Man vs. Nature

Economic Risk Education and Decision Management in the Face of a Storm

Tom Balmat, December, 2013

1. INTRODUCTION

The primary goals of an emergency preparedness system are to reliably identify and quantify risks to life and property and to develop decision methods and action plans to mitigate exposure to identified risks. Four terms in this statement draw on key human traits:

- *Reliable* Man trusts a system that has been proven effective in his personalexperience.
- *Quantify* He instinctively assesses degree of risk.
- *Decision* He weighs potential costs and benefits of his actions and projects likely outcomes.
- *Action* He acts on what he assesses to be the most beneficial outcome for himself and his community.

These traits are not uniquely human, but what separates man from his animal counterparts is that he has the capacity and has developed theoretical systems for modeling risk numerically, with results that are robust in his environment to a degree acceptable to him. This is significant. In addition to casual observation, as in all animals, man has the option of enhancing his intuitive assessment of risk with accumulated historical data and mathematical theory. Given this, man should fare better than his wild counterparts in any emergency situation.

This paper proposes an emergency preparedness system based on education, in advance of any emergency, of a target at-risk community on their risks, available decisions, potential actions, and likely outcomes. It would be tailored to the personal world view and economic paradigm of the target group so that they ultimately develop and maintain the risk-decision model and have incentive to use itin an impending emergency situation.

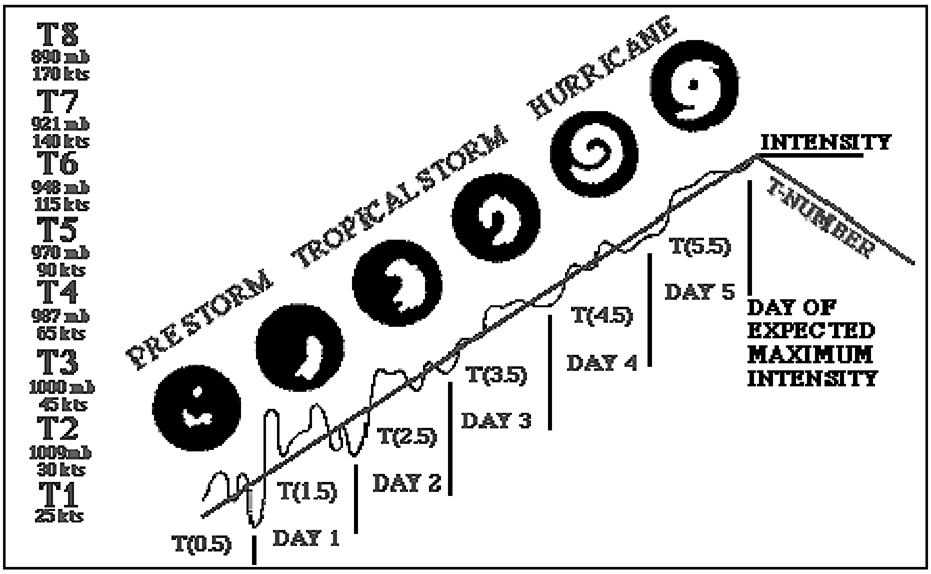
The target group studied is the rural Jamaican fisherman, the key indicator his risk of economic damage due to hurricanes. It is likely that, as with all humans, this person asks himself each morning, "Do I really want to go to work today?" which on most days is simple fantasy.

But in his part of the world where large, potentially devastating hurricanes are common, producing a potentially lethal workplace for him, he must ask himself when one is reported nearby, "Should I go to work today?" He knows this is a serious question[1]and, no doubt, performs some sort of risk-benefit analysis. Our goal is to help improve his outcome.

With respect to Caribbean hurricanes there are four dynamic, interacting quantitiesthat influence the fisherman's experience and risk of damage:

1. Storm category (0 through 5, in increasing destructive force, 0 is a tropical storm).
2. The vicinity of the storm with respect to the fisherman's village.
3. Storm dynamics that influence destructive force.
4. The likeliness that a fisherman goes to sea or remains on land to secure family and possessions and possibly seeks shelter.

Tropical storms develop into hurricanes at a relatively slow rate, taking days.



Rate of Hurricane Development[2]

[1]In a survey conducted by caribsave, 78% of Jamaicans have particularly high concern for hurricanes.
[2] Source: Johns Hopkins University.

And with modern advances in storm modeling, satellite television, and personal communication, the fishermanis aware of an approaching storm days in advance of any potential risk. Gone are the days of surprise attacks as in Galveston in 1900 and with Hazel in 1956. So the fisherman has time to plan. Unfortunately, of the four dynamic variables mentioned, numbers 1 through 3 are entirely outside of his control, which leaves number 4. With knowledge of risk, specific values and probabilities of change for items 1 through 3, how likely is he to go to work today, and what outcome should he expect?

2. A RISK EDUCATION MODEL

There are two dynamic systems to be modeled: a hurricane (its development and potential for damage) and the fisherman's set of decisions as he interacts with a storm.

2a.   A Stochastic[3] Hurricane Development and Damage Model

Given current atmospheric pressure, storm stage (before or after peak intensity), and its category (0 through 5), the probability that a hurricane remains in its current category or transitions to another is quantifiable. Table 1 lists, for storms prior to peak intensity, and by level of atmospheric pressure (in hPa), the probability of transition from one category to another.

[3]A method of predicting future states of a system from its current state and probabilities of transitioning to those states.

Table 1: Hurricane Category Transition Probabilities Prior to Peak Intensity[4]

Pressure	p00	p01	p10	p11	p12	p21	p22	p23	p24	p32	p33	p34	p35	p43	p44	p45	p55
890	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.00
900	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.33	0.67	-
910	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.00	-	1.00
920	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.93	0.07	-
930	-	-	-	-	-	-	-	-	1.00	-	0.78	0.22	-	0.11	0.89	-	-
940	-	-	-	-	-	-	0.86	-	0.14	-	0.87	0.09	0.04	-	1.00	-	-
950	-	-	-	-	-	-	0.43	0.57	-	0.06	0.92	0.03	-	-	-	-	-
960	-	-	-	-	-	-	0.87	0.13	-	0.25	0.50	0.25	-	-	-	-	-
970	-	1.00	0.04	0.74	0.22	0.03	0.94	0.03	-	-	-	-	-	-	-	-	-
980	-	-	-	0.86	0.14	0.33	0.67	-	-	-	-	-	-	-	-	-	-
990	0.25	0.75	0.01	0.99	-	-	1.00	-	-	-	-	-	-	-	-	-	-
1000	0.83	0.17	0.09	0.89	0.02	-	-	-	-	-	-	-	-	-	-	-	-
1010	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

The two digits in the column headings indicate the categories from and to which a transition is made (23 indicates a transition from category 2 to 3). So, for example, at atmospheric pressure 950 hPa, there is a 57% chance that, prior to peak intensity, a category 2 storm will develop into a category 3 storm. Cells with a dash (-) indicate that no storm has been observed making such a transition at the corresponding pressure and imply a 0 probability of transition. Table 2 lists transition probabilities after peak intensity.Several interesting features are apparent:

- In both stages, high category storms are associated with low pressure while low category storms are associated with high pressure.
- Transitions to another category are always to the one above or below, categories are never skipped.
- Transitions to a higher category tend to be associated with storms prior to peak intensity, while those to a lower category tend to be associated with storms after peak intensity.

[4] From "A Markovian Analysis of Hurricane Transitions," by R. D. Wooten and C. P. Tsokos, U. of S. Fla.

Table 2: Hurricane Category Transition Probabilities After to Peak Intensity[5]

Pressure	p00	p10	p11	p12	p21	p22	p23	p32	p33	p34	p43	p44	p54	p55
880	-	-	-	-	-	-	-	-	-	-	-	-	-	1.00
890	-	-	-	-	-	-	-	-	-	-	-	1.00	-	1.00
900	-	-	-	-	-	-	-	-	-	-	-	1.00	0.50	0.50
910	-	-	-	-	-	-	-	-	1.00	-	0.09	0.91	0.25	0.75
920	-	-	-	-	-	-	-	0.11	0.89	-	0.10	0.90	-	-
930	-	-	-	-	-	-	-	-	0.93	0.07	0.17	0.83	-	-
940	-	-	-	-	-	0.67	0.33	0.23	0.77	-	0.50	0.50	-	-
950	-	-	-	-	0.13	0.74	0.13	0.48	0.52	-	1.00	-	-	-
960	-	-	1.00	-	0.08	0.89	0.03	-	-	-	-	-	-	-
970	-	-	1.00	-	0.31	0.69	-	-	-	-	-	-	-	-
980	1.00	0.06	0.92	0.02	0.25	0.75	-	-	-	-	-	-	-	-
990	1.00	0.13	0.87	-	-	-	-	-	-	-	-	-	-	-
1000	1.00	0.67	0.33	-	-	-	-	-	-	-	-	-	-	-
1010	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-

We now have a means of modeling dynamic variable 1 (category) from our list of four. But we must be able to predict combinations of storm category *and* vicinity(dynamic variable 2) to accurately predict local strength (a strong, distant storm may pose less threat than a weaker, nearer one). Within the storm model, three distance zones are configured: A (0 nm from shore), B (40 nm from shore), and C (80+ nm from shore) and probabilities of transition from one zone to another (based on current meteorological predictions) are defined. Following is an example of zone transition probabilities:

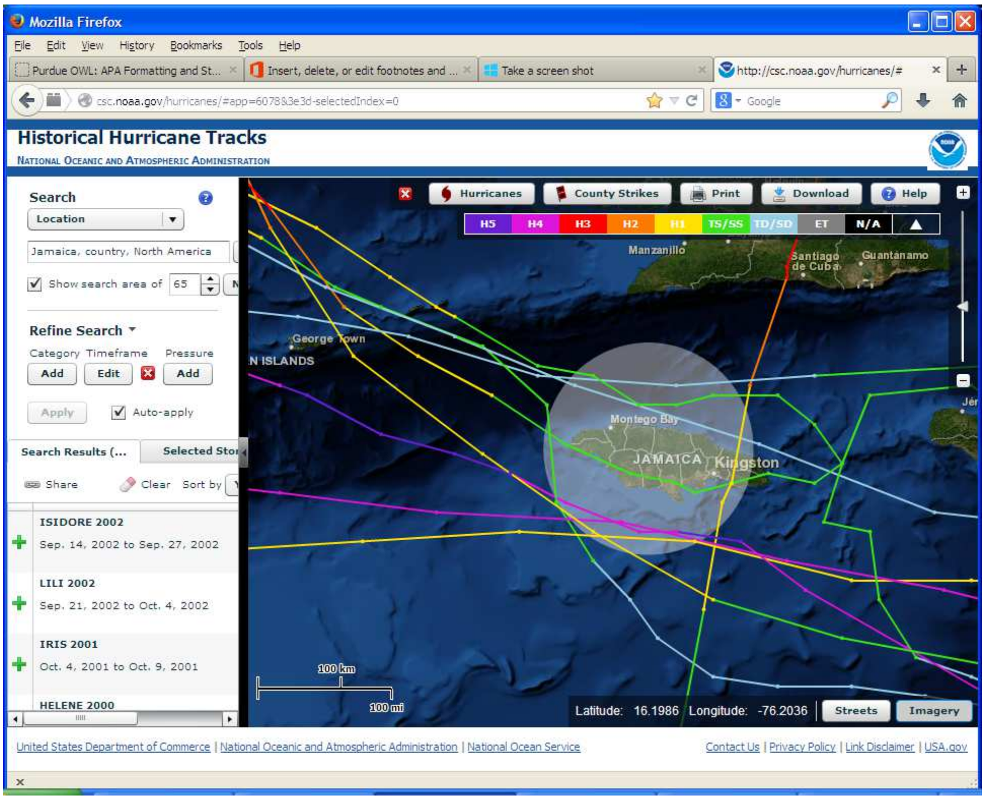
Table 3. Zone Transition Probabilities

Zone	A	B	C
A	.4	.6	0
B	.3	.5	.2
C	0	.5	.5

[5]From "A Markovian Analysis of Hurricane Transitions," by R. D. Wooten and C. P. Tsokos.

Here, for example, we estimate that a storm in zone B has a 30% chance of moving to zone A (nearer to shore), a 50% chance of remaining in zone B, and a 20% chance of moving to zone C (farther from shore). For predicting joint category-zone transitions, zone transition probabilities are combined with category transition probabilities to provide joint category-zone transition probabilities.[6]Note that we assume independence of category and zone transitions (storm movement between zones is independent of change in category).

Destructive capacity (dynamic variable 3) is, logically, a function of storm category and vicinity to land. Category (at nearest distance) and actual distance (in nautical miles) for recent storms in the vicinity of Jamaica were taken from the National Oceanic and Atmospheric Administration's historical hurricane tracking web site.[7]



NOAA's Historical Storm Tracking Site.

[6]Table A1 in the appendix contains the joint probabilities for a prior stage, 950 hPa storm combined with the example zone transition probabilities.
[7] csc.noaa.gov/hurricanes/#

Combining past hurricane category and vicinity with actual destructive capacity gives us a means of predicting expected damage given hypothetical atmospheric pressure, storm category, and vicinity. Following are damage estimates for select recent hurricanes in the vicinity of Jamaica.

Table 4.Damage Estimates of Recent Hurricanes in the Vicinity of Jamaica (million $US)[8]

Hurricane	Year	Category	Distance	Damage
Sandy	2012	1	0	107
Gustav	2008	0	0	155
Fay	2008	0	100	0
Dean	2007	4	40	238
Olga	2007	0	30	0
Dennis/Emily	2005	3	25	59
Wilma	2005	0	75	36
Ivan	2004	4.5	30	369
Bonnie	2004	0	75	0
Charley	2004	1	60	4.4
Lili	2002	0	10	0
Isidore	2002	0	20	0

Using these data and Proc REG from SAS, we have the following regression model for prediction of damage, given hypothetical storm category and vicinity:

$$\hat{y} = 44.56 + 54.60c - .65d$$

where $\hat{y}$ is the expected damage, in million $US, c is the storm category, and d is the distance of the storm to Jamaica, in nautical miles. The model is significant at .99 confidence[9]. Interaction between category and distance was tested for, but found to be insignificant. Note that $\hat{y}$ is an estimate of damage for the entire country of Jamaica. For an estimate of an individual fisherman's liability we must prorate it per capita (household). The present population of

[8] Sources: category and distance, NOAA's tracking site; damage estimates, Policy Institute of Jamaica.

[9]With the given data and regression model, 99% of the change in damage is explained by changes in category and distance. Alternatively, only 1% of the observed variation in damage is not attributed category and distance under the model.

Jamaica is estimated to be 2.7 million[10] and the average rural Jamaican family has 3.2 members[11], giving an expected household damage estimate of $\frac{3.2}{2{,}700{,}000}\hat{y}(c,d)$.

By combining the hurricane transition probability model with the damage regression model, along with knowledge of current atmospheric pressure, storm stage, category, and vicinity, we have a means of predicting future individual cost of damage as a storm develops.

2b. Fisherman's Risk Assessment Model

A fisherman must fish to survive but, also to survive, he must avoid drowning at sea. Average per capita income in Jamaica is approximately $5,000 (US).[12]Assuming a six work-day week and a 50 work-week year, this equates to $16.67 per work day. If the fisherman can be convinced (if we can train him to convince himself) that, assuming storm conditions and projected damage estimates warrant, he stands to incur a net loss by going to sea, he may remain on land, secure his family and possessions, and actually improve long term income. Of course, our model and advice from it must be reliable, and we want the fisherman to forgo fishing only when conditions warrant, that is, when expected net losses are greater by going to sea. Note that for our purposes, gains and losses do not account for human safety or suffering.

We have modeled expected damages, given current storm conditions and expected development. To model expected net gain or loss, we must predict a fisherman's actions under varying conditions and from that action estimate gaincombined with expected loss due to damage. Define a *policy* as a set of decisions with a measurable result. For our purposes, a policy will consist of some combination of three possible decisions:

1. Go to (or remain at) sea
2. Go to (or remain on) land and secure family and possessions
3. Go to (or remain on) land, secure family and possessions, and go to (or remain in) storm resistant shelter

[10]World Bank
[11]Statistical Institute of Jamaica
[12]World Bank

By *combination*, it is meant that a fisherman might, say, go to sea in the morning, but return to land before noon, and finally go back out to sea in the evening. A policy can be deterministic (the current state always dictates the next state), probabilistic (there are predictable patterns of state transition), or random (transitions with no apparent pattern). Since we are trying to convince the fisherman to engage in reliable and predictable patterns of using available storm danger and economic impact estimates to base his decisions on when to go to sea (or not) and when to return (or not), we willuse probabilistic policies for evaluation and education.

Probability is a treasured asset that each of us uses in almost everything we do, although many cannot explain what it is or how to precisely define or derive numerical estimates for the likelihood of various possible outcomes, given a set of hypothetical circumstances. And, of course, there are different interpretations and methods of presenting probabilistic concepts. No doubt, to our subject fisherman, a 90% chance of rain means a greater chance of experiencing rain than on a day with a 10% forecast. But to the probabilist, a 90% chance of rain is the expectation that, given 10 identical days, 9 will experience rain. How would our fisherman interpret the statement, "There is a 75% chance that your neighbor goes to sea today?" For our purposes, 90% will mean 9 out of 10 ten (people will take a certain action) and 45% will mean roughly 4 or 5 out of 10 (times an action is taken), etc. Following is an example policy.

Table 5. Fisherman's Risk/Relocation Policy

State	**Sea**	**Land**	**Shelter**
Sea	.8	.2	0
Land	.4	.4	.2
Shelter	0	0	1

Here, 8 of 10 are expected to stay at sea, 2 of 10 are expected to return to land from sea, 4 of 10 are expected to go to sea from land, 4 of 10 are expected to remain on land when there, 2 of 10 are expected to go to shelter when on land, and 10 of 10 are expected to remain in shelter once there. Our task, now, is to associate benefit or cost with a policy. This is our final dynamic variable, number 4.

To incentivize safety and reduction in net losses, transitions to land or shelter earn a discount on damages. They are scaled by storm category on the assumption that the more destructive the storm, the less man is able to mitigate damage. For the purposes of our study, discounts are as follows:

Table 6. Damage Mitigation Discounts

Category	Move to Land	Move to Shelter
0	0.95	0.95
1	0.7	0.75
2	0.6	0.65
3	0.4	0.45
4	0.3	0.35
5	0.2	0.25

3. THE RISK EDUCATION MODEL IN ACTION

Imagine presenting the risk model to a group of fishermen. You explain the storm dynamics, over which they have no control, and their potential effect. They understand the concepts completely, although how risks and results are modeled, they may not (which is fine as long as, through demonstration, our method earns their trust and they buy into the plan). Next, you introduce what they do control, that is, their decision to consider (or not) the calculated and expected results of their actions when planning their day in the face of possible danger. For the sake of argument, and to get things going, you might propose modeling (but should refer to it as "making up") three fishermen with different risk-tolerant personalities: high, medium, and low. You have three policies already configured (although the fishermen never see them, a matrix, an actual probability value, or hear the sea being called a state). They could be:

Policy H (high risk)

State	Sea	Land	Shelter
Sea	.8	.2	0
Land	.6	.3	.1
Shelter	0	0	1

Policy M (medium risk)

State	Sea	Land	Shelter
Sea	.5	.5	0
Land	.25	.5	.25
Shelter	0	0	1

Policy L (low risk)

State	Sea	Land	Shelter
Sea	0	.6	.4
Land	0	.5	.5
Shelter	0	0	1

You confirm the expected wages for a day of fishing and possible losses for leaving family and possessions unsecured. Now, invent a hurricane, or use data from a recent one. Category 1 Sandy, in 2012, had an atmospheric pressure reading of 971mb (milibars, near equivalent to our hPa, we must round to 970) as it approached Jamaica, was intensifying, and was a direct hit (zone A).[13] Set the clock back to October 25, 2012 and generate expected results for the three policies.[14] Understanding that an early morning decision limits, but does not prevent, later decisions[15], you project results in four hour periods – revenue and losses are incurred, or accumulated, three times in a day.[16] Let's see what the earnings/damage forecast would have been.

Table 7.Fisherman Net Gain/Loss Forecast with Sandy

Risk	AM Forecast	Noon Forecast	Evening Forecast
H	-2.4	-7.1	-13.0
M	-2.4	-6.4	-11.1
L	-2.4	-5.8	-9.8

In the morning when Sandy was distant from Jamaica (zone C), all three risk categories were roughly equal (losses, but equal), but as the day advanced, and Sandy, higher risk carried an expectation of higher cost. It would be interesting to compare these projections with actual fishermen experience.

[13]From NOAA's storm tracking site.
[14]My solution was programmed in the Interactive Matrix Language (IML) of SAS.
[15]A policy defines probabilities of transitioning to a given state from an initial state. The analysis, here, assumes that, regardless of risk tolerance, a fisherman's initial state is on land followed by an immediate transition according to policy probabilities.
[16]Although the Wooten-Tsokos category transition frequencies were not specified (they use the phrase "probability at next measurement"), I obtain an approximate 4 hour period by dividing one day's wages and expected damages by 3, commensurate with a reasonable expected 12 hour exposure to risk.

One obvious case to present is when a weak storm (one with minimal risk, e.g., post-peak intensity, 1010 hPa, category 0, zone C)is present:

Table 8. Fisherman Net Gain/Loss Forecast with Minimal Risk Storm

Risk	AM Forecast	Noon Forecast	Evening Forecast
H	2.5	3.9	4.9
M	1.0	1.4	1.6
L	-.1	-.2	-.4

The moral, here, is "Fish when you can."

An interesting variation is to change policies as new information becomes available, which assumes the fishermen have means of being informed of changes in risk. Table 9 shows the projected gains/losses, under “Sandy” conditions, when a fisherman changes policy from H to M at mid-day and to L in the evening.

Table 9. Changing Policies with Sandy

Risk	AM Forecast	Noon Forecast	Evening Forecast
H	-2.4	-6.7	-10.8
M	-2.4	-6.4	-11.1
L	-2.4	-5.8	-9.8

Although significant, projected total losses have been reduced considerably, in fact to less than when M is adhered to throughout the day.

4. THE RISK REDUCTION MODEL IN ACTION

Once the fishermen are educated, all that is required is for someone who is familiar with the model and can interpret its results to enter storm parameters when a developing storm is reported, then to inform the fishermen of their expected risk exposure. The model must be updated with the latest storm parameters throughout the day and risk updates communicated to the fishermen.

5. CONCLUSION

A method for risk assessment and avoidance has been proposed based on personalincentives that the target at-risk group both understands and appreciates. Using a combination of science (meteorology), technology (satellite television weather channels), and statistics (data, regression, and stochastic modeling) a simple, yet effective result is obtained that can inform and, therefore, help protect the livelihood and assets of those who use it. They will have an incentive to use it.

APPENDIX

Table A1. Joint Category Zone Probabilities for a Prior Stage, 950 hPa Storm

	0A	**0B**	**0C**	**1A**	**1B**	**1C**	**2A**	**2B**	**2C**	**3A**	**3B**	**3C**	**4A**	**4B**	**4C**	**5A**	**5B**	**5C**
0A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2A	0	0	0	0	0	0	0.172	0.258	0	0.228	0.342	0	0	0	0	0	0	0
2B	0	0	0	0	0	0	0.129	0.215	0.086	0.171	0.285	0.114	0	0	0	0	0	0
2C	0	0	0	0	0	0	0	0.215	0.215	0	0.285	0.285	0	0	0	0	0	0
3A	0	0	0	0	0	0	0.024	0.036	0	0.368	0.552	0	0.012	0.018	0	0	0	0
3B	0	0	0	0	0	0	0.018	0.03	0.012	0.276	0.46	0.184	0.009	0.015	0.006	0	0	0
3C	0	0	0	0	0	0	0	0.03	0.03	0	0.46	0.46	0	0.015	0.015	0	0	0
4A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Headings combine category with zone (0-5 with A-C). Note that categories 0, 1, and 5 have no probability of transition to or from in any zone. This is because no such hurricanes have been observed at 950 hPa, prior to peak intensity.