649599	.0300

Behavior, Stepwise

Predicted

Actual	Camp David	Lebanon	Taba	Intifada	Kuwait	Madrid	Oslo	N
Camp David	**85.7%**	2.9%	8.6%	0%	2.9%	0%	0%	35
Lebanon	2.8%	**63.9%**	16.7%	2.8%	5.6%	8.3%	0%	36
Taba	10.0%	6.7%	**56.7%**	10.0%	3.3%	13.3%	0%	30
Intifada	0%	0%	9.4%	**68.8%**	12.5%	6.3%	3.1%	32
Kuwait	6.7%	0%	6.7%	0%	**73.3%**	13.3%	0%	15
Madrid	9.1%	4.5%	4.5%	9.1%	0%	**68.2%**	4.5%	22
Oslo	0%	0%	4.5%	0%	4.5%	13.6%	**77.3%**	22

Percent of "grouped" cases correctly classified: 70.31%

Function	Var Explained	Cumulative Pct	Wilks' Lambda	Signif
1	32.95	32.95	.155750	.0000
2	27.45	60.41	.310626	.0000
3	19.97	80.38	.535314	.0000

4	10.89	91.27	.746473	.0000
5	5.54	96.80	.896191	.0058

Table 2. Discriminant analysis of factors

All Factors

	Predicted							
	Camp David	Lebanon	Taba	Intifada	Kuwait	Madrid	Oslo	N
Camp David	**82.9%**	0%	2.9%	0%	11.4%	2.9%	0%	35
Lebanon	0%	**66.7%**	11.1%	5.6%	0%	16.7%	0%	36
Taba	3.3%	10.0%	**60.0%**	3.3%	3.3%	20.0%	0%	30
Intifada	6.3%	3.1%	6.3%	**62.5%**	15.6%	3.1%	3.1%	32
Kuwait	6.7%	0%	0%	0%	**73.3%**	20.0%	0%	15
Madrid	9.1%	0%	0%	0%	0%	**81.8%**	9.1%	22
Oslo	0%	0%	0%	0%	0%	36.4%	**63.6%**	22

Percent of "grouped" cases correctly classified: 69.79%

Function	Var Explained	Cumulative Pct	Wilks' Lambda	Signif
1	36.58	36.58	.161541	.0000
2	28.74	65.32	.339410	.0000
3	19.17	84.49	.588694	.0006
4	8.97	93.46	.791120	.1770
5	4.49	97.95	.927176	.6446

Stepwise

	Predicted							
	Camp David	Lebanon	Taba	Intifada	Kuwait	Madrid	Oslo	N
Camp David	**82.9%**	0%	2.9%	0%	8.6%	5.7%	0%	35
Lebanon	5.6%	**58.3%**	16.7%	5.6%	0%	13.9%	0%	36
Taba	13.3%	16.7%	**46.7%**	3.3%	3.3%	16.7%	0%	30
Intifada	0%	12.5%	12.5%	**40.6%**	21.9%	12.5%	0%	32
Kuwait	6.7%	0%	6.7%	0%	**66.7%**	13.3%	67%	15
Madrid	9.1%	0%	13.6%	4.5%	0%	**59.1%**	13.6%	22
Oslo	0%	0%	0%	9.1%	4.5%	27.3%	**59.1%**	22

Percent of cases correctly classified: 58.85%

Function	Var Explained	Cumulative Pct	Wilks' Lambda	Signif
1	42.43	42.43	.343078	0000

2	25.13	67.56	.537922	.0000
3	22.17	89.73	.807348	.0001
4	8.88	98.61	.969371	.4548
5	1.05	99.66	.992374	.4944

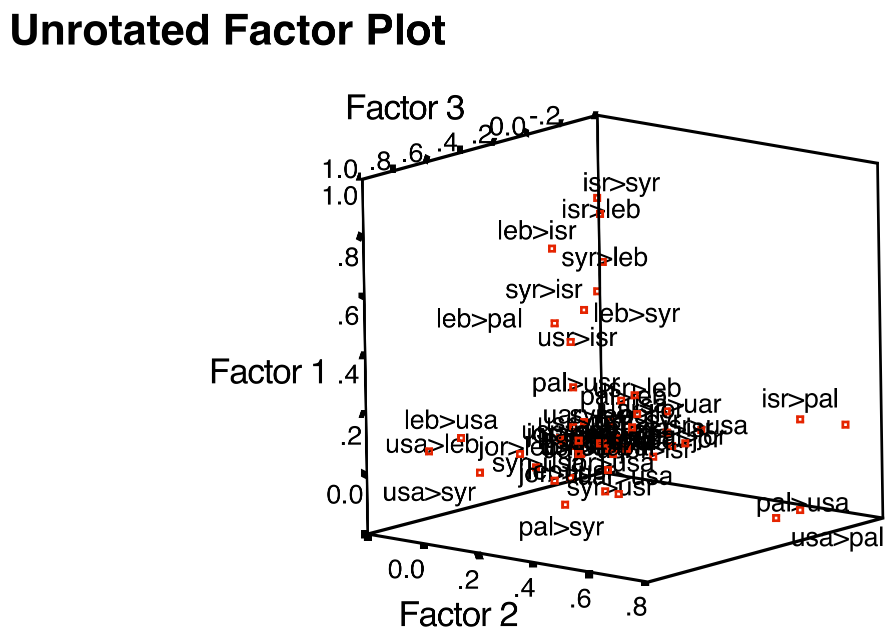


Figure 2: Unrotated factor space of dyadic behaviors

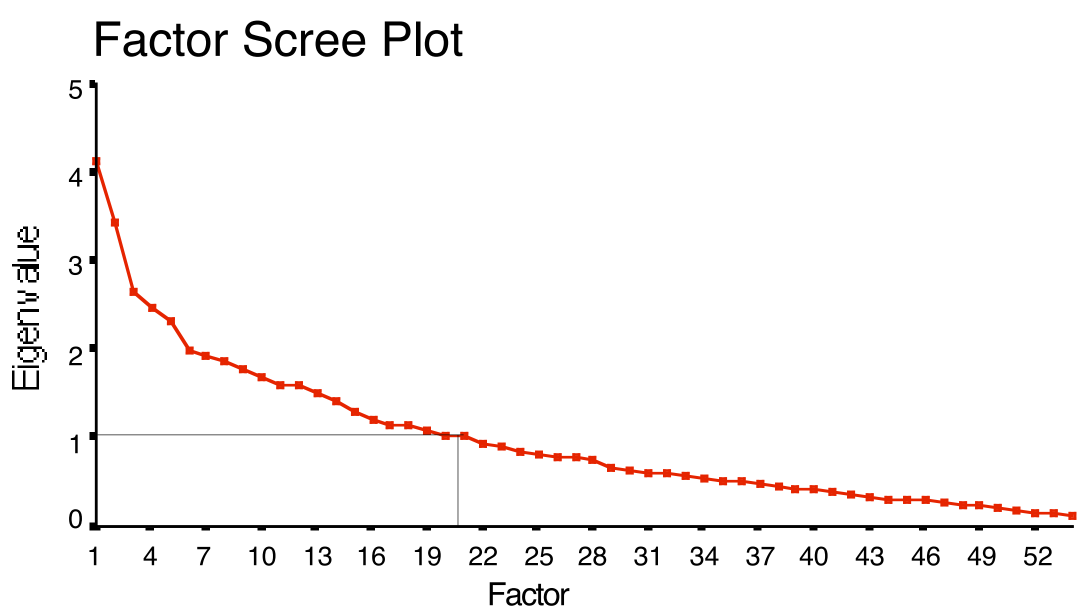


Figure 3: Scree plot of eigenvalues

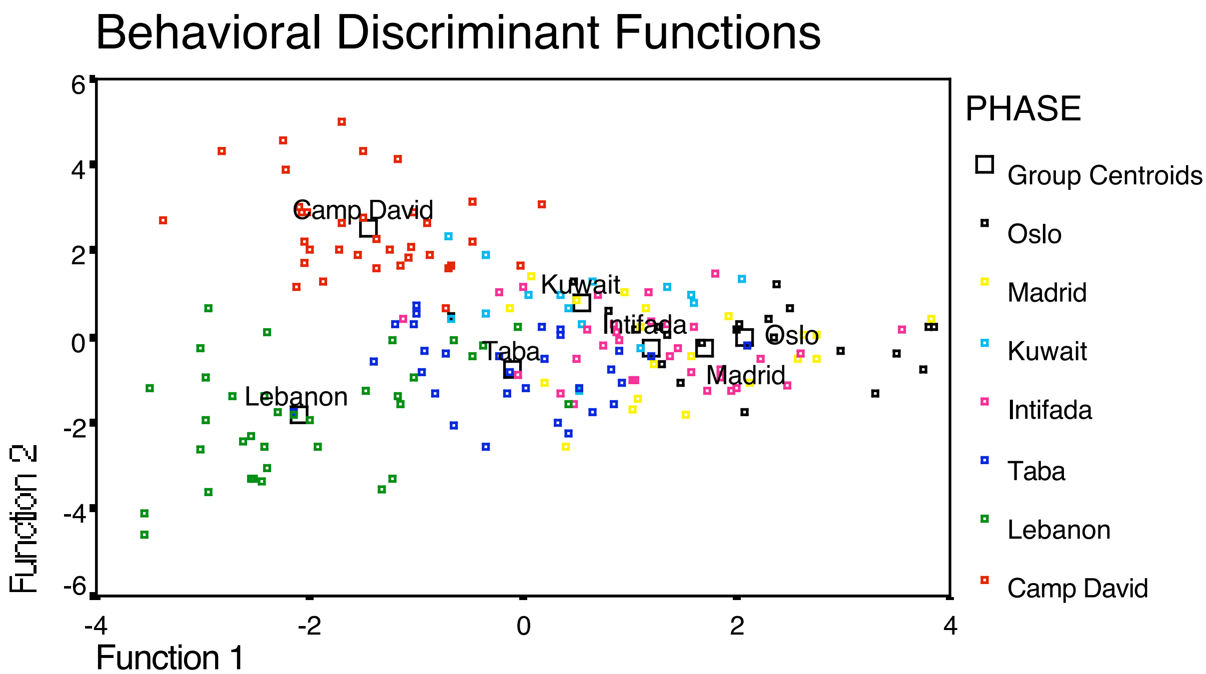


Figure 4: Behavior discriminant space [color]

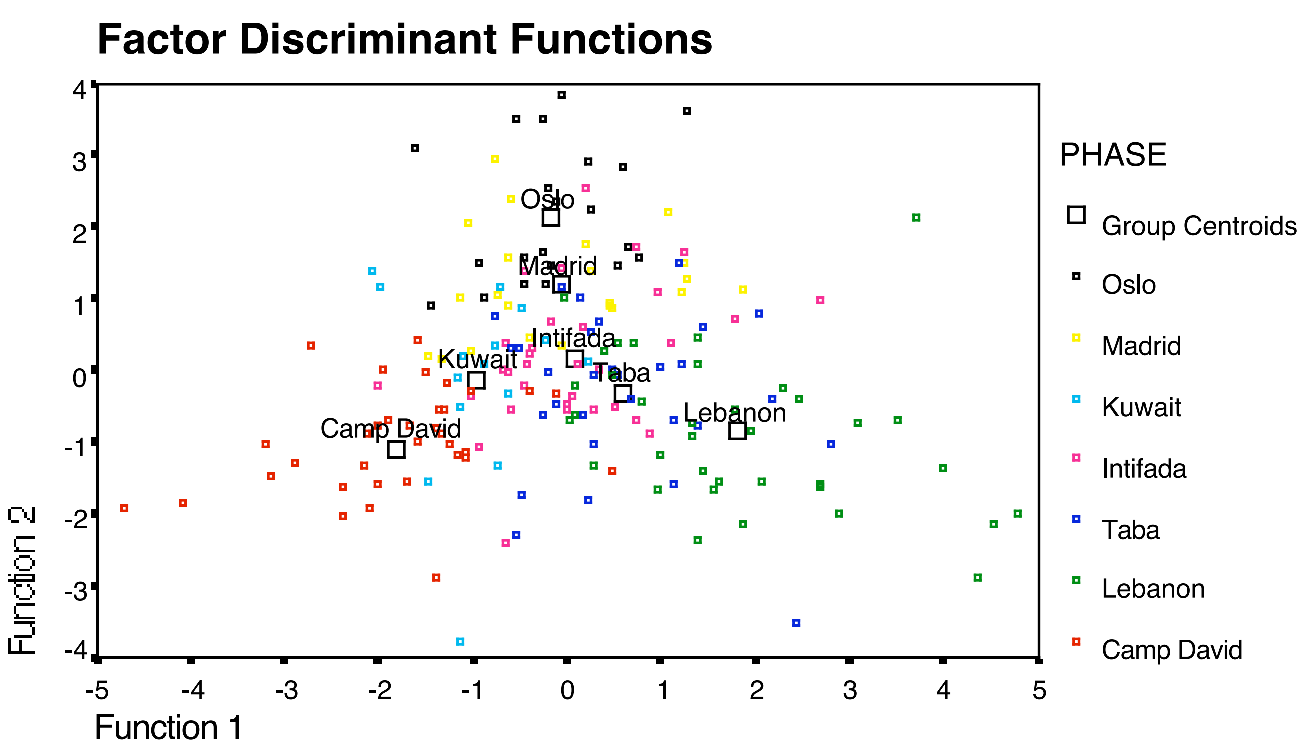
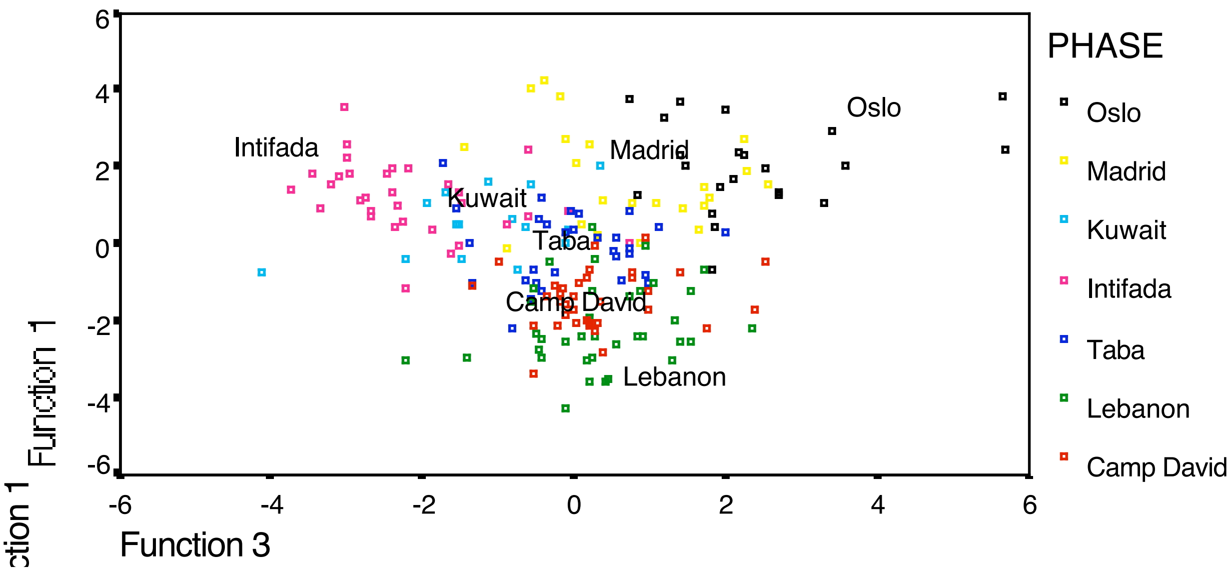


Figure 5. Factor discriminant space [color]

Behavior Discriminant Space

Dimensions 1 and 3



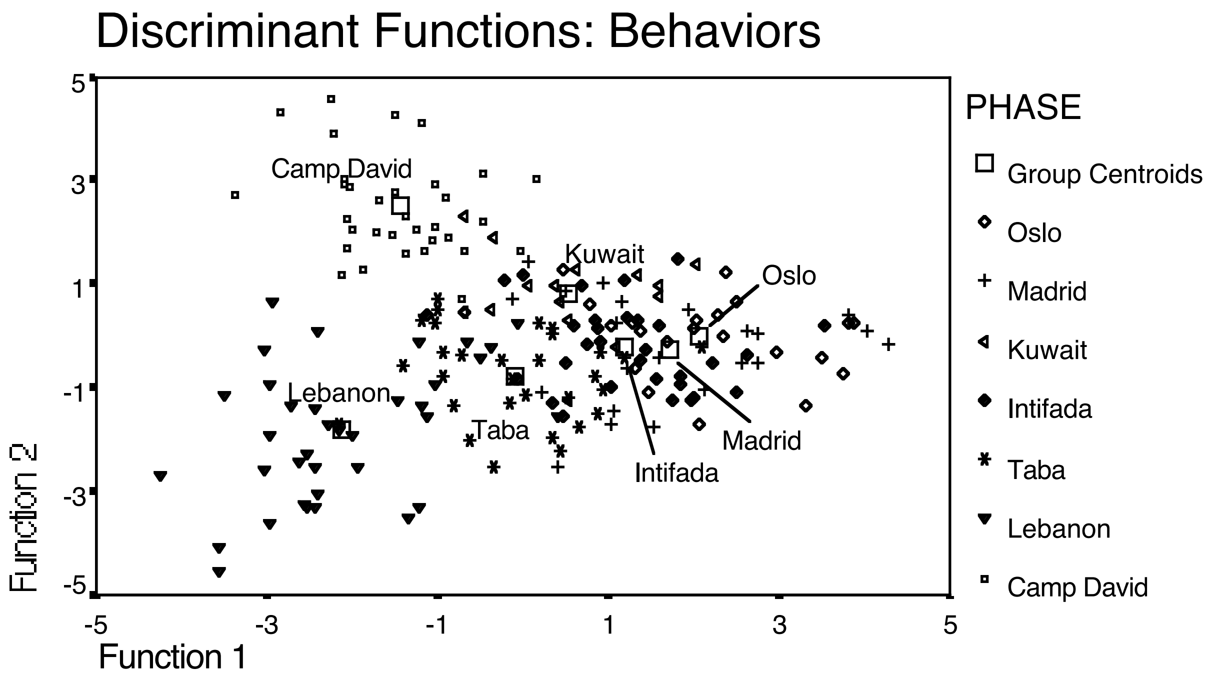


Figure 4: Behavior discriminant space[B&W]

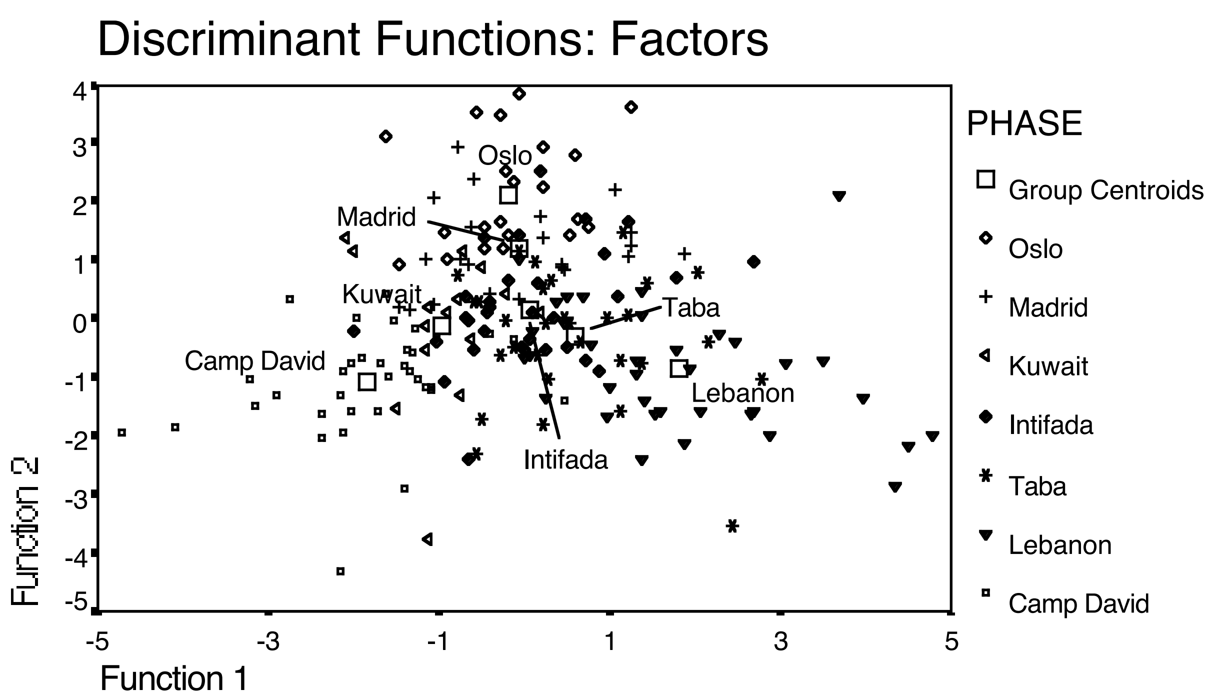


Figure 5: Factor discriminant space [B&W]

Figure 6. Dimensions 1 and 3 of behavior discriminant space

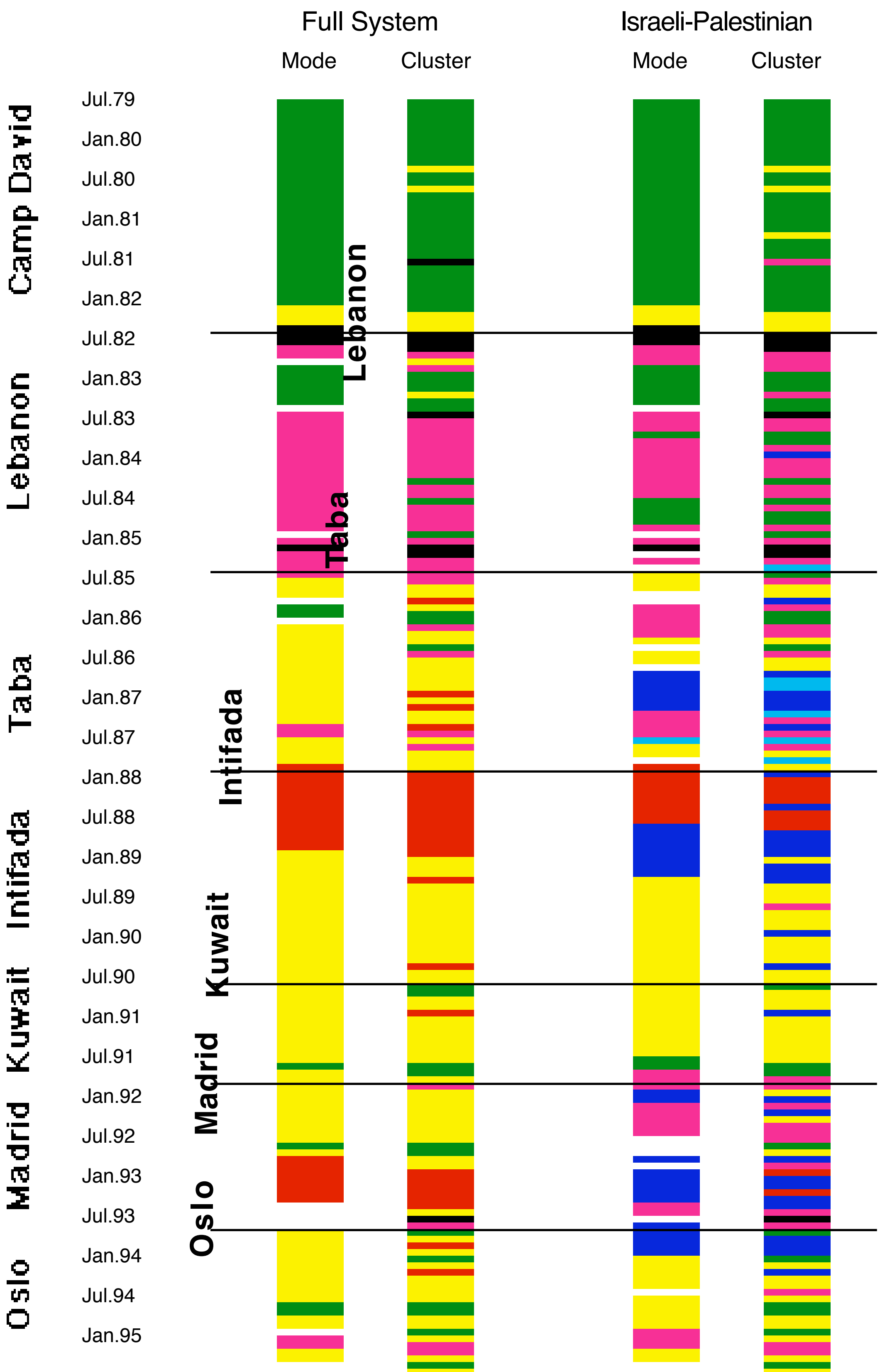


Figure 7. Behavioral clusters

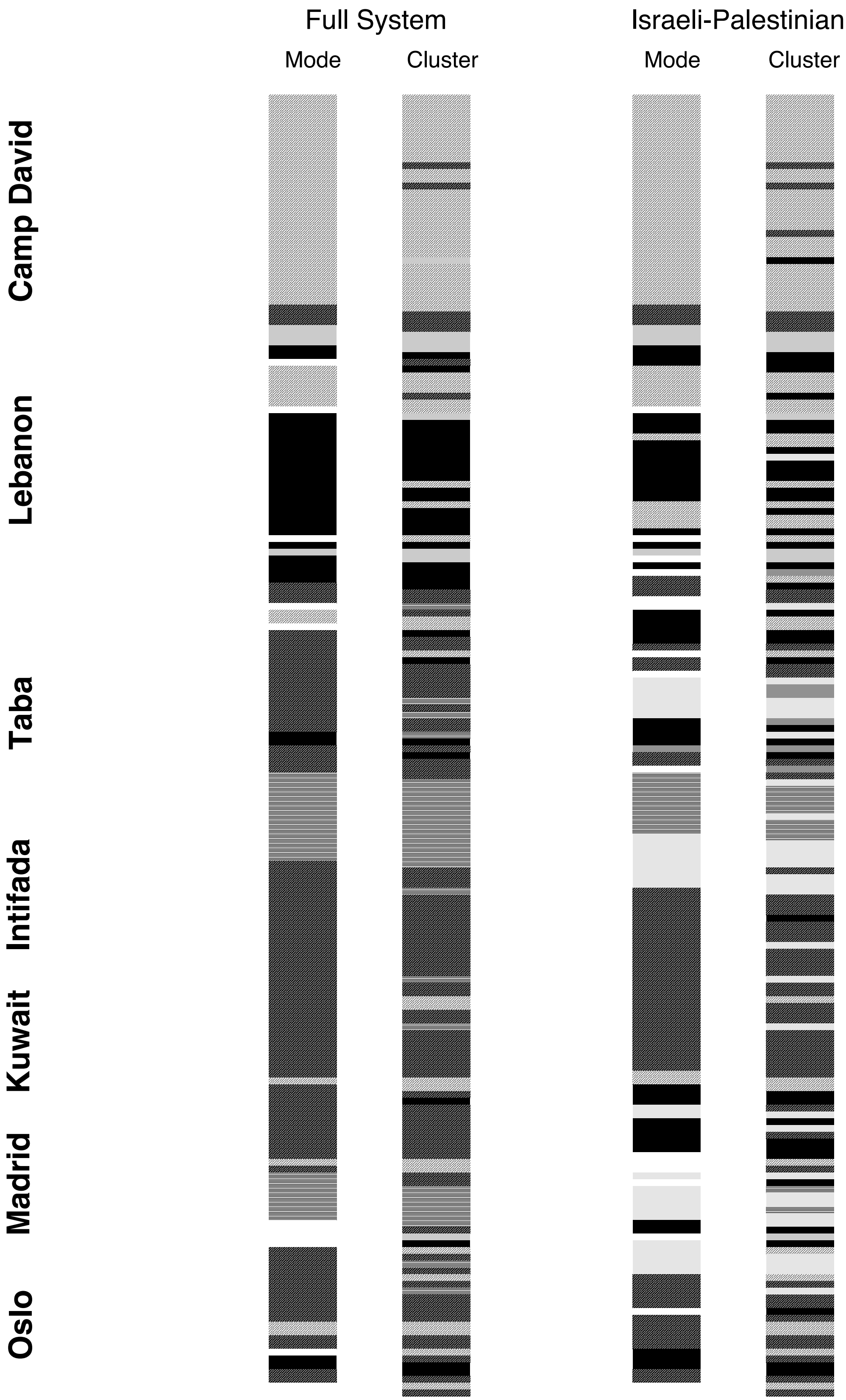


Figure 7. Behavior clusters

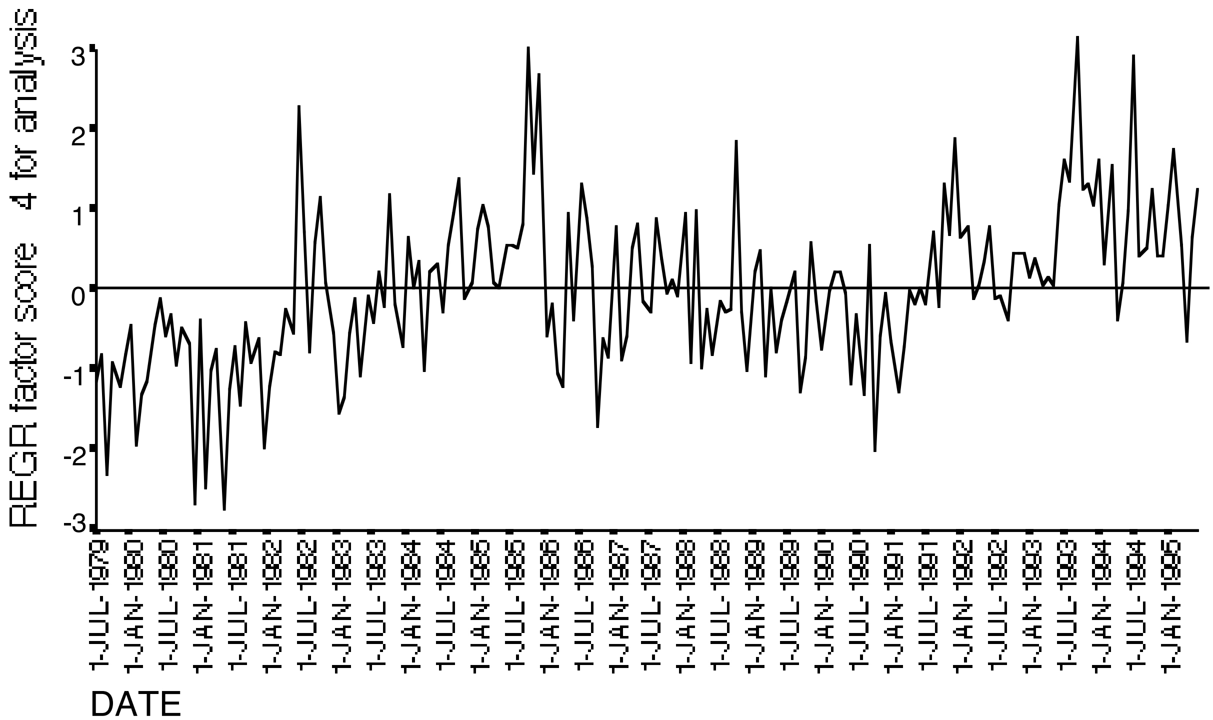


Figure 8: Time series plot of Factor 4