Assessing Nation-State Instability and Failure[1]

by

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"Abstract"–DARPA initiated a six-month Pre-Conflict Anticipation and Shaping (PCAS) initiative to demonstrate the utility of quantitative and computational social science models (Q/CSS) applied to assessing the instability and failure of nation-states. In this program ten different teams of Q/CSS researchers and practitioners developed nation state instability models and then applied them to two different countries to assess their current stability levels as well as forecast their stability levels 6-12 months hence. The models developed ranged from systems dynamics, structural equations, cellular automata, Bayesian networks and hidden Markov models, scale-invariant geo-political distributions, and multi agent-based systems. In the PCAS program we also explored a mechanism for sensitivity analysis of Q/CSS model results to selected parameters, and we also implemented a mechanism to automatically categorize, parse, extract and auto-populate a bank of Q/CSS models from large-scale open source text streams. Preliminary yet promising results were achieved, and the utility of the results can provide added value for decision-making problems around planning, intelligence analysis, information operations and training. This paper describes the motivation and rationale for the program, the Q/CSS models and mechanisms, and presents results from some of the models. In addition, future research and key challenges in using these Q/CSS models within an operational decision making environment will be discussed.

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1. Introduction

The end of the Cold War has changed the geopolitical dynamics of U.S. Government interaction with foreign governments. The venerable Cold War strategic defense triad has become obsolete in a 21st century strategic threat environment comprised of asymmetric and unconventional activities by terrorists, Weapons of Mass Destruction (WMD) proliferators, and failed states. Illustrated in Figure 1 (and described in more detail in [Popp 2005]) is a new 21st century strategic threat triad with "failed states" being a key element of this triad, and the convergence of it with terrorism and WMD proliferation representing the greatest modern day strategic threat to the national security interests of the United States. A prime safe haven and breeding ground for these unconventional activities are fragile and failing nation-states which are unable or unwilling to enforce national and international laws.

From February – September 2005 DARPA initiated a small initiative called Pre-Conflict Anticipation and Shaping (PCAS) to assess the utility and merits of applying quantitative and computational social sciences (Q/CSS) models and tools from a wide range of non-linear mathematical and non-deterministic computational theories to assess and forecast nation-state instability and failure. In PCAS we did not integrate the multiple Q/CSS models and tools into one framework; nor did we attempt to tackle the problem of defining a universally accepted or consensus definition of state failure. Different social science perspectives yield different definitions, and as noted in [Rotberg 2002], "… failed states are not homogeneous. The nature of state failure varies from place to place." Also pointed out in [Rotberg 2002] is the problem of nation-state instability and failure as one of assessing the governance ability of a nation-state. By governance is meant the ability of a nation-state to provide the services its citizens and constituents require and expect in order to maintain order and conduct their daily lives. Such services include security, law enforcement, basic services and infrastructure, defense, education, and observation of human rights.

Little work within the DOD has been focused on addressing in an objective, unbiased, systematic and methodological way identifying the causes and symptoms of nation-state instability, and mitigating their effects on US interests. Operationally, it was envisioned that the PCAS program could provide the Regional Combatant Commander (RCC) planning and intelligence staff with a decision support tool comprised of various Q/CSS models to inform the decision-makers about causes and events that may threaten US interests and activities within their area of responsibility. Some of the Q/CSS models could allows RCC staff to assess the effects of events, develop mitigating options for potentially destabilizing events, evaluate the ability of those options to exert a corrective influence, analyze their sensitivity to environmental and contextual parameters, and develop explanations for the effects of events and the impact of the options. The structure of this decision support framework is depicted in figure 2.

Figure 1. 21st Century Strategic Threats

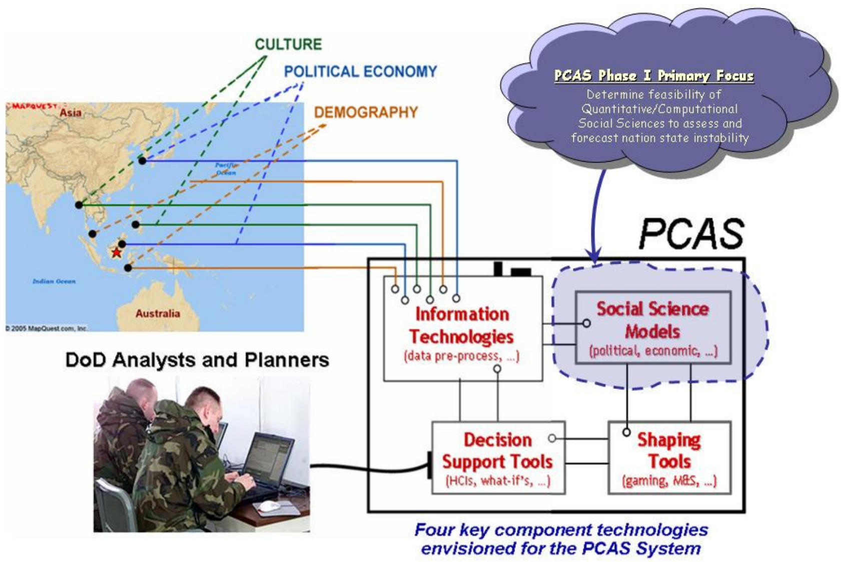

Figure 2. PCAS Decision Support Framework

PCAS Phase I, which began in February 2005, progressed through three stages. In the first two months, the performers refined their hypotheses, conducted initial data collections, and developed initial versions of their models. During the mid-months, the performers tested their models, refined and enhanced their data collection efforts, and became more knowledgeable about the two countries being modeled and assessed. In the final two months, the models were stable enough to perform initial forecasts, which led to refined data gathering and coding. In August 2005, performers used their models to provide the assessments and forecasts to satisfy the requirements of Phase I. As of this writing we are awaiting approval for Phase II which will expand the scope of the models, integrate them into a framework that provides interoperability, and emplace them at several regional combatant commands to support and inform the Theater Security Cooperation Planning (TSCP) process.

2. Q/CSS Models and Results

For Phase I, ten teams were selected: eight teams to develop and apply Q/CSS models to two different countries of interest, one team to work on a decision support framework that would embed the various Q/CSS models, and one team to implement a mechanism to automatically categorize, parse, extract and auto-populate a bank of Q/CSS models from large-scale open source text streams. In an effort to ensure that the teams' assessments and forecasts for the two countries were objective, unbiased, systematic and methodological (vice expert opinion elicitation), each team needed to develop a basic theory of nation state instability, build and refine their instability models based on those theories, process in their models a wide range of open-source text-based multi-lingual data, and then provide an interpretation of the model outputs and results. Figure 3 illustrates the theory/model/data approach that was paramount in PCAS – this approach allowed DARPA to assess the merits and utility (or lack thereof) of the technology, not peoples' opinions.

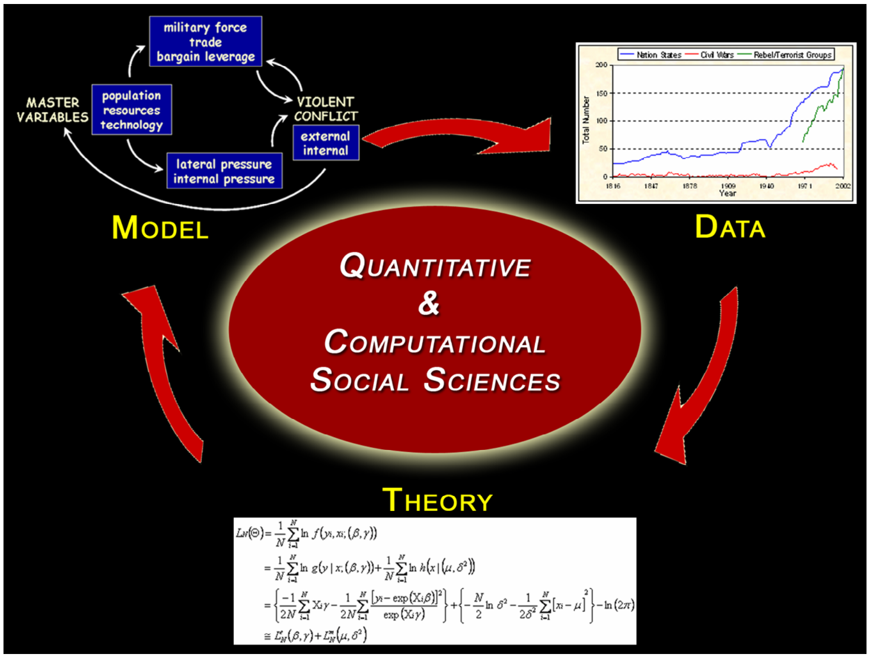

Figure 3. Quantitative/Computational Social Sciences Key Elements

The ten teams, their principal investigators and their primary methodologies are depicted in figure 4. Each team was free to determine its own modeling approach, because we wanted to explore the breadth of modeling techniques to see which ones had the greatest promise for assessing a nation-state's fragility and forecasting the impact on fragility of systemic shocks.

The modeling approaches included regressive equations, cellular automata, Bayesian Networks and Hidden Markov Models (HMMs), system dynamics, and agent-based models. Figure 5 surveys the models from several dimensions: model description, modeling analysis level, focus, data and perspective. Model description characterized the models from a technological and mechanistic perspective, e.g., how was the model implemented and what key result did it produce. Model level described the level of detail: Micro = city/individual; Middle = province/district, Macro = country. Focus describes the segment of a nation-state modeled. For example, BAH focused on how grievances of interest groups and subpopulations at the provincial level could result in civil unrest, and then how it could propagate across provinces within the country. Data described the primary sources of data for the models. Perspective described the primary social science domains for the models.

Teams	Performer	PI	Discipline / Approach
1	Institute for Physical Sciences	Dr. David Meyer	• geo-political scale-invariant distribution models • causal models; real analysis
2	MIT	Dr. Nazli Choucri	• system dynamic models • info and context mediation; ***multi-lingual processing***
3	Claremont Graduate University	Dr. Jacek Kugler	• political capacity and econometric regression models
4	Booz Allen	Dr. Elisa Bienenstock	• civil unrest grievance and social diffusion models • structural equations; cellular automata
5	BAE	Dr. Desmond Saunders-Newton & Dr. Rob Axtell	• multi-agent system models • societal transition to/fro nation-states and chiefdoms
6	Evolving Logic	Dr. Steven Bankes	• multi-model decision support framework • robust strategies over ensemble of future scenarios
7	QSI/SAIC	Dr. Krishna Pattipati and Dr. Greg Mack	• quantitative and qualitative models (Bayesian, HMMs, Rebel Activity Model); ***multi-lingual processing***
8	Aptima/CMU	Dr. Kari Chopra and Dr. Kathleen Carley	• multi-agent system models • multiple groups enhanced with cultural ethnographies
9	LM/ATL	Dr. Janet Wedgwood	• multi-agent system models • cognitive-agents, infrastructure models, and JSAF
10	ISX	Dr. Mark Hoffman	• collaborative decision support framework through • GUI and HCI focus; TSCP authoring/monitoring tools

Figure 4. PCAS Phase I Teams

	Model Features and Characteristics																						
	Model Descriptor				Level of Analysis			Focus					Data						Perspective				
Q/CSS Model	Model Type	Model Class	Defining Characteristic	PCAS Sapling Focus	Micro	Middle	Macro	Elites (Stake Holders)	Individual	Interest Groups	(Sub)Population	Govt / State Functions	Solidly Data Docked?	Individuals	Villages	Districts	Provinces	Govt / State	Psychology	Sociology	Economics	Political Science	Anthropology
Claremont	Regression	Quantitative	Politico-Econometrics	Relative Political Capacity			√				√	√	√				√	√			√	√	
Booz Allen	Strucural Equations; Automata	Quantitative & Computational	Lattices & Emergence	Civil Unrest & Diffusion		√	√			√	√	√	√			√	√	√	√	√			
MIT	System Dynamics	Computational	Dynamics & Feedback Loops	State Capacities & Loads		√	√				√	√						√				√	
QSI/SAIC	Bayesian & HMMs	Qualitative & Quantitative	Merging Qualitative & Quantitive	Rebel Activity		√				√			√		√		√	√				√	
Aptima	Multi Agent System	Computational	Lattices & Emergence	State & Group Dynamics		√	√			√	√	√					√	√		√			
IPS	Statistical Scale Invariant Distributions	Quantitative	Population Distributions & Triggers	Geo-Political Distributions			√				√		√		√		√	√		√		√	
BAE	Multi Agent System	Computational	Lattices & Emergence	States & Chiefdoms	√		√				√	√						√			√		√
LM/ATL	Multi Agent System	Computational	Lattices & Emergence	State & Group Dynamics	√	√			√	√		√						√	√				

Figure 5. Survey of Phase I Models

We selected two countries as the subjects of this modeling effort. For purposes of this paper, we will refer to them here as country A and country B. Each performer had to provide the following results at the end of the Phase I effort:

- An assessment of the fragility of each of the two countries using data up through March 31, 2005. The assessments were to be current as of the final program review on August 24th & 25th.
- Forecasts for 6-12 months for the fragility and trend of change in fragility for each country for 3-5 events or incidents occurring within the country. These forecasts could use data up through the final MPR.

Performers were free to select the events that they would seed their models with to provide the 6-12 month forecasts from August 2005.

2.1 MIT

MIT modeled nation-state fragility using a System Dynamics approach (Forrester 1958). Figure 6 depicts the top-level of their model. MIT's model is based on the theory of loads versus capacities. The problem is to determine and ‘predict’ when threats to stability override the resilience of the state and, more important, to anticipate propensities for ‘tipping points’, namely conditions under which small changes in anti-regime activity can generate major disruptions. Dissidents and insurgents create loads on the state, e.g., they draw down disproportionate amounts of resources that could otherwise be used to perform the governance functions. As people perceive this reduction in governance, they protest and, perhaps, riot or engage in acts of violence. These acts undermine overall political support for the government or regime, which shifts power balances. Counterbalancing the dissidents is regime resilience (lower left corner), which is the regime’s ability to withstand shocks that lead to fragility and instability, and, possibly, dissolution of the state.

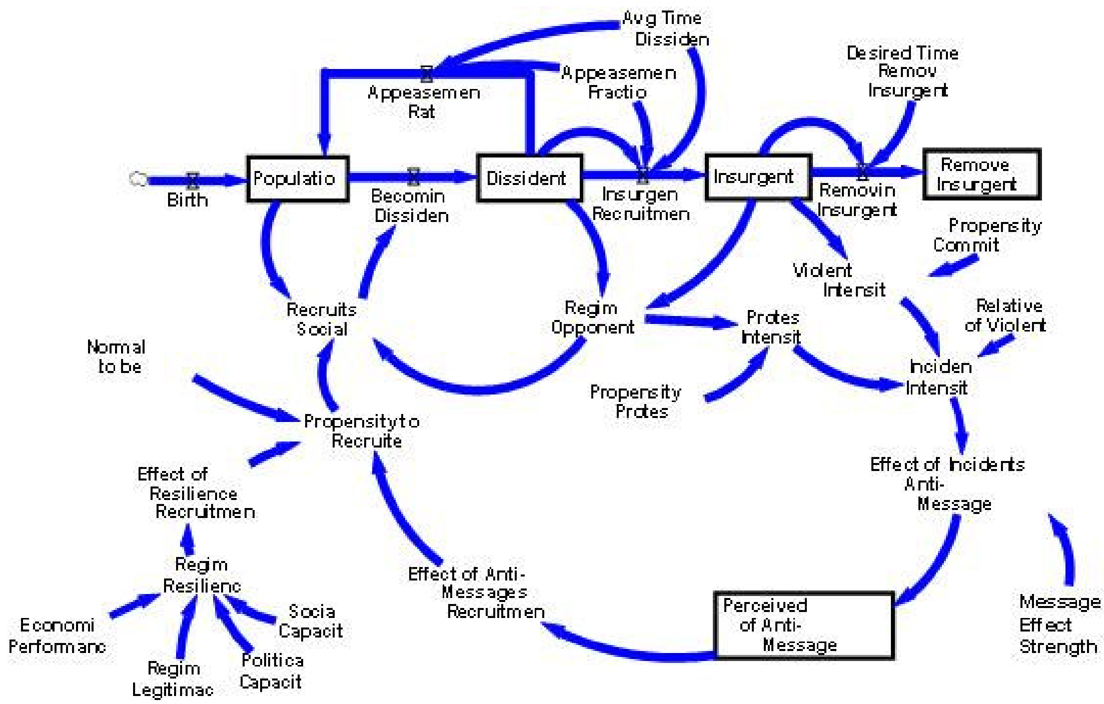

Figure 6. MIT Systems Dynamics Model

Increasingly, the evolution of thinking on sources of state stability and instability has converged on the critical importance of insurgents and the range of anti-regime activities that they undertake. The escalation of dissidents and insurgence is usually a good precursor to propensities for large scale instability if not civil war. By the same token, to the extent that the resilience of the regime is buttressed by requisite capabilities and attendant power and performance, the expansion of insurgency can be effectively limited. MIT focused on the problem of modeling the factors affecting the size of the insurgent population. They hypothesized that some portion of the population becomes disgruntled with the regime and turns to dissidence. Some smaller proportion is dissatisfied with regime appeasement and turns to insurgency and commits acts of violence. To reduce insurgent population, the regime needs to either remove the insurgents or reduce their recruitment rate.

Insurgents attempt to create more dissidents who become potential recruits for the insurgency. Through acts of violence and other incidents, insurgents send anti-regime messages to the population, which increases civil unrest and disgruntlement and leads to further disruption. Effective anti-regime messages reduce the capacity of a regime to govern. Such messages also create more disgruntlement by reinforcing the fervor of those who are already dissatisfied as well as encouraging the perception of those tending towards insurrection. To reduce the increase recruitment of in dissidents, MIT found that the regime needed to affect the intensity of the message rhetoric as depicted in figure 7. MIT identified a “tipping point” in the balance between regime resilience and insurgent population growth. Tipping points refer to sudden changes from small events (Gladwell 2002).

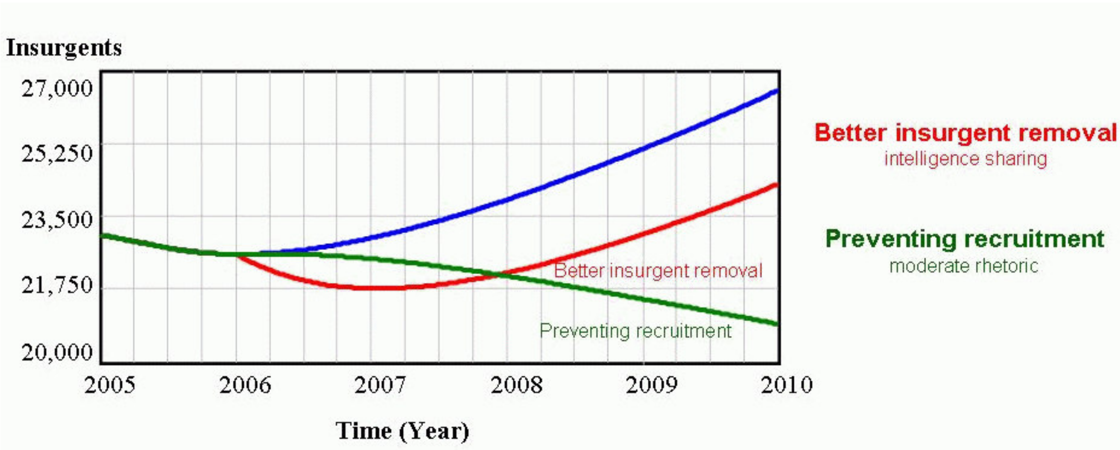

Figure 7. Tipping Point for Reducing Dissident Recruitment

The blue curve represents the nominal insurgent growth with no intervention by the regime. If the regime attempts aggressive removal of insurgents, the red curve projects that the insurgent population is reduced for a short period of time, but then increases again. However, by preventing recruitment through mediating anti-regime messages, the regime can reduce the number of dissidents recruited and, ultimately, the number of insurgents. Where the red and green curves intersect is called a *tipping point* – a point at which positive action by the regime is projected to yield favorable results for the regime.

The key result from MIT's model was that physical removal of the insurgents was significantly less effective in the long term than shaping (*the "s" in PCAS*) their behavior through mediating anti-regime messages. Both affect other family members and villagers, but message mediation, which could be coupled with financial or quality of living aid, was more effective in creating a positive attitude towards the government.

For country A, regime resilience increased due to relief aid flowing into the country in response to a natural disaster. Additionally, insurgence has been dampened by the need to survive. Over time, insurgency is likely to grow and anti-regime messages increase, particularly with an increased perception of corruption. For country B, increased regime resilience has stabilized insurgent growth. However, any loss if regime resilience would lead to a tipping point in which insurgent growth would 'take off' and severely impact state stability.

2.2 Sentia Group

Sentia's model uses two indicators developed by Jacek Kugler (Kugler 1997) of the Claremont Graduate School: relative political capacity (RPC) and instability (as measured by number of deaths). Sentia's model takes the form of a set of nonlinear regression equations in five variables: Income y, Fertility b (or birth rate), Human Capital h (measured as high school graduates), instability S, and political capacity X. The POFED model (Feng 2000) was developed to understand dynamic interactions between per capita income, investment, instability, political capacity, human capital, and birth rates. Figure 8 depicts the five equations of the model.

The model demonstrates that a nation is fragile when the per capita income of its population declines over time generating a "poverty trap". An important predictor of fragility is the extent to which government extracts resources from its population. Weak governments fall below average extraction levels obtained by similarly endowed societies, while robust societies extract more than one would anticipate from their economic endowment and allocate such resources to advance the government's priorities. Instability results from the interaction between economic and political performance. Weakening states decline in their ability to extract resources but still perform above expectations while fragile states under-perform relative to others at comparable levels of development, continuing to lose ground in relative terms. Finally, strengthening states are still relatively weak but begin to gain in relation to their relative cohort. In general assistance provided to strong or strengthening states will have positive effects on stability, while similar contributions to weak and to a lesser degree weakening states will be squandered.

Births: $b_t = By_t^{-1}$ births/thousand

Income: $y_{t+1} = Ay_t^{\eta} S_t^{\alpha} \chi_t^{1-\alpha} h_t^{1-\alpha}$ GDP/capita

Human Capital: $h_{t+1} = \omega h_t / b_t^{\theta}$ % population completed H.S.

Instability: $S_{t+1} = S_t^{a} p_{\chi_t} d\chi_t g(\chi_{t-1} / \chi_t)$ rates of participation in and deaths from political violence

RPC: $\chi_{t+1} = Cy_t^{\gamma} p_{x_t}^{\phi} / b_t^{\gamma}$ ratio of tax receipts Govt extracts to receipts expected

Figure 8. Sentia Group Model

The relative political capacity is the ability of the government to extract resources (usually measured in dollars, for example) from the country through various means taxes, labor, military service, etc. The instability, measured in deaths, reflects the level of political violence and anti-regime sentiment in the country. An RPC of zero is the norm, e.g., it indicates the government is acting in a nominal capacity compared to other countries that have been assessed using these techniques. A negative RPC indicates that a government is underperforming and weak, while a positive RPC indicates that a government is efficiently extracting resources. Figure 9 depicts the RPC computed over 144 countries.

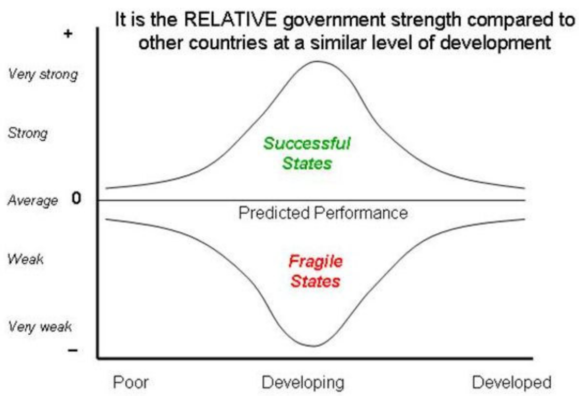

Figure 9. Aggregate RPC

Computing the RPC for a country allows us to determine the tendency of a particular country toward behavior that could lead to state failure. The accompanying instability metric, based on violent incidents, provides a metric for assessing the resilience of the country to insurgency and to natural disaster events that undermine the state's ability to govern. In country A, we determined that a decline in political capacity or income can have damaging effects on accelerating instability, however these effects will be minimal. The model anticipates a threshold effect: if the economy falters, instability is expected to rise swiftly but then halt. Long-term serious instability is associated with political rather than economic decline. In country B, declines in current levels of political capacity could have a very large impact on instability. POFED shows that positive political actions and economic advancement have marginal effects on stability, while potential declines will accelerate the decline of stability – consistent with the political assessment that country B is a strengthening society that is improving a weak political base.

2.3 Institute for Physical Sciences(IPS)

IPS developed a model to assess the potential for spread of the results of an incident. This model, based on geopolitical distributions, demonstrated that spatial dynamics, such as the spread of conflict, can differ and depend on the scale invariance of subpopulation distributions as defined by political, ethnic, religious or economic features. Underlying IPS's analysis is the assumption that violent events that occur repeatedly, and thus establish a time series, have long-term correlations. These long-term correlations are self-similar and, thus, scale invariant. Scale invariance means that a particular phenomenon occurring in a subpopulation will scale proportionately to a larger population. This model is in accord with recent work by King & Zheng (King 2001) who noted that "internal conflict requires people to be near others who might disagree".

IPS computed the fractal dimension for a series of violent events drawn from Countries A and B for given subpopulations and showed that, possessing the scale invariance properties occurred at the same rate when the population of the respective countries as a whole was taken into account. In addition, they showed that at a particular fractal dimension, susceptibility to the spread of violence or other insurgency occurring in one province to other colocated provinces would occur if the neighboring province's fractal dimension was higher than the originating province's.

2.4 Booz Allen Hamilton(BAH)

Booz Allen (BAH) investigated how civil unrest diffuses through a population. When salient groups within a population perceive deprivation, their grievances, when unaddressed by the government, can lead to riots, intense protests, and ultimately to political violence. If the state is unable to meet the demands of the populace, the unrest will spread. The speed and breadth with which the unrest spreads across the state can affect state stability. To model the spread of unrest, BAH developed a set of structural equations describing civil unrest that yielded six key parameters (see figure 10).

$$Y = \alpha + \beta_1 I + \beta_2 G + \beta_3 E + \beta_4 U + \beta_5 C + \beta_6 R$$

$$where \begin{cases} \alpha = 0.454 \\ \beta_1 = -0.003 \\ \beta_2 = 0.004 \\ \beta_3 = -0.087 \\ \beta_4 = 0.005 \\ \beta_5 = 0.001 \\ \beta_6 = 0.566 \end{cases}$$

- Inequality
  - Contrast Group Industry GDP vs Other GDP, Gini Index
- Government Effectiveness
  - Sanitation, IM
- Education
  - level of education for population
- Urban
  - % population in urban setting
- Percent Contrast Group
  - Javanese, Balinese, Chinese, Maderese
- Recent Unrest
  - Sum of intensity of recent events

Figure 10. Booz Allen Structural Equation Model

These structural equation models (SEMs) were derived as follows. The first step was to define and characterize prior acts of civil unrest. Multiple data sets and series of violent events from over 50 sources, including newspapers and news reports for the respective countries were collected and coded. The coding scheme is depicted in figure 11. The event intensity is a score for each data item used in the subsequent model. Interestingly, the events for country A were organized and non-violent, while country B's events tended to be independent and violent. The

SEMs produced a model that yielded grievance levels of each of our target countries.

These parameters are used to seed a cellular automata model that estimates the probability of diffusion of unrest across the population. It yields a probability of occurrence of the types of events depicted in figure 11 (under Index Score). The overall approach is depicted in figure 12.

Index Score	Deaths (number of individuals killed)	Number of Injuries	Number of People (total participants)	Property Damage (total structures)
1 Act of Civil Unrest	0	0	1 - 99	0
2 More Extreme Act of Civil Unrest	1 - 9	1 – 9	100 - 999	1 - 9
3 Organized Act and a Result of Diffusion	10 - 99	10 – 99	1,000 – 9,999	10 - 99
4 Organized Act, a Result of Diffusion, Potentially Disturbing	100 - 999	100 – 999	10,000 – 99,999	100 - 999
5 Serious State Threat or Failure	1,000+	1,000+	100,000+	1,000+

Event Intensity = (Deaths Index Score + Number of Injuries Index Score + Number of People Index Score + Property Damage Index Score) / 4 + Police/Military Death/Injuries (0 or 1)

Figure 11. Violent Event Coding

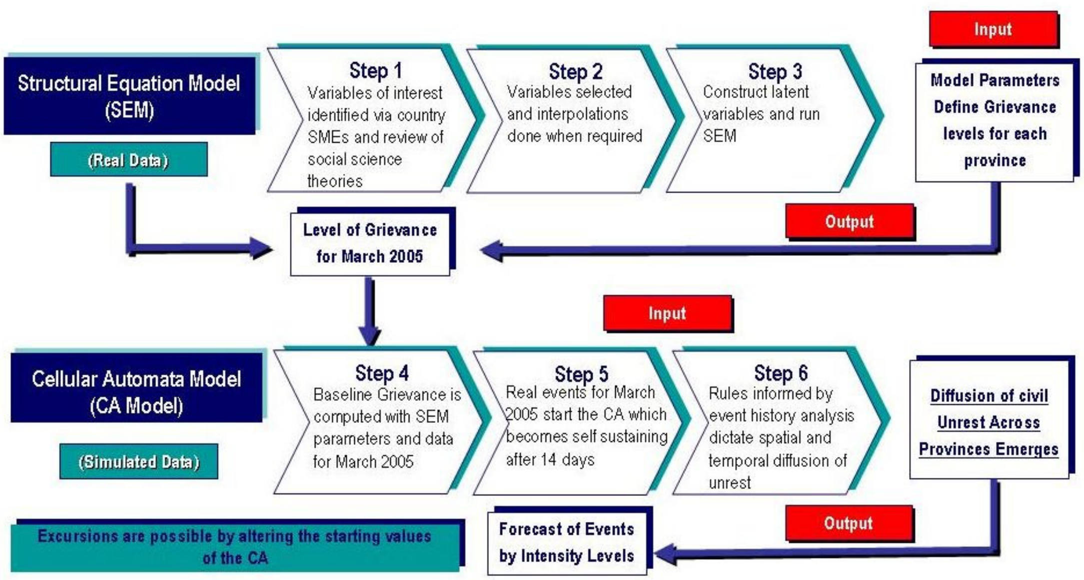

Figure 12. Civil Unrest and Diffusion Model

In this simulation BAH found that country A's unrest grows the more violent its events become. In country B, which already has a large number of violent events, even level 1 and 2 events have better than 50% probability of diffusing unrest across the country. Moreover, in country B, level 4 events continue to be likely to occur, but a level 5 event which tips the country into instability is unlikely to occur.

This model has shown how simple micro-level grievances or preferences from a small number of actors can diffuse and spread in counter intuitive ways. The models are based on historical data gathered form multiple sources across each target country. We have seen surprising macro-level outcomes. For example, in Schelling's segregation model (Schelling 1978), even moderately tolerant neighboring groups can produce significant ethnic segregation over time.

For countries A and B, there was no significant probability of a type 4 or 5 event. While big demonstrations occurred, principally in the capital cities, they were found to be cathartic, e.g., diffusion of unrest occurred prior to the demonstration which was a way to "let off steam". This suggests that government intervention should be class sensitive in order to reduce further perceptions of inequality. Interestingly, while unrest bubbled up from the grass roots, country B had no identifiable leaders of unrest; it was truly a synthesis of the right people at the right time at the right place with the right grievance. Unrest was localized in one set of provinces, but should it spread to the rest of the country (due to an increase in level 1 and 2 events), the government would be unable to control the original set of provinces. Significant events, such as an economic downturn or massive refugee flows, could then lead to state failure in country B.

2.5 QSI/SAIC

The "Conflict Analysis, Forecasting and Mitigation (CAFM) System" automatically extracts indicators of nation state instability by analyzing massive amounts of text data in near real-time (six documents per second). The indicators are used to

1. Estimate the current status of conflict risk in a nation state;
2. Forecast the trends in observed indicators and, consequently, predict future risk; and
3. Evaluate options and monitor the effects of mitigating actions.

The CAFM system is built based on QSI's RCMS (Remote Conflict Monitoring System) environment, which is a platform for designing and executing multiple analysis algorithms simultaneously. A hierarchical model, comprised of hidden Markov models (HMM) for indicator tracking and Bayesian networks (BN) for indicator fusion, analyzes the nation state instability. The HMMs, one for each indicator, receive their inputs from SAIC's Linguistic Pattern Analyzer (LPA); it categorizes multi-language text data and converts it into a language independent format for analysis by RCMS (Popp 2006). Since a small fraction of the documents contain information relevant to nation state instability, it is imperative to remove irrelevant documents prior to performing linguistic pattern analysis. Primentia's Hilbert engine automatically ingests and categorizes millions of documents a day using text transform techniques and thus enhances the efficiency of the system. This multistage architecture (Documents → Hilbert engine → LPA → RCMS) provides flexibility, runtime adaptation, and user control.

Reasoning with uncertain knowledge and beliefs leading to optimal decision making has always been difficult. Due to its wide range of applicability, the probabilistic approach is the most popular. Knowledge representation networks, such as *hidden Markov models* and *Bayesian networks* serve as the mainstays of the probabilistic approach (Yongman et al 2002).

The Rebel Activity Model (RAM) was used as an illustrative example of the overall CAFM process. The lowest level of the model consists of nine (9) indicators. The indicators are partitioned into two groups; by combining the concomitant indicator values, one group evaluates the derived indicator, termed "rebel group capacity", while the other group evaluates "threat to stability". High levels of capacity indicate that a group can sustain itself over the long-term and is a contentious political force. High rebel threat levels indicate that a group is willing to and/or has struck at national or international targets and is therefore of more concern to U.S. policy makers. (Byman 2001)The top level indicator, "rebel activity", is computed by combining the values of these derived indicators. Figure 13 illustrates the hierarchy of RAM.

<u>Generation of Input</u>

Each indicator is rated by the LPA based on a set of pre-defined phrases associated with it. To determine an indicator value, the LPA searches through a document for the set of phrase (or a subset of it) associated with the indicator. Based on the subset of phrases present in the document, a preliminary indicator value is computed. This value is later updated via weighted averaging and quantizing the averaged value into six levels, ranging from 0-5. The weights associated with the phrases are context-dependent, and also depend on the frequencies of occurrence. The quantization levels of indicator ratings are labeled as: **0** → ***Insufficient Data*** (not enough phrases to determine the indicator value), **1**→ ***Calm***, **2**→ ***Noteworthy***, **3**→ ***Caution***, **4**→ ***Severe***, and **5**→ ***Critical***. The documents are analyzed on daily basis, and indicator ratings from all documents are averaged to compute their daily values. For weekly and monthly analysis, expected values of the indicators for that time period are used as inputs to indicator HMMs.

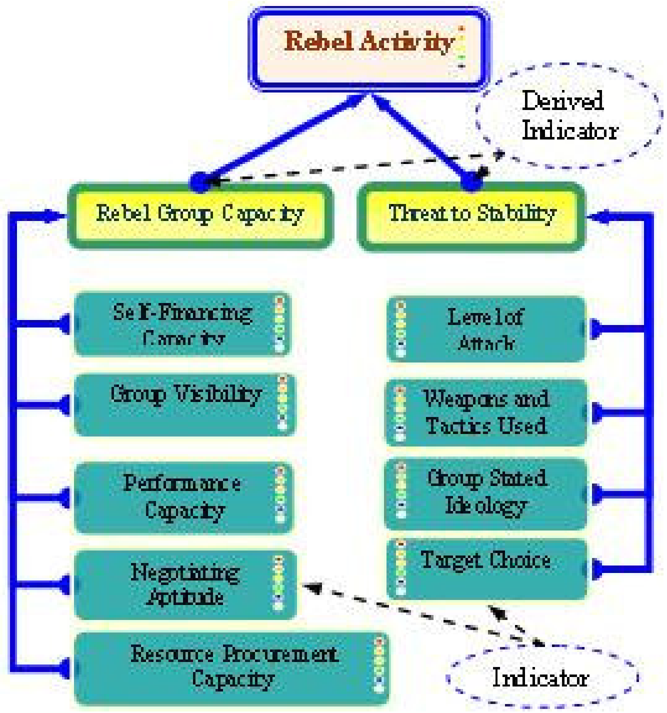

Figure 13: Structure of the RAM

Indicator Value Update Via HMM and BN

The indicator values generated via the aforementioned process has certain shortcomings; firstly, the values are sensitive to noise; secondly, if due to some reasons the news gathering process is disrupted, then an indicator value might erroneously go to zero (insufficient data). Moreover, a raw indicator value (obtained directly from LPA) instantiates a particular state (i.e., state probability for that state is 1, and 0 for all other states); designing a decision fusion process using such hard evidence is quite challenging.

In RAM, a HMM is trained to follow the trends in each indicator. Each HMM has one of six observations (Insufficient Data, ……, Critical) at each sampling points, and is in one of five states (Calm, ……, Critical). The HMM inference algorithm provides the state probabilities (i.e., the probability mass function) of the corresponding indicator.

State probabilities from the HMMs are fed to two BN nodes (see figure 14). These BN nodes evaluate the state probabilities of the derived indicators (rebel capacity and threat to stability). State probabilities for the derived indicators are fused to obtain the state probabilities for the top level indicator (rebel activity) via a third BN node.

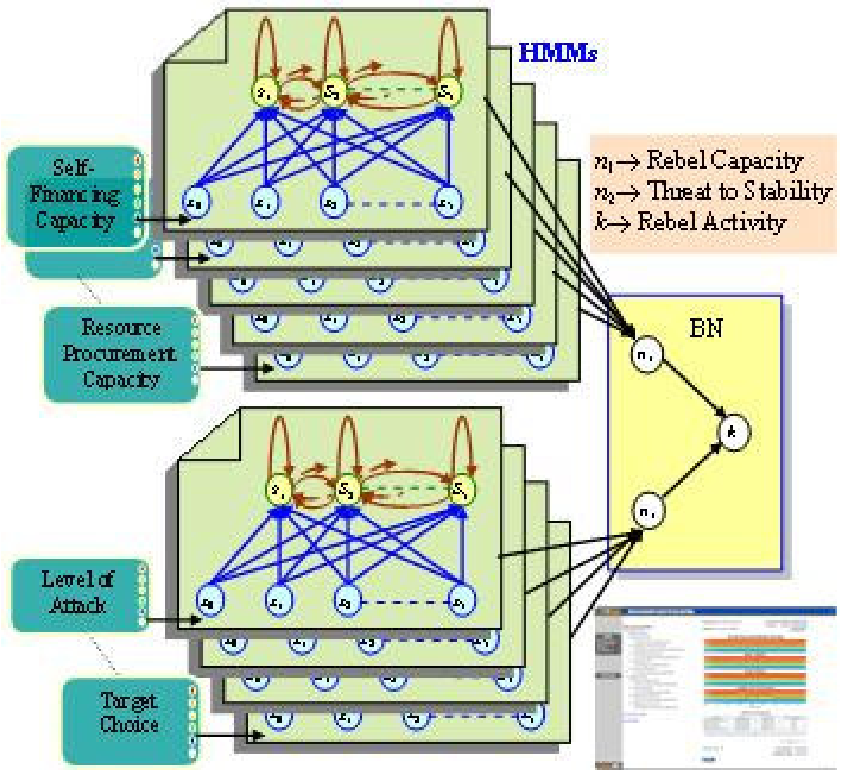

Figure 14. HMM Structure

Extension to Nation Sate Instability

The SAIC/QSI Nation Sate instability Model (developed for PCAS proof-of-concept sapling effort) evaluates the overall stability of a nation state using the following seven factors:

1. Capacity to maintain security
2. Viability of economic structures
3. Strength of political and civil system
4. Environmental fragility
5. Capacity of governing bodies
6. Social welfare and quality of life
7. Level of public infrastructure

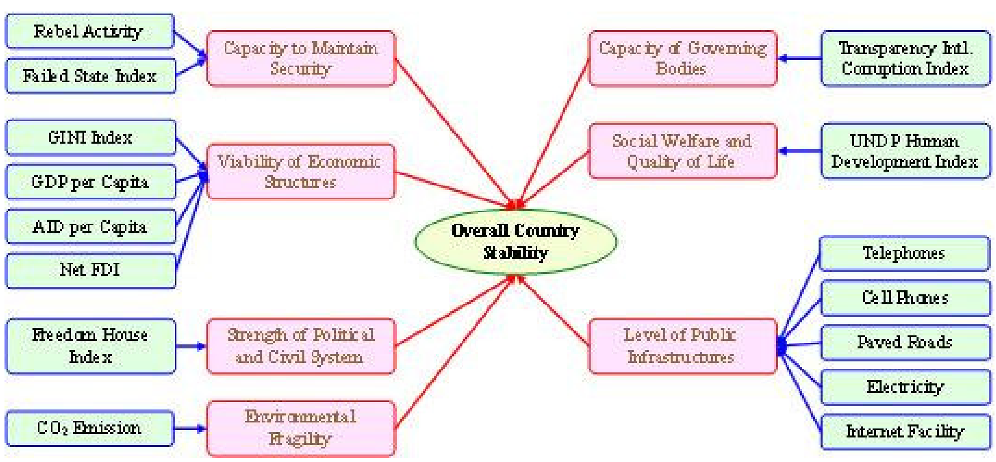

Figure 15: Evaluation of Nation State Instability

Each of these factors has a number of top-level indicators underneath. State probabilities for these top-level indicators can be computed via combined HMM-BN models that have identical structures as that of RAM. The state probabilities of a factor are computed by fusing the state probabilities of its underlying top-level indicators via a BN node. Similarly, by fusing the factor values via another BN node, the nation state instability value can be computed (see Figure).

RAM was applied to the target countries A and B using data extracted from multiple sources, including the UN Development Program, World Bank, Freedom House, and Transparency International. The expected values of overall stability were computed for both countries on a yearly basis for the period of 2000-2005. Figure 16a & b depicts some of the results for country A.

Based on expert analysis of the model results, we are confident that the model is providing good forecasts of rebel activity . Similar results accrue for country A. An interesting result obtained from RAM was that unknown insurgent groups seem to be largely responsible for the recent spates of violence as opposed to more established, well-known and documented groups.

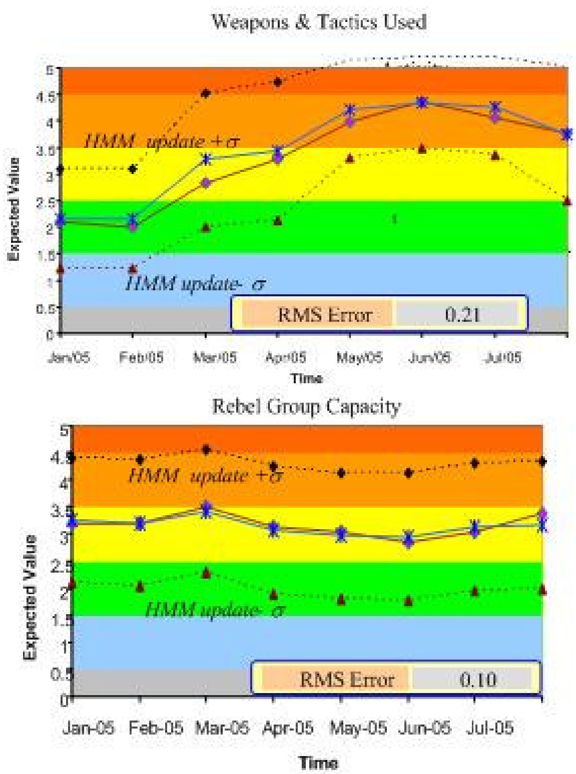

Figure 16a. Country A Selected Results

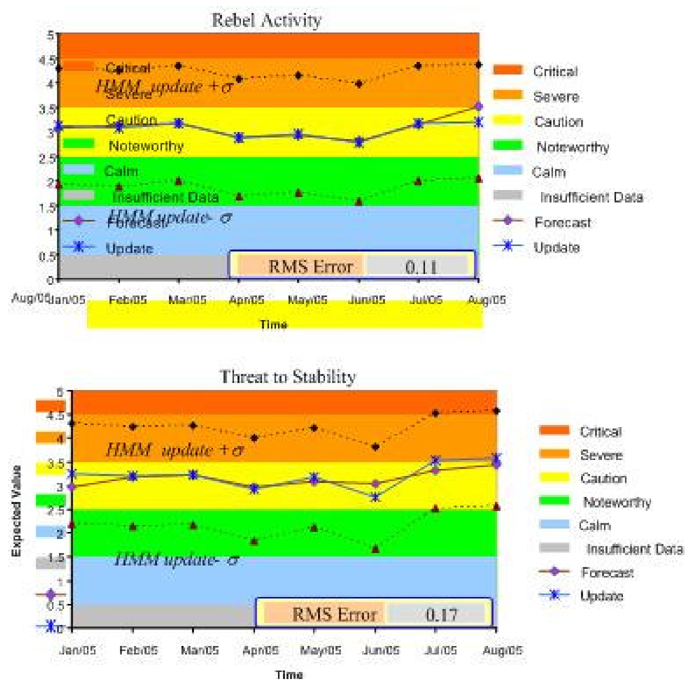

Figure 16b. Country A Selected Results

2.6 Aptima

Aptima and Carnegie-Mellon University (CMU) jointly developed a multi-level, multi-agent model, called Acumen, for assessing state failure based on the notion that inter-group conflict is due to a combination of tension (Horowitz, 1985) and social comparison (Festinger 1954), the effects of which can be modulated by social pressure (Friedkin 1998). Their model, which uses an agent-based approach, is depicted in figure 17.

Agents who are more tense and see themselves at more of a disadvantage relative to others are more likely to engage in hostile actions; whereas lower tension and higher advantage lead to non-hostile actions. Agents who have influence can use that influence to escalate or de-escalate the impact of tension and social comparison. Specifically, an agent who is influenced by others who themselves are tense or feel deprived will feel more tense and deprived than will an agent surrounded by others who are less tense or less deprived. Social Influence derives from shared attributes such as culture, knowledge, borders, goals and co-evolves with those attributes (Carley, 1991) The more heterogeneous a population and the more the lines of differentiation among population elements line up, the greater the potential for hostility (Blau 1977).

The Acumen Model is a multi-agent network model of state failure. Bounded rational agents interact and take actions to achieve goals. When agents act, they take into account the resources they have available, the cost and benefits of the action, and the opinions of others whom they are influenced by. Thus, agents are more likely to take the kinds of actions against the kinds of targets that social pressure suggests are appropriate and will be sanctioned by other agents for inappropriate action or target choice.

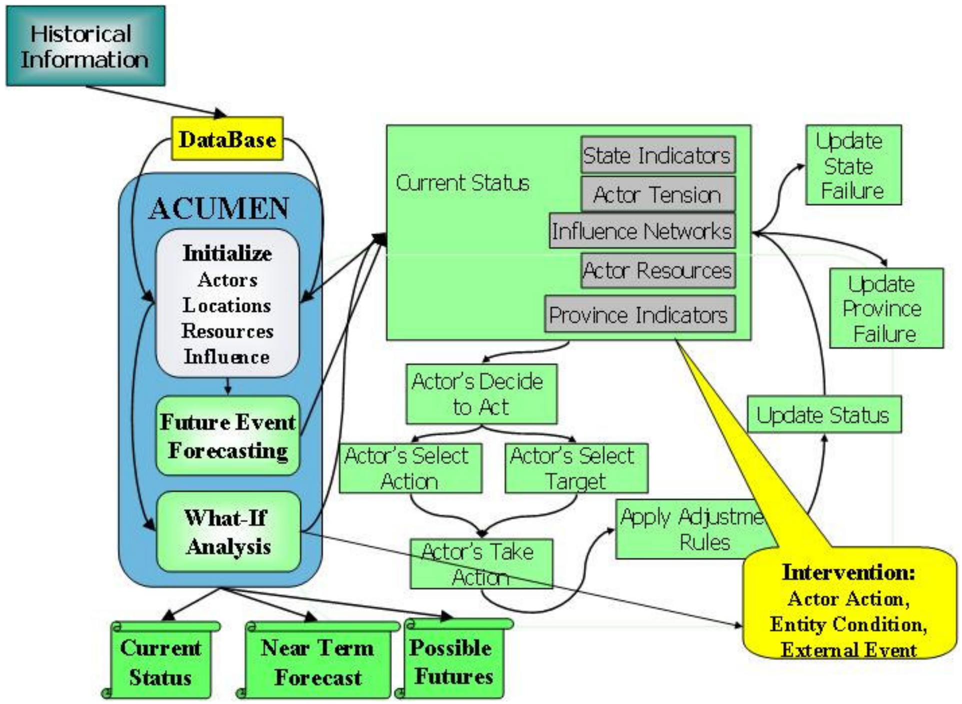

Figure 17. Aptima/CMU Model of State Failure

These actions influence the likelihood of state failure. State failure is measured at the national level using nine factors and a composite indicator: lack of state legitimacy, potential for province secession, hostility, tension, level of corruption, level of terrorist activity, level of criminal activity, level of foreign military aid, and lack of essential services. State failure is also measured at the province level using similar indicators.

The model is initialized using real world data and then the agents proceed to interact and take actions which consume or generate resources. Activity at the agent level then leads to changes in these agents, their resources, the non-agent targets, and these indicators. For example, forced migration of a population from one province to another is likely to decrease tension in the province left, increase tension and hostility and decrease essential services in the province migrated to, increase tension in the population that migrated and decrease their resources.

Agents vary in level (entity, province, and state), type (NGO, government, military, corporate, etc.), nature, tension, tendency to take risks, historical activity level, goals and level of resources. Goals are defined in terms of preferences for social, symbolic or economic effects. Each time period, agents decide whether or not the situation warrants them taking action. If it does, they choose both an action and a target, and then take that action. In Acumen, all agents act effectively in parallel. So, agent actions may conflict with each other. A time tick represents a week of real time. Once an agent has taken an action, that action consumes various resources on the part of the agent and the target, impacts the tension of the agent and effected agents, and alters the influence of the agent on others and their influence on the agent. Agents can engage in multiple actions at once.

Agents are connected into a set of networks. These include the influence network that determines which agents affect other agent's action choices and the hostility/non-hostility network that determines the type and direction of action one agent takes on another. Influence is a function of proximity, socio-demographic similarity, resource levels, and historical influence. Hostility/non-hostility is historically based. Both of these networks evolve over time. As agents take hostile acts toward each other, the level of hostility increases whereas taking a non-hostile act decreases the level of hostility. As agents do not follow the "advice" of those who have influence over them, the influence of those others decreases. So, disagreement lowers influence and agreement tends to increase it.

The actions taken by the agents vary in type, direction, resources consumed, damage generated, social, symbolic and economic impact, the level of physical, planning and resource effort needed to take an action, and the number of time-periods for which they last. The types of action are military, political/diplomatic, social, economic, information, infrastructure, and criminal. Action directions are hostile, neutral or friendly. Strength is measured on a three point scale – low, medium, high. So, a low hostile political action does less damage to the target's social resources on average than a high hostile military action. Actions can be directed to another agent or toward a physical target e.g., radio station. Hostile actions tend to increase tension and non-hostile actions lower tension. Actions can also consume or generate resources for the agent or a targeted agent. The impact of each action on the agents and the state and province indicators is implemented using a series of weight and adjustment rules.

Each time period, agents choose whether or not to take an action. This is modeled using a social influence model in which the desire to take an action is a function of both the level of tension and the influence by others encouraging or discouraging the taking of action. If an action is to be taken, the agent selects an action and a target using a cost-benefit calculation modified to account for both resources and rationality bounds; i.e., agents cannot take actions or attack targets that require substantially more resources than they have and not all options are evaluated. This cost-benefit calculation takes into account the combined potential social, symbolic and economic impact and the planning, resource, and physical effort needed. This calculation results in a preference for an action and target by that agent, which is then modified using a social influence module to account for the social influence of other agents on what action this agent should take and what the target should be. Agents, when "giving advice" to the acting agent use their opinion about the impact and effort required by the actor; but, they may be wrong because they have a flawed understanding of the capabilities of the actor.

When agents take an action, their tension decreases, their resources are modified, and their activity level increases. There may also be collateral effects. For example, if agent a takes a hostile action on agent b that will decrease a's tension and increase b's. In addition, if agent c is socially influenced by or proximal to b, then c's tension will also increase using the social influence model.

Figure 18 depicts a 'spider chart' which is used to present the eight indicators of nation-state fragility computed by their model. Spider charts can be used in two ways. First, as additional countries are analyzed, we expect key patterns to become apparent that will be significant indicators of nation-state fragility. Thus, computing these indicators and examining the pattern will provide a quick assessment of nation-state fragility. Second, over time, we will be able to discern trajectories (e.g., differences in the shapes) that will inform us when nation-states are heading towards fragility by examining a sequence of spider charts.

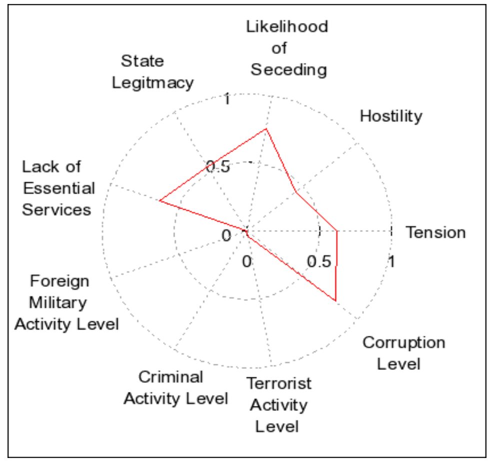

Figure 18. State Failure Spider Chart

The model shows both countries A and B to be fairly stable with the level of instability in country B increasing slightly in the next 12 months. A major natural disaster will not lead to instability in either state. Moreover, country A may become more stable, but relief aid is likely to cause increased corruption, because after critical needs are met, attention turns to rebuilding infrastructure which is subject to massive corruption. Both countries can withstand a moderate increase in terrorism, although country B may see increased terrorism focused on provincial secession. However, the reaction of the central government will be critical. Protection of military sites will increase violence, while protection of civilian sites will decrease violence.

3. Challenges and Issues

The PCAS Phase I Program helped us to identify the challenges and issues that must be addressed going forward to developing a usable, useful capability for combatant commanders to assist them in managing their AORs. Some of the challenges are:

Data Definition and Acquisition: As the models evolved, data requirements were refined. Sources for data proved to be a difficult to identify and acquire. While substantial data is available on the Internet, it is often available only in the host language of the specified country. Thus, a translation process is necessary to understand and retrieve data from these sources. Many times the data is only available in hard copy and, often, only within the particular country. Generally, these are government publications in the host country language which are not sent out of country. One performer sent personnel in-country to acquire some of these hard copy reports. Once the data is acquired, it must be cleansed and coded for the respective models. Each modeler developed their own code book for Phase I. Going forward, we will have to standardize our data cleansing and coding procedures to ensure proper reconciliation and interoperability of the models.

Model Interoperability: In PCAS Phase I, each model was developed and executed independently in order to assess the efficacy of the particular model approach. However, in an operational support system, models must be coupled together to ensure complementarity and correlation of results. A particular example is inserting Sentia's RPC results into MIT's system dynamic model in the regime resilience loop.

Macro vs. Micro Models: The PCAS Phase I models operated at both the macro and the micro level. For example, the MIT model is a high-level model while the QSI-SAIC and Aptima models focus on more granular data. We need to develop methods to resolve and reconcile models at different levels of granularity to meet the interoperability objective. Going forward to support the TSCP, we need to develop a hierarchical problem framework into which models can be plugged to support different levels of analysis.

Inclusion of Cultural Knowledge: None of the PCAS Phase I models incorporated explicit cultural knowledge. However, we know that cultural knowledge must be included in order to properly assess the impacts of shaping actions within individual countries. Representing cultural knowledge in a suitable computationally usable form is a basic research problem. Determining what cultural knowledge and how much cultural knowledge is relevant is a basic research problem that is only just beginning to be explored.

4. Conclusions and Future Work

PCAS Phase I has demonstrated the utility of Q/CSS models to forecast nation-state fragility based on historical sequences of data and current events. Specifically, we accomplished the following actions: (i) demonstrated the utility of Q/CSS models to addressing the question of nation-state fragility, (ii) showed that a variety of models at different levels of granularity and drawn from different social science disciplines are necessary to adequately represent and model the causes and events affecting nation-state fragility, and (iii) recognized that our models cannot predict explicit, specific events, such as a particular bombing on a particular day, but can forecast likely results of types of events.

Going forward, the PCAS Program will focus on a larger array of problems. As a result of various interactions with DOD personnel, it is clear that mitigating nation-state fragility is one element of the Theater Security Cooperation (TSC) Planning. TSC planning is an overarching strategy used by several RCCs to pursue US security interests within their AORs. The PCAS Phase I effort covered only one element of TSCP – prediction. The existing PCAS models as well as additional Q/CSS models need to be defined and developed to support three key RCC missions in TSCP: (i) assessment – if an event occurs in the world, assess its impact on a country, region, etc, (ii) risk mitigation for decision support – determine the costs and benefits associated with various long-term strategic objectives and short-term tactical activities that the RCC has for each of the given countries in their AOR, and (iii) prediction – the focus of the PCAS Phase I effort.

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Dr. Stephen Kaisler *is currently a Senior Associate with SET Associates, a firm specializing in science, engineering, and technology research, development and integration. He supports the PCAS Program in the Information Exploitation Office (IXO) at DARPA. Prior to joining SET, he was Technical Advisor to the Chief Information Officer of the U.S. Senate, where he was responsible for systems architecture, modernization and strategic planning for the U.S. Senate. He has been an Adjunct Professor of Engineering since 1979 in the Depts of Electrical Engineering and Computer Science at George Washington University. He earned a D.Sc. from George Washington University, and an M.S. and B.S. from the University of Maryland at College Park. He has written four books and published over 25 technical papers.*

Dr. David Allen *earned M.A. and Ph.D. degrees in experimental psychology from the University of Arizona. He holds a Bachelor's degree in psychology from Lake Forest College in Lake Forest, Illinois. As Program Director for SRS Technologies, a defense technology company headquartered in Newport Beach, California, Dr. Allen is currently the Senior Engineering and Technical Advisor to Dr. Robert Popp – Deputy Director of the Information Exploitation Office in the Defense Advanced Research Projects Agency. Prior to joining SRS Technologies, Dr. Allen served as Director of Program Development at Mitretek Systems in McLean, Virginia, where he identified and developed new business opportunities for the company, particularly in the national security arena. At Mitretek, he developed corporate marketing proposals for Information Systems Security initiatives, and helped to implement the recommendations of the President's Commission on Critical Infrastructure Protection (PDD-63). Before joining Mitretek Systems, Dr. Allen spent 27 years as a career intelligence officer at the Central Intelligence Agency.*

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Dr. Kathleen M. Carley*, Harvard Ph.D. 1984, is a Professor of Computer Science at Carnegie Mellon University and the Director of the center for Computational Analysis of Social and Organizational Systems. Her research combines cognitive science, social and dynamic network analysis, artificial intelligence and multi-agent systems to address complex social and organizational problems. She and the CASOS lab have developed several large scale systems including: BioWar – a city, scale model of weaponized biological attacks and response; DyNet – a model of the change in covert networks, naturally and in response to attacks, under varying levels of uncertainty; and a statistical package for dynamic network analysis called ORA that has been used for vulnerability analysis for both red and blue forces. She is the founding co-editor of the journal Computational Organization Theory, the founding president of the North American Association for Computational Social and Organizational Science (NAACSOS), and has written or edited over 5 books and 150 article in the areas of computational social and organizational science area and dynamic network analysis.*

Mohammad Azam *obtained M.S. in Electrical Engineering from University of Connecticut, USA, in 2002, and B.S. in Electrical Engineering from Bangladesh University of Engineering and Technology, Bangladesh, in 1997. Currently, he is pursuing his PhD in Electrical Engineering in University of Connecticut. His area of research includes fault detection and estimation in complex systems, reliability analysis, and modeling and analysis of human-centric systems. As a researcher, he is affiliated with Qualtech Systems Inc., Wethersfield, CT, USA.*

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Dr. Nazli Choucri *is Professor of Political Science at the Massachusetts Institute of Technology, and Director of the Global System for Sustainable Development (GSSD) a distributed multi-lingual knowledge networking system to facilitate uses of knowledge for the management of dynamic strategic challenges. The author of nine books and over 120 articles, her core research is on conflict and collaboration in international relations. She is presently working on challenges of 'e-connectivity for sustainability'.*

Dr. Jacek Kugler *is the Elisabeth Helm Rosecrans Professor of International Relations and Political Economy in the Department of Politics and Policy, School of Politics and Economics. He also serves as the Co-Editor of International Interactions (a Political Science Journal) and is President-Elect of International Studies Association. He recently founded a new corporation, Sentia Group Inc. dedicated to the formal study of decision making, policy analysis and advice. He has been a consultant to the IMF, State Department and a number of U.S governmental agencies and private businesses. He received his Ph.D. from the University of Michigan following an M.A. and B.A. in Political Science from UCLA.*