Reinterpretation of Relations Between Vegetation Removal and Water Yield

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ABSTRACT

While the relation between vegetation clearance and increasing streamflow appears to be strong for data aggregated among geographic regions, results are equivocal in local areas. Earlier data are re-analyzed to consider the role of hydroclimatology. While vegetation clearance increases absolute streamflow, the proportional change is not significant. Residuals of regressions of absolute and proportional change in streamflow on vegetation clearance are related to precipitation, with positive and negative slopes, respectively. A few outliers with high responses are important in creating a pattern, and hydroclimatology is a better predictor of change in streamflow than is vegetation clearance for aggregate data. With data disaggregated in five classes of precipitation, significant regressions are found only in one class. No significant relations are found for selected regional data sets. Regional hydroclimatology affects responses at both global and local scales. The aggregate result, influenced by outliers, cannot be used to guide water resources management at particular locations.

KEY WORDS: deforestation, forest hydrology, scale, streamflow, water yield.

INTRODUCTION

Many studies have examined data on changes in basin water yield or streamflow following vegetation management treatments. The standard reference is to Hibbert (1967), who examined changes in 39 catchment experiments. In summary he made three generalizations:

1. Reduction in forest cover increases water yield.
2. Establishment of forest cover on sparsely vegetated land decreases water yield.
3. Response to treatment is highly variable, and for the most part, unpredictable.

Despite the caveat of the third generalization, Hibbert's summary has led
to use of formulas for predicting the effects of forest cover on water yield in local regions, at least in the U.S. (Hewlett, 1982), to conclusions that vegetation management for water yield is a basis for resources planning (e.g., Ponce and Meiman, 1983), and to a textbook view of the relation. Some individual studies note, however, that the response is equivocal. Veen and Dolman (1989) specifically noted that the methodology of experimental basin studies permits neither extrapolation nor prediction and they rejected the conclusion of Bosch and Hewlett (1982) that more such studies are needed.

The textbook case is well illustrated by Dunne and Leopold (1978) who showed linear increase in first year water yield with percentage of vegetation cut in the basin, based on Hibbert (1967). It is notable that the results for different studies vary greatly in slope, from a minor response in the southwestern U.S. to a sensitive response in the Oregon Cascades. The textbook case has led to cogent arguments for the management of vegetation as an indirect means to manage water (e.g., Douglass, 1983). The research data support the notion that forest harvest will increase water yield, but adds complicating factors for specific cases. Both views are based on experimental results, but are often analyzed at different degrees of generality. The first view is supported by aggregation of results of several studies, the latter view by analysis of individual studies. Trimble et al. (1987) best expressed the scale-dependence of the analysis by noting that the change in yield was not linked to the proportional change in vegetation in their study, but that their data fit well within the universal model for many studies. The within region applicability of the concept was demonstrated by Kucera (1987) for use in South Australia.

Our purpose is to examine a general trend in the sensitivity and variability of the response of basin water yield to vegetation management. We are particularly interested in elucidating Trimble et al.'s (1987) finding of a difference between local and aggregated, or universal, results. To this end we re-examine data from past studies as did Hibbert (1967); Bosch and Hewlett (1982), and, in part, Trimble et al. (1987).

Several factors lead to variability in response. One of the most notable complicating factors is seasonality of precipitation and snowmelt. Kattelman et al. (1983) and Troendle (1983) both noted that the secondary deposition and subsequent fate of snow in forested catchments is influenced by the pattern of forest cutting as well as by the proportional area. Another factor is the pattern of vegetation within the basin. Some individual experiments have varied the location of cut sections in the basin, but the results were not conclusive (cf. Patrick and Reinhart, 1971). Others have found that basin geomorphology and vegetation, including the existence of wider floodplains supporting deciduous riparian tree species in a conifer environment, would have an effect on the sensitivity of the basin to cutting practices (Verry, 1986; Hicks et al., 1991). A more general phenomenon is the effect of actual precipitation amounts on the response (Troendle and King, 1985). Harr (1983) found that yield increases were greatest during the rainy season and in years with the most precipitation. Trimble et al. (1987), examining the effects of reforestation, found that yield was decreased more in dry years. This importance in seasonal and annual precipitation is also expressed over a geographic range related to vegetation type. As noted above, the response is most sensitive in those areas with most precipitation and high biomass. Thus Hibbert (1983) argued that water yield would not be increased by cutting or removing low-density shrubs and woodland trees in arid regions, while Harr (1983) noted that sustained increases in flow would be unlikely in the very mesic forests of Oregon and Washington.

The water yield for a drainage basin can be calculated using a simple water balance equation:

\[ P = E + Q + (S_t - S_{t-1}) \]

where P is precipitation, E is evapo-
transpiration, \( Q \) is volume discharge, and \( S \) is storage at two time intervals. The mechanism behind the argument about cutting is that decreases in vegetation will lead to decreased \( E \), through a reduction in both interception and transpiration, and thus increased runoff and \( Q \) or storage. The flux to \( E \) is dependent on the amount of vegetation in the system. Changes in vegetation have usually been measured as area or proportional area of the basin changed by management. The biomass per unit area usually has not been considered, although basic hydrological studies indicate the importance of specific characteristics such as biomass and leaf area. This distinction may help to explain the regional differences in sensitivity shown by the summary and textbook interpretations: streamflow responds more dramatically in areas of large vegetation structure (i.e., high biomass in productive areas with high precipitation) than in arid areas with sparse vegetation because a unit area cut in the former affects more biomass and leaf area (Figure 1).

Here we examine three questions:

- Is response primarily a function of treatment?
- Does the response vary with hydroclimatological conditions?
- Do patterns of response show a difference between analyses of local data versus aggregated data?

METHODS

In this study we re-analyze the data presented by Bosch and Hewlett (1982). We analyze the relation between water yield and vegetation management including, however, the influence of long-term precipitation and streamflow. Trimble et al. (1987) calculated a regression equation for the data of Bosch and Hewlett (1982) based on the first-year increases in streamflow. We proceed differently. First, we use an average value for the first 5 years following vegetation treatment (in some cases where only a single figure within 8 yr was given we used it; in other cases where only longer intervals were given, or where no quantitative result was reported, we did not use that observation) because water yield implies water resource; although the different processes of initial cutting and later recovery are combined in this approach, the chosen variable is meaningful. We thus derived 53 cases.

Second, we additionally examine the proportional increase in streamflow because absolute differences depend strongly on regional climatology, although in the data there is no systematic relation between treatment area and precipitation. Third, we did not constrain our equations to pass through the origin, but not only because Trimble et al. (1987) found no significant difference in doing so. This constraint assumes that the form of the relation between zero and our lowest data point is the same as for the rest of the data. Notwithstanding Trimble et al.’s (1987) improvement in regression fit by adding such points for large, non-experimental basins, this assumption may not be generally acceptable. Bosch and Hewlett’s (1982) con-
tended that low area treatments will not produce interpretable results, and unknown nonlinearities may exist.

The data presented by Bosch and Hewlett (1982) (and codes we used) included four background variables: mean annual precipitation (MAP), mean annual stream flow (MAS), basin area (AREA), mid-basin elevation (ELEV); a treatment variable: percent of basin cleared (%CLEAR); and a result variable: the incremental change in streamflow (INC) over various intervals. We used the incremental change in streamflow to calculate a proportional increment (PINC) by dividing it by mean annual streamflow. This value became an additional dependent variable in our analyses. We also calculated a percentage of the incoming precipitation that we assigned to evapotranspiration: %ET = (MAP-MAS)/MAP, and its complement %MAS = 1 - %ET. We used these data and some transformation thereof. While the background variables are long term averages and data specific to the experiments would be more useful, these are not readily available.

We began our analysis by producing a table of Pearson correlation coefficients to examine general relations among the possible pairs of variables and to consider multicollinearity in additional analyses. Based on those results we then used stepwise regressions of the dependent variables on several independent variables. Our next step was to regress both INC and PINC on %CLEAR. The general concept that we examined was:

\[
\text{INC or PINC} = f(%\text{CLEAR}, \text{MAP}, \text{MAS}, \text{ELEV}, \text{AREA}, %\text{ET}, %\text{MAS}).
\]

After examining these results we also computed the residual of simple regressions of INC and PINC on %CLEAR and then regressed those values on mean annual precipitation. Because of a wider range of hydrological inputs, it might be expected that larger residuals for INC and PINC were found in areas of greater and lesser precipitation, respectively, there is no a priori reason to expect that the residuals would be biased in terms of positive or negative sign.

To further analyze the data we separately examined cases in five classes of precipitation. Because earlier reports suggest that the response differs among regions, we subdivided the data into five groups of approximately equal number of cases in classes of MAP (<815 mm, -1440 mm, -1895 mm, -2150, >2150) and repeated each of the two regressions. We also examined data for drainage basins in four specific areas: Coweeta, North Carolina; Andrews, Oregon; Fernow, West Virginia; and Three Bar and White Spar, Arizona (Figure 2). Because of the apparent importance of outliers, we performed the regressions of INC and PINC on CLEAR a second time after deleting four and three cases, respectively.

RESULTS

Our initial results indicate high correlations among the general hydrological variables for the basins: MAP and MAS and also for the calculated or transformed variables such as %ET; the treatment variable, %CLEAR, is not highly correlated with any other variable (Table 1). Regression of the increase in runoff on treatment produced:

\[
\text{INC} = 38.829 + 1.652\%\text{CLEAR};
\]

adjusted \(R^2\): 0.108,

standard error 137,

\(p < 0.01\).

\[
\text{PINC} = 0.128 + 0.005\%\text{CLEAR};
\]

adjusted \(R^2\): 0.017,

standard error 0.77,

\(p > 0.17\).

Examination of scatter plots (Figure 3) indicated that additional analyses should include natural log transformations of the independent variables (labeled as LN ...). The plots do indicate that streamflow does increase following clearing, but the predictability is low, especially where clearing exceeds 30% of the catchment.
FIGURE 2. Locations of the experimental sites analyzed as four separate groups.

TABLE 1
Pearson Correlation Coefficients of the Primary Variables Used in the Analysis

<table>
<thead>
<tr>
<th></th>
<th>INC</th>
<th>PINC</th>
<th>%CLEAR</th>
<th>MAP</th>
<th>MAS</th>
<th>ET</th>
<th>%MAS</th>
<th>AREA</th>
</tr>
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<tbody>
<tr>
<td>PINC</td>
<td>-0.780</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%CLEAR</td>
<td>0.354</td>
<td>0.189</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAP</td>
<td>0.500</td>
<td>-0.468</td>
<td>0.059</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAS</td>
<td>0.445</td>
<td>-0.455</td>
<td>0.012</td>
<td>0.917</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ET</td>
<td>0.255</td>
<td>-0.154</td>
<td>0.121</td>
<td>0.450</td>
<td>0.057</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%MAS</td>
<td>0.392</td>
<td>-0.570</td>
<td>-0.059</td>
<td>0.807</td>
<td>0.931</td>
<td>-0.063</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AREA</td>
<td>-0.161</td>
<td>-0.091</td>
<td>-0.392</td>
<td>-0.053</td>
<td>-0.087</td>
<td>0.063</td>
<td>-0.121</td>
<td></td>
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<tr>
<td>ELEV</td>
<td>-0.305</td>
<td>0.036</td>
<td>-0.228</td>
<td>-0.396</td>
<td>-0.397</td>
<td>-0.102</td>
<td>-0.417</td>
<td>0.522</td>
</tr>
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</table>

In stepwise regressions of INC only two independent variables entered the equations at significant levels, in the order shown:

\[
\text{INC} = -120.72 + 0.107 \text{MAP} + 1.519 \%\text{CLEAR};
\]

standard error 118.888;

\[p < 0.01.\]

The cumulative adjusted \(R^2\)'s were 0.278 and 0.328. For the proportional increment four variables entered.

\[
\text{PINC} = -3.945 - 1.71 \ln \%\text{MAS} + 8.344 \%\text{MAS} + 2.101 \ln \%\text{ET} + 0.004 \%\text{CLEAR};
\]

standard error 0.377;

\[p < 0.01.\]

This equation had cumulative adjusted
$R^2$s of 0.593, 0.710, 0.744, and 0.764. This equation may have value for management, but because of the multicollinearity induced by using MAS in the calculation of both PINC and %MAS may be difficult to interpret, however, the actual hydrological connections should be considered.

In the regression of the residual (RES) of the regression of INC on %CLEAR on MAP the equation was:

$$RES = -168.013 + .107 \ MAP,$$

adjusted $R^2$: .247,

standard error 117.791,

$p < .001$.

Here the residuals increase linearly with increasing precipitation, with negative residuals in areas of low precipitation, a balance of negative and positive residuals in the middle ranges, and positive residuals with high precipitation (Figure 4a). In the regression of the residual (%RES) of PINC on %CLEAR, the equation was:

$$%RES = 0.355 - 0.0002 \ MAP,$$

adjusted $R^2$: .254,

standard error 0.214,

$p < .001$.

Here the residuals are highest in the driest areas (Figure 4b).

Given the relations of the residuals to precipitation, the subdivision by precipitation level becomes interesting. Table 2 shows the regression equations for the five precipitation classes for INC on %CLEAR, and for PINC on %CLEAR. Among the classes a significant relation is found only in the 1896-2150 mm class. Within small ranges of precipitation, such as might be found within a given region, no predictable relation between vegetation treatment and altered streamflow is found except for this one class. Why this class should show a pattern when higher or slightly lower classes do not cannot
be explained by these data. Of these nine points, two are in Douglas fir in Oregon, five are in mixed hardwoods in North Carolina, and two are in high montane bamboo in Kenya. This result may represent Type I error. It is also notable that in both cases the significant regressions have intercepts closest to the origin. It may be that there is less variation in the kinds of secondary influences discussed above among these cases.

None of the regressions are significant for the specific areas examined: Douglas fir at Andrews, mixed hardwoods at both Coweeta and Fernow, and chaparral at Three Bar and White Spar. This lack of predictability within given areas reinforces Trimble et al.'s (1987) finding for the Georgia Piedmont.

For the absolute increase, four outliers are particularly noteworthy (i.e., those greater than 400 mm) (Figure 3a). These four outliers are from areas of high precipitation (Table 3), but they are not the only such cases. The two sites at Maimai, N.Z., however, represent only the first year increase, and the two sites in Oregon were burned as well as cleared; the former difference would certainly contribute to the higher responses, the latter might also. When

<table>
<thead>
<tr>
<th>Location</th>
<th>Site</th>
<th>MAP</th>
<th>MAS</th>
<th>%CLEAR</th>
</tr>
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<tr>
<td>For equations of INC on %CLEAR (INC&gt;400):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alsea, OR</td>
<td>Needle Branch</td>
<td>2483</td>
<td>1855</td>
<td>82</td>
</tr>
<tr>
<td>Andrews, OR</td>
<td>#1</td>
<td>2388</td>
<td>1376</td>
<td>100</td>
</tr>
<tr>
<td>Maimai, N.Z.</td>
<td>M7</td>
<td>2600</td>
<td>1500</td>
<td>100</td>
</tr>
<tr>
<td>Maimai, N.Z.</td>
<td>M9</td>
<td>2600</td>
<td>1500</td>
<td>75</td>
</tr>
<tr>
<td>For equations of PINC on %CLEAR (PINC&gt;2):</td>
<td>Three Bar, AZ</td>
<td>582</td>
<td>11</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>B2</td>
<td>582</td>
<td>11</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>B1</td>
<td>582</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>681</td>
<td>36</td>
<td>100</td>
</tr>
</tbody>
</table>

TABLE 3
Sites with Unusually High Residuals
these four cases are deleted, the equation changes to:

\[ \text{INC} = 53.36 + 1.009 \% \text{CLEAR}, \]

adjusted \( R^2: 0.091, \)

standard error: 0.419,

\( p < 0.05. \)

For the proportional increase, three outliers are noteworthy (i.e., those greater that 200\%) (Figure 3b). These three outliers are from areas of low precipitation (Table 3), but they are not the only such cases. All are from the same area, and all were subjected to multiple treatments, which may have lead to higher responses. When these three cases are deleted the equation changes to:

\[ \text{PINC} = 0.138 + 0.002 \% \text{CLEAR}, \]

adjusted \( R^2: 0.048, \)

standard error: 0.001,

\( p > 0.06. \)

**DISCUSSION**

Unlike earlier interpretations of the same data we find that the predictability of water yield to vegetation treatment is low. Because we use the less sensitive five-year average, wherein different recovery rates are combined, instead of first-year response, the amount of variation explained in our study drops from 38 percent (Trimble et al. 1987) to 10 percent. When we examined the proportional change in streamflow, the relation lost significance altogether. When we examined the overall statistics and the residual of the relation between yield and treatment we see that regional hydroclimatological variables explain much of the response. When we examine a subdivision of the data by precipitation class significant relations are rare, and when we examine specific experimental areas they are nonexistent.

If the experiments had varied so that cleared area varied with precipitation, then the difference in significance between the separate precipitation classes and the aggregated data would be due to a data problem, but there is no systematic relation between precipitation and management treatment. The differences in Figure 1 a and 1 b may give some indication of a physical explanation. Where precipitation and biomass are high, changes in area cleared will have a greater effect on absolute changes because of the high rates of water transfer along all pathways. For the same reason any change will have less proportional effect in this system. Conversely, in the dry areas with less biomass any treatment will have less absolute effect, but can be proportionally higher.

The analysis of the residuals indicates that the effects of treatment are, however, biased by precipitation. The actual changes in streamflow show better response for treatment area in wet areas, while the proportional increase in streamflow shows a better response to treatment in the dry areas, but this response is influenced by outliers. This bias in the outliers may be the strongest explanation for why significance of universal pattern for aggregated data is found while local patterns are not significant. This effect of outliers is demonstrated in part for the absolute change in streamflow, where the deletion of the four highest residuals leads to decreased explanation, but in the analysis of the proportional change the deletion of the three highest residuals leads to an improvement of the regression into the area that some would consider marginally statistically significant. These effects may also arise because precipitation more strongly affects the initial response while differences in vegetation recovery affect the five-year response.

**CONCLUSION**

Both the universal and local effects of vegetation management are conditioned by the regional pattern of hydroclimatology. At the local scale the effects of treatments seem to be relatively unpredictable. Within local areas the variability of secondary influences become important. Notable local influences are patterns of natural vegetation, vegeta-
tion treatment geomorphology, and of snow, which are themselves related. The pattern of riparian vegetation may be especially significant (Malanson, 1993).

In the future more site specific approaches using process models will be more useful. Many spatially explicit basin hydrological models are being developed (Band and Wood, 1988). These models can take into account patterns of vegetation, geomorphology, and hydrology and calculate a hydrological budget for specific basins with hypothetical vegetation management plans. The wider availability of process models eventually will render the statistical approach obsolete, but in the meantime its problems must be recognized.

The statistical approach shows that at the aggregate level a general pattern emerges, but although significant, it is weak. Part of this result may be due to the increase in sample size alone. An additional problem which should be considered is the lack of independence among cases both serial and spatial autocorrelation are probable in these data. It is clear that the general result, which is presented in hydrology textbooks without caveat, cannot be used to guide water resources management at particular locations.

REFERENCES


