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## 1. INTRODUCTION

The National Oceanic and Atmospheric Administration's (NOAA) National Weather Service (NWS) has established performance goals for various NWS warning programs expressed in terms of the False Alarm Ratio (FAR) and Probability of Detection (POD) statistics. Improvements in these statistical measures can be achieved in at least two ways: 1) increasing forecast skill by the infusion of scientific advancements, and 2) adopting warning strategies that specifically target deficiencies in either FAR or POD. The latter involves examining FAR and POD statistics to assess "over-warning" or "under-warning" of various phenomena. If, for example, both the FAR and POD tend to be high, it may suggest that over-warning has occurred. A pattern of over-warning can be compensated for by increasing the required level of confidence that the event will occur before a warning may be issued. A difficulty inherent in such targeted warning strategies is that, absent any increase in skill, attempts to improve FAR tend to worsen POD, and vice-versa.

Although the Critical Success Index (CSI) provides no unique verification information since it is a function of both FAR and POD, understanding its behavior can help identify which component would be more beneficial to target in a warning strategy. This study establishes that changes in FAR have a larger (smaller) impact on CSI than equivalent changes in POD when POD is greater (less) than  $1 - FAR$ , and that equivalent changes in FAR and POD have the same impact on CSI when  $POD = 1 - FAR$ . It is important to note that this analysis will focus solely on the statistical implications of the warning decision-making process. Customer service, which should occupy a central role in any warning strategy, is not taken into account for the purposes of this manuscript.

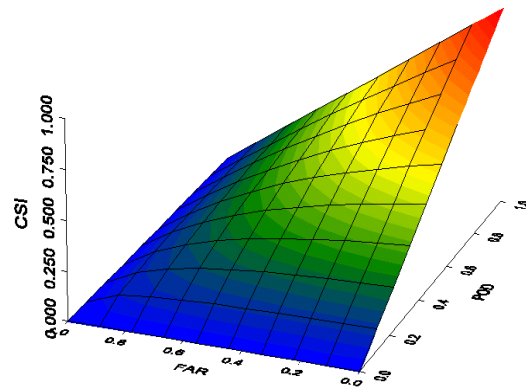
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## 2. ANALYSIS

CSI is defined as a function of FAR and POD by:

$$(1) \quad CSI = \frac{1}{1/(1-FAR) + (1/POD) - 1}$$

where FAR is the ratio of warnings without an event to total warnings, and POD is the ratio of warned events to total events. (Wilks 1995) This relation is shown graphically by a contour plot of the CSI surface in Fig. 1.

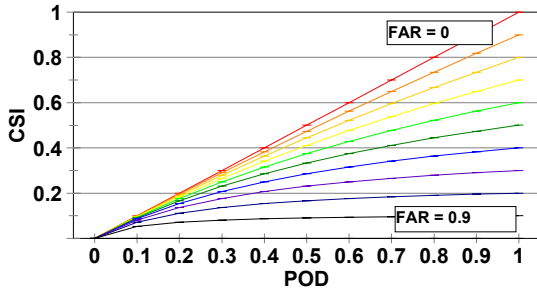


**Figure 1.** CSI as a function of FAR and POD.

Since any set of verification statistics must, by definition, lie on the CSI surface, insight into the mutual interaction of POD, FAR, and CSI can be gained by further examination of Eq. 1 and Fig. 1. For example, if  $POD = 0$  (i.e. the FAR axis),  $CSI = 0$  irrespective of the value of FAR. Similarly, if  $FAR = 1$ ,  $CSI = 0$  regardless of the value of POD.

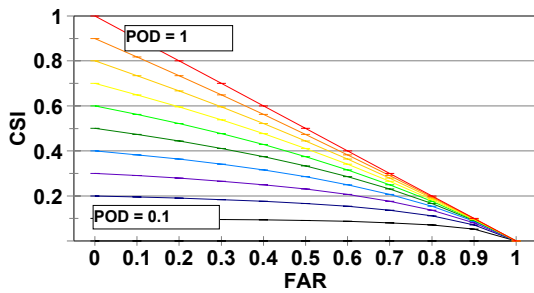
The two-dimensional relationships between CSI and POD for fixed values of FAR, and between CSI and FAR for fixed values of POD are shown graphically in Figs. 2 and 3, respectively. These plots more readily depict that CSI is a non-linear function of both FAR and POD individually (except for the limiting values of 0 and 1).

## CSI vs. POD (Constant FAR)



**Figure 2.** CSI as a function of POD for various constant values of FAR.

## CSI vs. FAR (Constant POD)



**Figure 3.** CSI as a function of FAR for various constant values of POD.

Each (POD, FAR) data pair occupies a unique position on the CSI surface (Fig. 1). Any changes made to either component will move the CSI value along the surface from its original position to a new position. By comparing the slope of the CSI function with respect to both POD and FAR it is possible to determine which component moves CSI more strongly for any given location on the CSI surface, i.e., for any set of current verification statistics.

The value of this variation with respect to each component is given analytically by partial derivatives of CSI with respect to FAR and POD.

From equation (1) it can be shown that:

$$(2) \quad \frac{\partial \text{CSI}}{\partial \text{FAR}} = \frac{-1}{(1-\text{FAR})^2(1/(1-\text{FAR}) + (1/\text{POD}) - 1)^2}$$

Likewise:

$$(3) \quad \frac{\partial \text{CSI}}{\partial \text{POD}} = \frac{1}{(\text{POD})^2(1/(1-\text{FAR}) + (1/\text{POD}) - 1)^2}$$

So, for any combination of FAR and POD, the variation of CSI with respect to FAR and POD may be determined by substituting values in (2) and (3), respectively. In particular, for the limiting cases,

$$\text{If POD} = 0, \quad \frac{\partial \text{CSI}}{\partial \text{FAR}} = 0$$

and

$$\text{if POD} = 1, \quad \frac{\partial \text{CSI}}{\partial \text{FAR}} = -1 \quad \text{from (2)}$$

and

$$\text{if FAR} = 0, \quad \frac{\partial \text{CSI}}{\partial \text{POD}} = 1$$

and

$$\text{if FAR} = 1, \quad \frac{\partial \text{CSI}}{\partial \text{POD}} = 0 \quad \text{from (3)}$$

Thus, the relative effects of changes in POD and FAR on CSI can be determined by comparing the magnitudes of their respective partial derivatives, using Eqs. (2) and (3). It is important to note that the variation of CSI with respect to POD and FAR is a function of POD and FAR. In other words, any strategy to improve CSI by concentrating on improving either POD or FAR should take into account the current value of each component.

FAR and POD will affect CSI equally when the magnitudes of their respective slopes are equal, that is:

$$\left| \frac{\partial \text{CSI}}{\partial \text{FAR}} \right| = \left| \frac{\partial \text{CSI}}{\partial \text{POD}} \right|$$

or:

$$\frac{1}{(1-\text{FAR})^2(1/(1-\text{FAR}) + (1/\text{POD}) - 1)^2} = \frac{1}{(\text{POD})^2(1/(1-\text{FAR}) + (1/\text{POD}) - 1)^2}$$

which yields

$$(4) \quad \text{POD} = 1 - \text{FAR}$$

So, when POD is equal to 1 - FAR, equivalent changes in POD or FAR will each change CSI by the

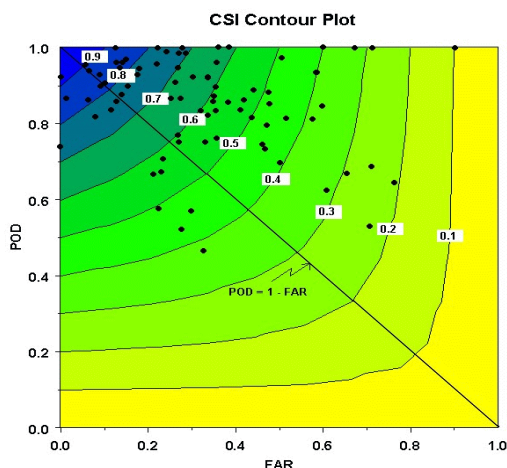
same amount. From equations (2) and (3), it can be seen that when POD is greater (less) than  $1 - FAR$ , changes in FAR have a greater (lesser) influence on CSI than changes in POD. Thus, by comparing the historical POD and  $1 - FAR$  values, any warning decision maker can quickly determine which component's improvement would produce a larger improvement in CSI.

### 3. DISCUSSION

Developing a warning strategy based on historical performance is complicated by the fact that skill levels generally improve with time. The more skillful that forecasters become, the more reliable will be their confidence level that the event will or will not occur. Targeting either the FAR or POD component in a warning strategy is thus only useful when recent scientific and technological advancements are not significant enough to produce large jumps in predictability.

The success of the forecast then, as measured by CSI, is the result of two factors: (1) The forecaster's skill at assessing their confidence that the event will occur, and (2) the strategic selection of a *warning threshold* such that CSI has the greatest likelihood of being maximized. For example, if a historical pattern of over-warning has been detected, the confidence threshold for issuing a warning can be raised above the 50% percent threshold in order to favor FAR at the expense of POD.

Just such an approach has been used recently by the NWS Eastern Region with regard to the Winter Weather Warning program. The Eastern Region Winter Weather Best Practices Team (Watling et al. 2001) examined Winter Storm Warning statistics



**Figure 4.** 2-D contour plot of CSI as a function of FAR and POD, with data points from Eastern Region Winter Storm Warnings 1994-2001.

from several forecast offices from the period of 1994-95 to 2000-01. The POD and FAR statistics from this study are overlaid on a contour plot of CSI in Fig. 4. From the figure it is clear that the vast majority of the data points fall on the  $POD > 1 - FAR$  portion of the plot. Thus, the greatest improvement in CSI, for the Region as a whole, can be achieved by targeted improvements in FAR.

Eastern Region policy (ROML E-7-01) subsequently set the required confidence level for issuing a Winter Storm Warning to 80 percent. This approach is largely motivated by the goal of reducing the FAR since, based on the historical bias, FAR changes will have a greater impact on CSI than equal changes in POD.

### 4. SUMMARY

By considering the slope of the CSI function with respect to POD and FAR, it was demonstrated that equal changes in FAR and POD produce an equal change in CSI when  $POD = 1 - FAR$ . When POD is greater than  $1 - FAR$ , CSI is more sensitive to changes in FAR, and when POD is less than  $1 - FAR$ , CSI is more sensitive to changes in POD.

The best way to improve warning statistics is simply to be correct more often. This would result in an improvement in both FAR and POD, and a corresponding improvement in CSI. In the absence of such an increase in forecast skill, however, a targeted warning strategy can be used to increase CSI by adopting warning thresholds consistent with improving the component to which CSI is most sensitive.

In reality, a successful warning program must also clearly take into account users' needs. Issuing warnings with greater accuracy would lead to both increased customer satisfaction and improved CSI scores, but it is not at all clear that a "false alarm" and a "hit" affect customers in the same proportion that they affect the value of CSI. An ideal verification system is one in which the only way verification scores can be improved is by issuing warnings with greater "utility", i.e. the warnings do a better job of fulfilling their basic purpose - protection of lives and property. Although CSI is one surrogate by which to measure the utility of our warnings, it should be acknowledged that optimizing CSI may not necessarily lead to more effective warnings.

### 5. REFERENCES

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