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# Can a vegetation index derived from remote sensing be indicative of areal transpiration?

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## Abstract

Monthly, maximum-value-composited normalized difference vegetation indices (NDVI), calculated from NOAA-AVHRR images, were correlated with annual transpiration (TR) estimates (i.e. annual precipitation minus runoff) for seven watersheds in Pennsylvania. A moderate relationship between the standardized variables was detected. The NDVI–TR relationship dramatically improved with improved watershed TR estimates. At the Little River watershed in Georgia, where the water balances of two sub-catchments could be reliably estimated over water cycles of variable length (about 2 months to 1½ years), the correlation coefficient between NDVI and TR was found to be 0.94 (a sample size of 13). The present approach avoids the common practice of applying arbitrary hydrological models to validate the NDVI–TR relationship and attempts to minimize the effects of possible spurious correlations between the two variables that may stem from well-defined annual cycles in both the TR process and the foliage development of vegetation. It is concluded here that NDVI seems to reflect temporal changes in areal TR in a humid environment under well-vegetated conditions. © 2000 Elsevier Science B.V. All rights reserved.

*Keywords:* Areal transpiration; Remotely sensed vegetation index

## 1. Introduction

Terrestrial vegetation plays a crucial role in the energy, mass, and momentum exchange between the Earth's surface and the atmosphere (Chong et al., 1993). More specifically, transpiration (TR) of vegetated surfaces allows for the transfer of significant amount of energy across the land–atmosphere interface due to the large amount of latent

heat involved in the vaporization of water. As has been recently re-emphasized, the Earth's vegetation has a profound impact on the global circulation of the atmosphere and oceans and, consequently, on the Earth's climate (e.g. Luthi et al., 1997). A thorough understanding of this spatially and temporally highly variable interaction between the biosphere and the global atmosphere/hydrosphere requires the quantitative description of areal flux rates.

The applicability of local water vapor flux measurements (Bowen ratio or eddy correlation techniques) to obtain spatially representative values is

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restricted as the physical extent of the study area increases due to a general increase in the level of heterogeneity of the surface properties. As a consequence, satellite-based remote sensing techniques have recently proved to be instrumental in overcoming these difficulties due to the large field of view of their sensors. Concurrently, classical theoretical approaches describing the physics of land–atmosphere interactions have been reformulated to specifically incorporate available remotely sensed properties of the land–atmosphere interface. A recent development is the vegetation index/temperature (VIT) approach of Moran et al. (1994a) and more recently its modified version by Yang et al. (1997) to estimate evapotranspiration (ET) rates of both full-cover and partially vegetated surfaces.

In the VIT approach, once the potential ET rates have been defined, actual ET rates are a function of the fractional vegetation cover and the temperature difference between the air and the fully or partially vegetated land surface. While air temperatures are obtained through the use of a thermometer, both fractional vegetation cover and composite surface temperatures are derived from remote sensing measurements of the spectral response of the land surface.

The application of the VIT approach becomes problematic at the watershed scale due to difficulties in: (a) defining catchment-representative potential ET rates; and (b) obtaining fractional vegetation cover and surface temperature measurements during cloudy conditions. In lieu of detailed micrometeorological measurements, catchment-representative potential ET rates can only be estimated (e.g. Singh, 1989) using generally available measured (e.g. temperature, pan evaporation) and/or frequently estimated (e.g. net radiation) meteorological variables. The fractional vegetation cover and surface temperature measurements can, in principle, be obtained from aircrafts (e.g. Moran et al., 1994b) during cloudy days when satellite sensors are seriously affected by the condensed water vapor in the air, but the high cost and logistics involved in such an endeavor practically inhibit the routine application of airborne spectral data collection. While it is true that vegetation conditions can be assessed

based on images composited bi-weekly to maximum value (Holben, 1986), the same approach cannot be used for obtaining useful surface temperature measurements. Maximum value composited images contain only the largest value of a measured property during a given period, thus minimizing the shielding effects of clouds. The technique works well for surface properties that change relatively little during the composite period such as the fractional vegetation cover estimated through the application of a vegetation index (e.g. Huete and Jackson, 1988; Huete, 1988; Moran et al., 1994a and Yang et al., 1998). Unfortunately, this cannot be said of the air-surface temperature differences. Different techniques have been proposed to incorporate atmospheric corrections in the derivation of the surface temperature. Kerr et al. (1992) give a short, critical review of the existing techniques which either require additional radiosoundings synchronous and colocated with the satellite measurements or employ time-consuming and very complex inversion algorithms. An alternative choice is the application of relatively simple differential absorption methods with a trade off in accuracy (Kerr et al., 1992). These techniques, although very encouraging, are still experimental and need empirical coefficients that are available only at specific sites. As an alternative, one may use only the satellite-derived vegetation index to estimate areal TR or ET.

A widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), which is defined as the ratio between two terms ( $NIR - Red$ ) and ( $NIR + Red$ ), where  $NIR$  and  $Red$  are the spectral responses of the vegetated land surface in the near infrared and red bands, respectively (Tucker, 1979). In the past decade NDVI has been related to ET by numerous authors (Running and Nemani, 1988; Kerr et al. 1989; Price, 1990; Wiegand and Richardson, 1990; Cihlar et al., 1991; Desjardins et al., 1992; Gao et al., 1992; Hall et al., 1992; Sellers and Hall, 1992; Chong et al., 1993; Kustas et al., 1994; Seevers and Ottmann, 1994; Nicholson et al., 1996; Szilagyi et al., 1998). The evaluation of the NDVI versus ET relationship in the above studies (except Desjardins et al., which was inconclusive)

Table 1  
Watershed drainage areas as well as the locations of the precipitation and gauging stations

|                         | Drainage area (km <sup>2</sup> ) | Precipitation station | Gauging station |
|-------------------------|----------------------------------|-----------------------|-----------------|
| Bixler Run, PA          | 39                               | Bloserville           | Loysville       |
| Blockhouse Creek, PA    | 98                               | Williamsport          | English Center  |
| Corey Creek, PA         | 32                               | Covington             | Mainesburg      |
| Letort Spring Run, PA   | 56                               | Bloserville           | Carlisle        |
| Quittapahilla Creek, PA | 192                              | Bloserville           | Bellegrove      |
| Tioga River, PA         | 396                              | Covington             | Mansfield       |
| Towanda Creek, PA       | 557                              | Towanda               | Monroeton       |

relies on the application of hydrological/ecological models and/or the comparison of NDVI and ET data generally expressing very strong seasonal behavior. Either of these circumstances may mask the true nature of the NDVI-versus-ET relationship. The former does so because model outputs of any kind generally express decreased variability when compared to the variability in the original process modeled, and the latter because the greening up of vegetation (measured by the vegetation index) and the ET process (like almost all geophysical processes) follow a well-defined annual course. In such a case, a meaningful linkage between the two processes may not follow from a high value of the correlation coefficient due to possible spurious correlations. Therefore, it is desirable to construct an experiment that: (a) does

not involve hydrologic/ecological model results to compare to the NDVI data, and; (b) avoids the correlation of data with strong seasonal trends. In this paper our main objective is such an approach.

**2. Methodology and description of the study sites**

The application of remotely sensed vegetation indices, which measure absorption of the sun’s radiation by the chlorophyll of the green leaf tissue, started in the late 1970’s for crop yield monitoring (Tucker et al., 1979). In the mid 1980’s NDVI was demonstrated to be more sensitive to changes in vegetation conditions (Tucker et al., 1985) than a simple vegetation index. As Wiegand and Richardson (1990) argued, a strong

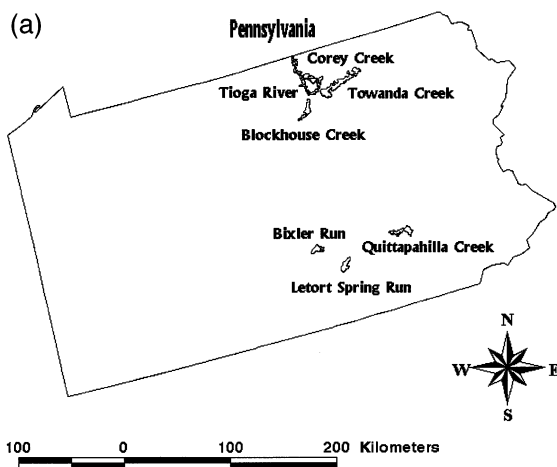


Fig. 1. (a) The seven watersheds in Pennsylvania; (b) watershed B of the Little River, GA. Gauging station F is at the outlet of watershed F, a headwater sub-basin of watershed B.

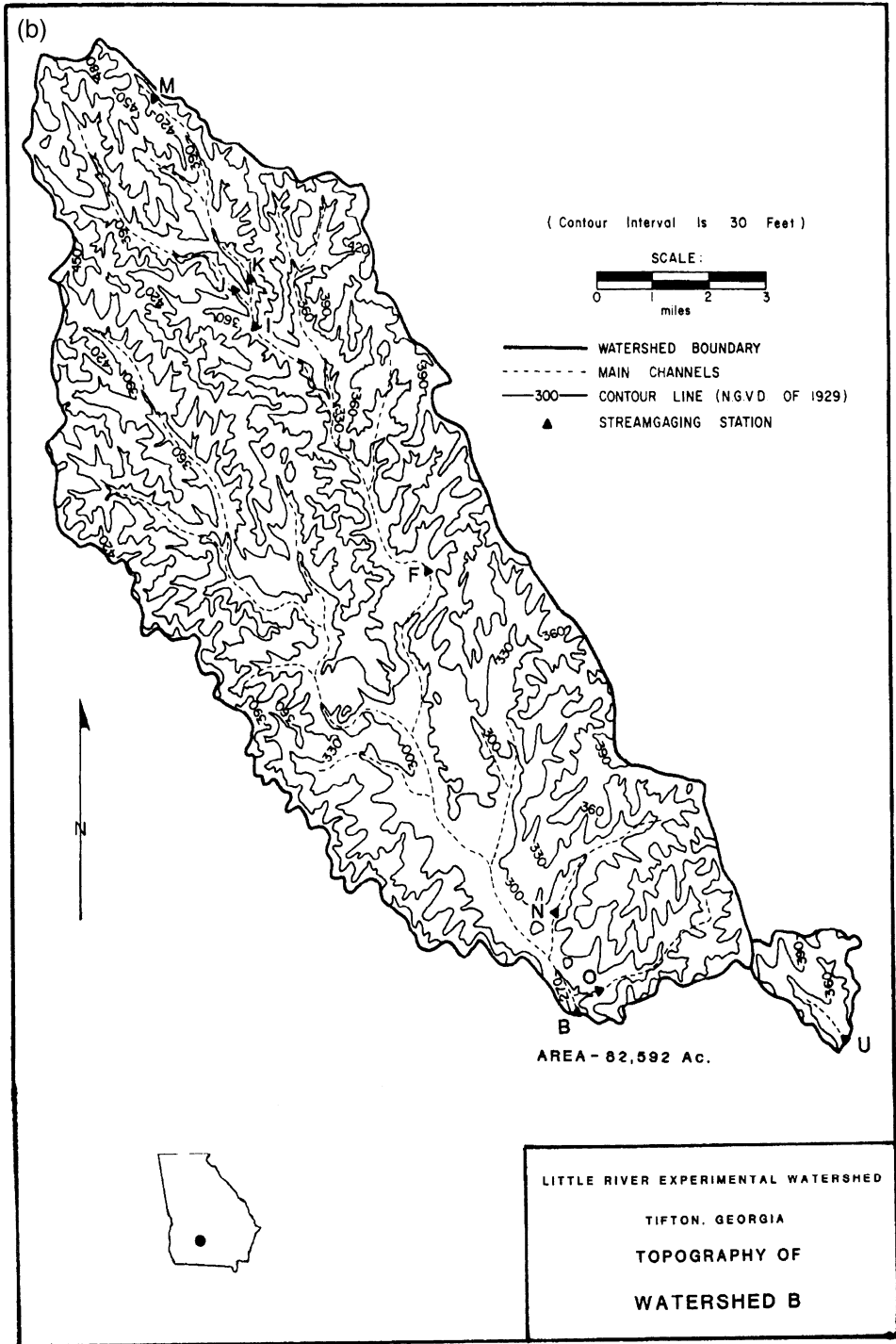


Fig. 1 (Continued).

Table 2

Measured mean daily rates (mm) of precipitation (P), runoff (RO), and pan evaporation (PAN); estimated mean daily rates (mm) of watershed transpiration (TR), as well as mean NDVI values for individual water cycles

| Start of the water cycle                | end     | Length (days) | P (mm day <sup>-1</sup> ) | RO (mm day <sup>-1</sup> ) | TR (mm day <sup>-1</sup> ) | PAN (mm day <sup>-1</sup> ) | NDVI (–) |
|---|---------|---------------|---------------------------|----------------------------|----------------------------|-----------------------------|----------|
| <i>Watershed B (334 km<sup>2</sup>)</i> |         |               |                           |                            |                            |                             |          |
| 5-12-90                                 | 9-29-91 | 506           | 3.88                      | 1.13                       | 2.75                       | 4.46                        | 139.31   |
| 10-10-91                                | 5-21-92 | 224           | 2.97                      | 1.26                       | 1.71                       | 2.81                        | 128.9    |
| 5-21-92                                 | 6-7-93  | 382           | 3.56                      | 1.23                       | 2.33                       | 3.43                        | 134.31   |
| 6-7-93                                  | 8-4-93  | 58            | 3.79                      | 0.03                       | 3.76                       | 5.44                        | 146.31   |
| 5-16-95                                 | 7-9-95  | 54            | 3.69                      | 0.36                       | 3.33                       | 5.19                        | 143.73   |
| 7-9-95                                  | 6-25-96 | 352           | 2.75                      | 0.56                       | 2.19                       | –                           | 138.06   |
| <i>Watershed F (114 km<sup>2</sup>)</i> |         |               |                           |                            |                            |                             |          |
| 5-3-90                                  | 9-15-91 | 501           | 3.99                      | 1.16                       | 2.83                       | 4.49                        | 139.79   |
| 9-15-91                                 | 5-14-92 | 242           | 2.95                      | 1.29                       | 1.66                       | 2.91                        | 129.81   |
| 5-14-92                                 | 6-29-92 | 46            | 3.09                      | 0.03                       | 3.06                       | 4.39                        | 138.71   |
| 7-9-92                                  | 9-19-92 | 72            | 4.13                      | 0.3                        | 3.83                       | 4.33                        | 145.68   |
| 9-19-92                                 | 5-27-93 | 250           | 3.82                      | 2.04                       | 1.78                       | 2.66                        | 129.73   |
| 4-29-95                                 | 7-6-95  | 68            | 3.28                      | 0.33                       | 2.95                       | 5.10                        | 142.31   |
| 8-15-95                                 | 6-25-96 | 315           | 2.76                      | 0.76                       | 2.00                       | –                           | 137.03   |

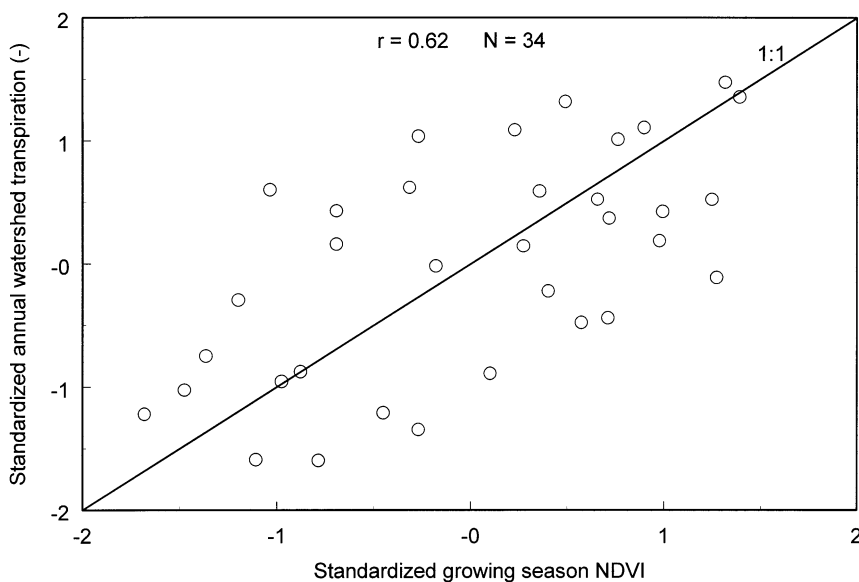


Fig. 2. Standardized warm-season (April–November) NDVI versus annual watershed transpiration for the seven Pennsylvania watersheds.  $r$ , linear correlation coefficient;  $N$ , number of observations.

relationship between NDVI and TR should not be surprising because the green plant tissue, of which chlorophyll activity is measured by NDVI (Sellers, 1985; Sellers et al., 1992), must be active both photosynthetically and transpirationally. This lat-

ter is so, because as the stomata open to let in CO<sub>2</sub> for photosynthesis, they lose water to the atmosphere (e.g. Kramer, 1983, p. 360).

Unfortunately, many factors other than vegetation properties may influence the measured value

of NDVI. Although NDVI has been shown to minimize view angle effects of the sensor (Huete et al., 1992) and the maximum value compositing drastically reduces cloud contamination (Chehbouni et al., 1994), the value of NDVI may still be influenced by solar zenith angle (e.g. Epiphanio and Huete, 1995), background soil conditions (e.g. Chehbouni et al., 1994; Cyr et al., 1995) and subpixel canopy cover (Jasinski, 1990; Price, 1990; Band et al., 1991). Numerous attempts have been made to account for these error sources in the NDVI values (e.g. Huete, 1988; Baret and Guyot, 1991; Huete et al., 1992; Qi et al., 1994; Chehbouni et al., 1994). While in general the modified vegetation indices may considerably reduce errors associated with the above listed sources, these new indices still need to be validated over a wide range of canopy covers and types (Chehbouni et al., 1994).

To check the NDVI–TR relationship on data *without* a seasonal cycle in the two variables (thus

minimizing any possible spurious correlations), first ten watersheds were randomly selected in the Susquehanna River basin, Pennsylvania. The watershed is the natural spatial unit for our investigation because an areal water balance can easily be applied over them and so our transpiration estimates can eventually be validated. The Susquehanna River basin is located in the non-glaciated part of the North Appalachian Ridge and Valley Region, an area characterized by long ridges of 300–400 m in elevation, alternating with broad valleys. The geology of the basin can be described as folded Pennsylvanian sandstone and shale and Devonian sandstone, siltstone and shale (NASA-EOS Progress Report, 1995). The moderately weathered loam soils are generally thin (1–3 m) with poorly developed horizons (ARS-USDA, 1976). The basin experiences a humid climate with an annual precipitation of about 1000–1100 mm. The typical vegetation cover (with a fractional vegetation cover larger than 0.9) is mixed forest

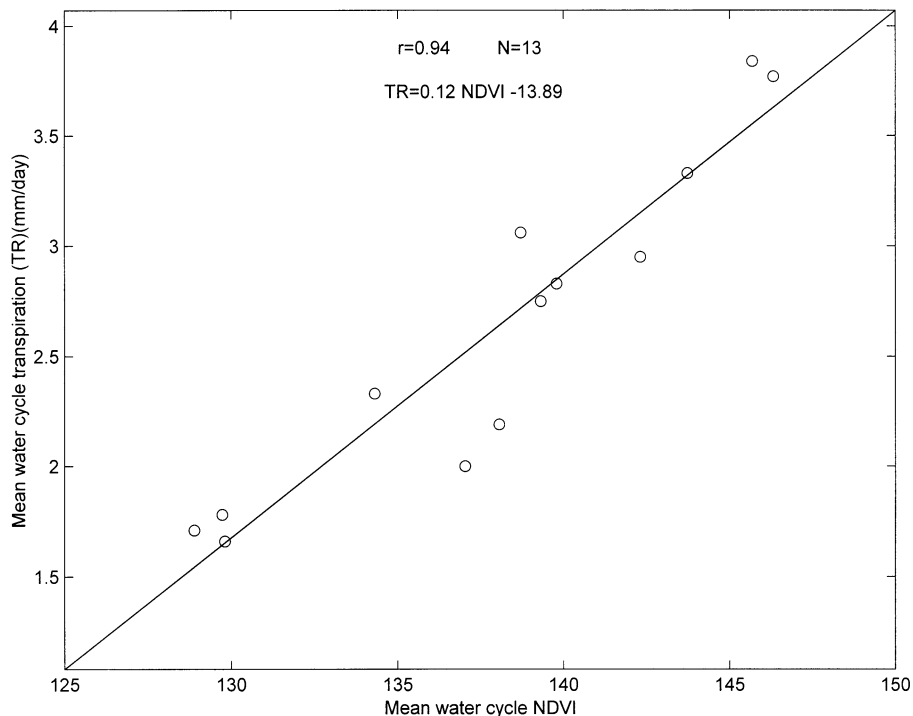


Fig. 3. Mean water cycle NDVI versus transpiration for watersheds B and F in Georgia.  $r$ , linear correlation coefficient;  $N$ , number of observations; the equation shown is the best fit line.

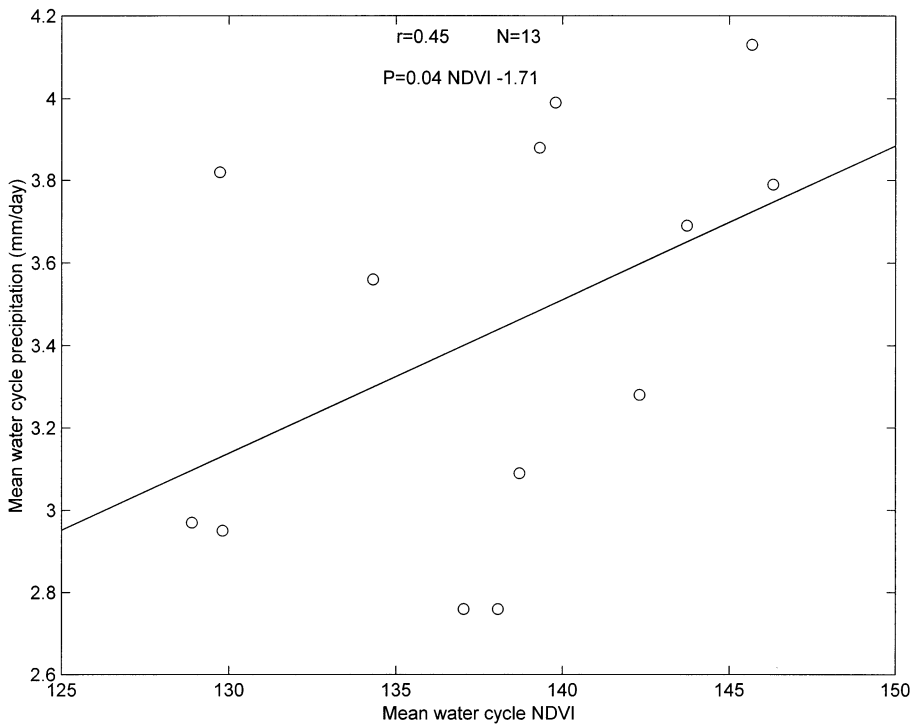


Fig. 4. Mean water cycle NDVI versus precipitation for watersheds B and F in Georgia.  $r$ , linear correlation coefficient;  $N$ , number of observations.

dominated by deciduous trees intermingled with fields of crop and pasture.

Annual watershed TR was estimated by the difference between annual precipitation and runoff. While this difference is generally used for estimating annual ET, it can also be used to estimate TR, since in general, at least 90–95% of the total ET comes from transpiration alone (excluding interception) in well-vegetated catchments (Maidment, 1993, p. 4.26). The above estimation of annual TR further assumes: (a) negligible water storage changes in the watershed between years; (b) negligible irrigated water volumes; (c) negligible groundwater exchange between unconfined and confined aquifers as well as across watershed boundaries; and (d) negligible level of evaporation during the winter (December–March). The TR estimates for each catchment were plotted against the monthly, maximum value composited NOAA AVHRR-derived NDVI-pixel values summed over the warm season (April through November)

and spatially averaged over each watershed for the period between 1990 and 1996 when NDVI data were available. This period, however, is discontinuous because in 1994 the AVHRR sensor malfunctioned. Out of the 10 watersheds, seven catchments with the least scatter in the NDVI versus ET graphs were retained for further analysis (Fig. 1a). In the discarded catchments one or several of the prerequisites, needed for annual watershed ET estimations, may have been seriously violated. Table 1 lists the names and the drainage areas of the selected watersheds with the accompanying precipitation and gauging station locations.

To reduce uncertainties in watershed TR estimations, a second study area was further selected in the Little River basin, Georgia. Catchments B and F, near the town of Tifton, are experimental watersheds operated by the US Department of Agriculture. The watersheds are representative of the Coastal Plain Province of the eastern United

States, which extends from New England along the Atlantic coast to Texas (Williams, 1985). Catchments B and F have a drainage area of 334 and 114 km<sup>2</sup>, respectively, watershed F being the headwater sub-basin of watershed B (see Fig. 1b). Catchment F had 20 and catchment B an additional seven rain gauges evenly distributed over the catchments for data collection (Sheridan et al., 1995). Class A evaporation pan data were also available at a location near the town of Tifton, approx. 3 miles southeast of watershed B. About half of the drainage area of each catchment is covered with mixed forests, while the other half is non-irrigated crops and pasture (Sheridan, 1997). The watersheds are covered with Quaternary sediments, poorly-sorted sands interbedded with partly-indurated sandy claystones and clays that are underlain by limestones over the Hawthorn Formation, an aquiclude at a depth of 1–3 m (ARS-USDA, 1976). The soils are permeable and the infiltration rates are high (Williams, 1985).

The surface topography is relatively flat (Shirmohamaddi et al., 1986). Less than 2% of the annual precipitation of 1200 mm is lost to deep percolation (Williams, 1985; Shirmohamaddi et al., 1986). Climate in the region is characterized as humid subtropical with long, warm summers and short, mild winters (Sheridan, 1997). Precipitation occurs almost exclusively as rainfall throughout the year (Sheridan, 1997).

A unique feature of the watersheds in Georgia is that their streams periodically experience no-flow conditions of variable length. Since low-flow drainage in the watersheds comes from thin, high-permeability aquifers, it can be assumed that the stored water volumes per unit drainage area are approximately equal as runoff approaches no-flow conditions (Williams, 1985). Consequently, a water cycle can be defined between the starting points of each subsequent no-flow period with an assumption of negligible change in the stored water volumes in the catchments. For each water

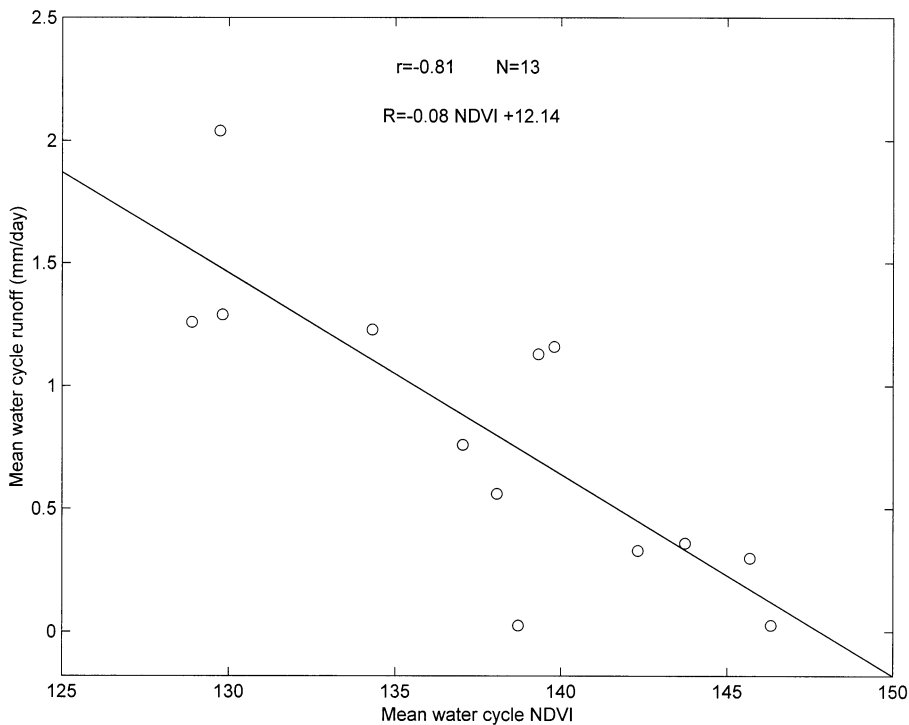


Fig. 5. Mean water cycle NDVI versus runoff for watersheds B and F in Georgia.  $r$ , linear correlation coefficient,  $N$ , number of observations.



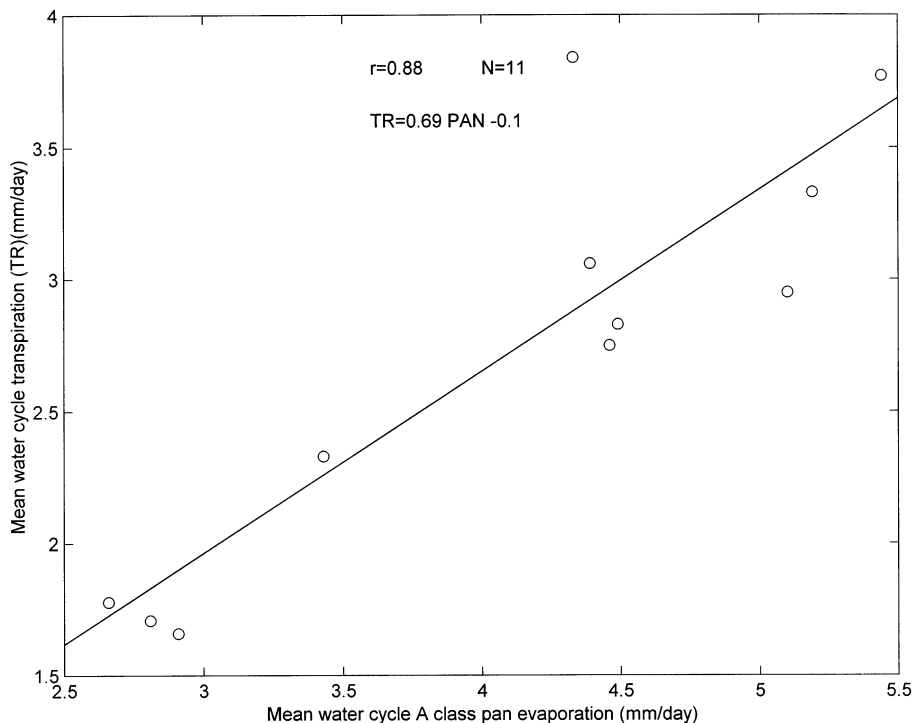


Fig. 6. Mean water cycle class A pan evaporation versus transpiration for watersheds B and F in Georgia.  $r$ , linear correlation coefficient;  $N$ , number of observations; the equation shown is the best fit line.

cycle, watershed ET and, as a consequence, TR can be estimated by the difference in precipitation and runoff (Williams, 1985).

To further reduce possible errors in water-cycle TR estimates (i.e. when the change in groundwater storage is not zero), only those periods were considered which had a minimum length of 46 days. Naturally, the longer the water cycle, the smaller is the relative error in the watershed TR estimates, since a possible non-zero storage term becomes ever smaller when compared to the estimated TR value. On the other hand, longer water cycles reduce the number of TR estimates available. A minimum length of 46 days for water periods seemed to be optimal.

When adjacent water cycles are less than 46 days, it is possible to combine them into one, larger period. At the same time, it is desirable to have water cycles with similar history, meaning the watersheds should generally become more or less saturated during water periods to let the

aquifer become recharged and then have it drained. During short water cycles the aquifers often do not become or become only minimally recharged, which violates our assumption that at the start of the no-flow period, the catchments should have the same stored water volumes. This effect is of importance, considering that in forested catchments with thin soils, trees withdraw moisture for transpiration from the saturated zone too (Federer, 1973). It likely is even more pronounced during periods of water shortage, which are typically characterized by short water cycles. As a consequence, the merging of short, adjacent water cycles were not attempted; neither water cycles with runoff less than  $10^{-2}$  mm day<sup>-1</sup> were included in the analysis for the same reason.

Watersheds B and F, through the introduction of water cycles, are thought to fully comply with the four prerequisites listed above in order to successfully estimate catchment TR. Table 2 lists

the water cycles defined, with the resulting daily mean precipitation, runoff, and estimated TR rates. The application of daily mean rates was important in order to eliminate the length of the water cycle as a corrupting variable. Table 2 also displays the watershed-averaged NDVI values, maximum value composited over a month and temporally averaged over each water cycle. Note that the original NDVI values were modified for convenience such that  $NDVI = (NDVI_{\text{measured}} + 1) \times 100$  (see Di et al., 1994). This notation is kept throughout the text.

### 3. Results and discussion

Before plotting the annual watershed TR estimates for the seven Pennsylvania catchments against NDVI in one graph, the following considerations had to be taken into account. NDVI itself can only reflect relative changes in the photosynthetic activity and in the accompanying tran-

spiration process since the same NDVI value may correspond to different rates of transpiration among catchments. This is so because the photosynthetic activity versus transpiration ratio (also called the water-use efficiency) is a function of vegetation and climate (Kramer, 1983, p. 405–408). Even across the Susquehanna River basin, both dominant vegetation type and climate can change among the selected catchments; consequently, the two variables, TR and NDVI, had to be standardized the following way:

$$f_n^* = \frac{f_n - \langle f_n \rangle}{\sigma_{f_n}}$$

where  $f_n^*$  is the standardized variable of the  $n^{\text{th}}$  catchment,  $\langle f_n \rangle$  is the multi-year (i.e. 5-year) average,  $\sigma_{f_n}$  is the standard deviation of the original variable of the  $n^{\text{th}}$  catchment.

Through the standardization it is possible to check if a higher/lower-than-average NDVI value results in a higher/lower-than-average watershed TR value on an annual basis. Fig. 2a displays the

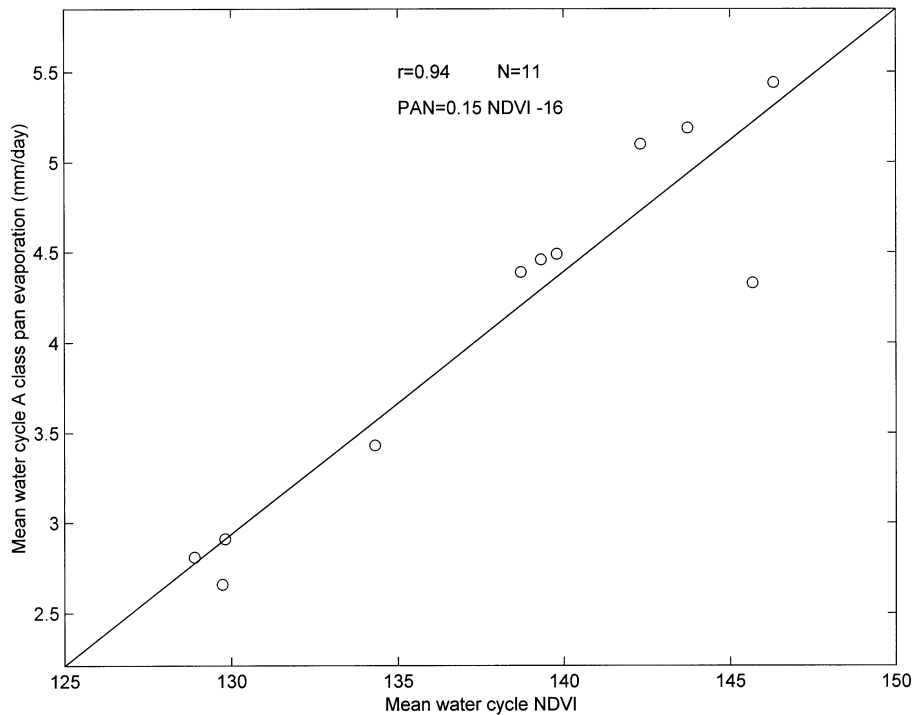


Fig. 7. Mean water cycle NDVI versus class A pan evaporation for watersheds B and F in Georgia.  $r$ , linear correlation coefficient,  $N$ , number of observations.

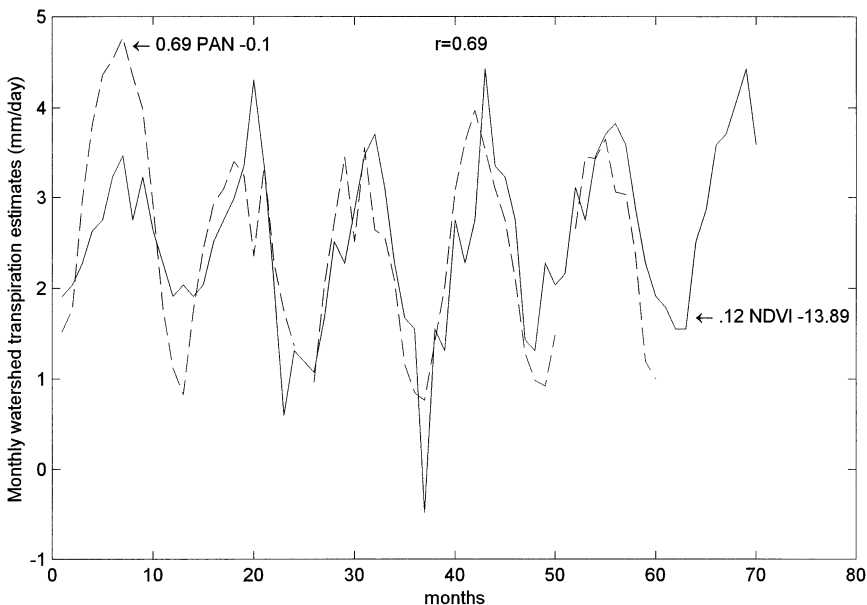


Fig. 8. Monthly watershed transpiration estimates based on monthly NDVI and class A pan evaporation data. Solid line: best fit equation of Fig. 3; intermittent line: best fit equation of Fig. 6.  $r$  is the linear correlation coefficient between the two types of monthly transpiration estimates.

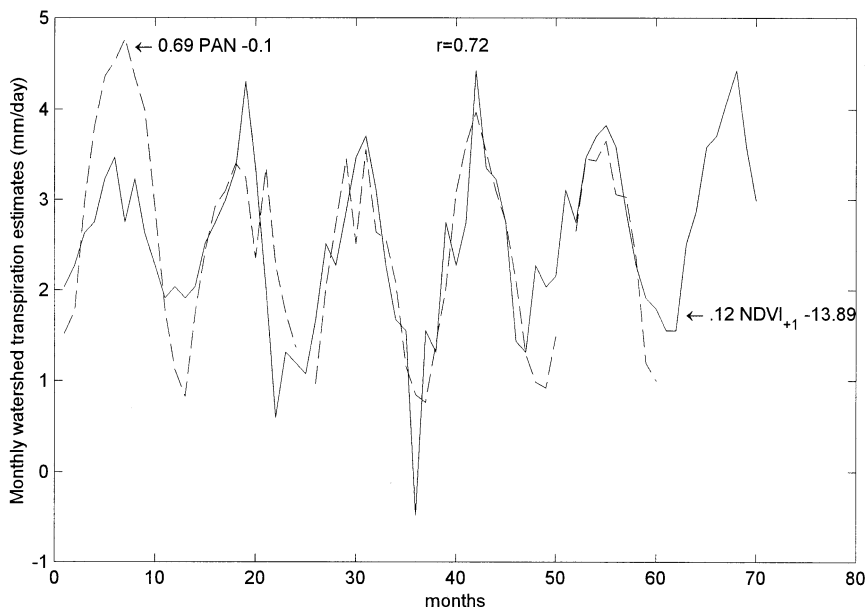


Fig. 9. Same as Fig. 8, except the transpiration rate in month  $i$  is estimated by the NDVI value of month  $i + 1$ .

resulting graph containing data for the seven Pennsylvania watersheds. While it can be generally stated that a higher/lower-than-average

NDVI value does indeed result in a higher/lower-than-average TR value, the scatter in the data points is striking, reflected by only a moderate

value, 0.62, of the correlation coefficient. The sample size is 34 because one watershed had a year with missing precipitation. However, the linear nature of the relationship is clear, as was first predicted theoretically by Sellers (1985). The large scatter in the graph may be the result of: (a) the assumptions required to estimate annual TR not being met completely; and/or (b) single point measurements being used (often the same precipitation station was the only one available) to estimate watershed precipitation (see Table 1).

Data in the Little River, Georgia, basin make it possible (for reasons detailed earlier) to estimate areal TR with higher reliability. The unique locations of the watersheds (i.e. catchment F is a sub-basin of catchment B) and their practically identical vegetation/soil/aquifer characteristics makes it possible to plot the NDVI-versus-TR values in the same graph without the need of any standardization, unlike the seven Pennsylvania watersheds. Fig. 3 displays the daily mean NDVI values plotted against the daily mean rates of estimated watershed TR corresponding to the 13 water cycles found over the temporal coverage of NDVI. The correlation coefficient ( $r$ ) value is 0.94, which means that 12% ( $= 100 [1 - r^2]$ ) of the variation in the TR values is not explained by variations in the NDVI values. This, however, should not be surprising because the precipitation minus runoff (P-RO) term really estimates ET and not TR. The reason that we can use the P-RO term to estimate TR has been discussed in the previous section (i.e.  $TR \sim 0.9-0.95 ET$ ). Note, the eight lowest ET values belong to multi-season periods, while the rest of the values (the five highest ET rates) belong to summer season measurements only; therefore, possible seasonality effects, discussed earlier, are greatly reduced.

Because photosynthetic activity reflects the integrated effects of numerous environmental factors, NDVI has been related to soil moisture (Henricksen and Durkin, 1986; Walsh, 1987; Choudhury and Golus, 1988; Farrar et al., 1994; Nicholson et al., 1996) and to precipitation (Tucker et al., 1985; Choudhury and Tucker, 1987; Seguin et al., 1989; Nicholson et al., 1990; Davenport and Nicholson, 1993; Schultz and Halpert, 1993; Di et al., 1994; Nicholson and Farrar, 1994; Grist et al., 1997;

Yang et al., 1997). While there is a direct physical link between photosynthetic activity, detected by NDVI, and transpiration, the relationship between NDVI and soil moisture is indirect only, with the link being transpiration, since, for transpiration to occur, the plant must deplete soil moisture. The same is true for precipitation. While we cannot check the NDVI-versus-soil moisture relationship with our data (because it is assumed that during a year or a water cycle, water-storage changes are negligible), the precipitation-versus-NDVI relationship can easily be checked, as demonstrated in Fig. 4. It can be seen that precipitation itself cannot explain changes in the photosynthetic activity of the watersheds and vice versa. (A relationship between precipitation and NDVI is expected, however, in watersheds with a more arid climate). The situation improves with observed runoff values (Fig. 5), resulting in a negative correlation, as expected, since the more intense the photosynthetic activity of the watershed, the more water will be transpired and less can occur as runoff over the water cycle.

Another interesting feature of the present data set is that it can be easily checked if pan evaporation can substitute for the generally unknown watershed ET through the application of a pan coefficient. It has been long held among hydrologists that in a water-abundant environment transpiration occurs at its potential level, which, in turn is controlled largely by atmospheric conditions; vegetation type and soil factors being only secondary (e.g. Eagleson, 1970, p. 227; Wilson, 1974, p. 35–36; Dunne and Leopold, 1978, p. 127 and 150). As a consequence, in such an environment transpiration, or ET to be more general, should be correlated to pan evaporation, since in both cases the major influencing factor is meteorologically related. Fig. 6 seems to corroborate this assumption with a correlation coefficient of 0.88 between class A pan evaporation measurements and watershed TR estimates. The best-fit equation parameters agree with a 0.7 value as the most commonly chosen constant class A pan coefficient (Dunne and Leopold, 1978, p. 101).

Because pan evaporation correlates strongly with watershed TR (Fig. 6), NDVI also correlates strongly with pan evaporation (Fig. 7), since wa-

tershed TR had a strong correlation with NDVI (Fig. 3). An interesting finding, however, can be seen in Figs. 8 and 9. In Fig. 8 monthly values of the daily mean watershed TR estimates (in watershed B) are displayed based on monthly class A pan evaporation and NDVI measurements using the best fit equations of Figs. 6 and 3, respectively. On a monthly basis the correlation coefficient between pan evaporation and NDVI-based watershed TR estimates is only 0.69, while at the same time the multi-year daily mean watershed TR averages are virtually identical: 2.52 (pan-based) and 2.54 mm/day (NDVI-based), respectively. Note that the NDVI-derived monthly TR values generally lag behind the pan-derived TR estimates by one month. Shifting the NDVI derived values to the left, the correlation coefficient value increases to 0.72 from 0.69, as seen in Fig. 9, although this change in the correlation coefficient values may not be statistically significant. Kerr et al. (1989), Cihlar et al. (1991) and more recently Szilagyi et al. (1998) found the same type of lag (i.e. 20 days, 15 days, and 1 month, respectively) between ET (TR) values estimated by a hydrologic model and NDVI. None of the above authors could explain the observed lag, partly, because the authors could not decide whether the lag was to be attributed to inadequate hydrologic model performance or was real. An explanation can be, however, that potential ET (PET) calculations, upon which actual ET estimations are based, are calibrated/validated with pan evaporation data. A good example can be seen in Dunne and Leopold (1978), p. 136). The fact, however, still remains that areal TR lags in time behind pan evaporation. An explanation for this can be found in Singh (1995), p. 319) by Burnash.

The moderate value of the correlation coefficient between monthly pan evaporation and monthly areal TR estimates, combined with a one-month lag between the two variables, however, raises the question: can pan evaporation, and consequently hydrologic/water-balance models accurately predict areal ET on a monthly or finer temporal resolution?

In summary, the present paper explored whether NDVI can reflect changes in areal transpiration rates of the vegetation. The method

described avoids the use of: (a) common simulation results of arbitrarily chosen hydrologic models; and (b) the application of monthly data, which intrinsically contain seasonal trends in the variables, leaving room for spurious correlations. Via the application of reliable precipitation and runoff data, a preliminary moderate relationship ( $r = 0.62$ ) found over seven watersheds in Pennsylvania has been improved to become a strong relationship ( $r = 0.94$ ) between NDVI and areal transpiration rates over two, well vegetated, humid catchments in Georgia. This result suggests that temporal changes in areal transpiration rates of vegetated surfaces may be tracked through the application of widely available and inexpensive satellite remote sensing images.

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