

## **DYNAMIC CURVE NUMBERS: CONCEPT AND APPLICATION**

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**ABSTRACT:** A runoff curve number (*CN*) is generally applied as a constant that reflects the expected depth of runoff that results from the storm event depth of rainfall. When it is applied to the temporal variation of rainfall, it contributes to several problems: (1) an unconventional initial abstraction coefficient, (2) an infiltration function that inaccurately models as a decay function at the end of the storm, and (3) an insensitivity to the temporal variation of the physical processes over the duration of a storm. The use of a dynamic curve number, which is a curve number that changes over the duration of a storm, overcomes these issues and provides better regeneration accuracy of observed runoff hydrographs. For the eight storm events analyzed, the use of dynamic curve numbers resulted in less bias and an improved standard error compared with the result of the traditional constant storm event *CN*. The initial abstraction coefficient varied from 0.02 to 0.17, with an average value of 0.09. The dynamic *CN* method provides a more flexible infiltration function than the one inherent to the *NRCS* rainfall-runoff equation with a static *CN*.

### **1. INTRODUCTION**

The Soil Conservation Service developed the curve number (*CN*) technique to estimate the depth of rainfall excess from the storm rainfall depth for varying land uses and soil types. The method was developed through the analyses of storm events on small agricultural watersheds (Rallison and Miller, 1982; Rallison and Cronshey, 1979). The equation was then extended for use to separate losses from rainfall excess for temporally varying storm event data. The design method is most frequently applied to ungauged watersheds for the purposes of peak discharge estimation, not just runoff depth estimation. A peak discharge and hydrograph is the usual output. Its use, which has been applied well beyond the original intent, has created considerable critical assessment and recommendations for improvements.

A curve number is obtained from a table using the following factors: soil type, land use/cover, and land treatment, and hydrologic condition. However, others have recognized that the storm size (Hawkins, 1993), duration (Woodward, 1973), and intensity (Simanton *et al.*, 1973, Hawkins, 1982); the season of the event (Capece *et al.*, 1986, Price, 1998); the portion of the drainage area subjected to intense rainfall (Simanton *et al.*, 1973, Hawkins, 1979); and the drainage area (Simanton *et al.*, 1996) may influence a computed curve number. Proposals have been made to incorporate these factors into modified curve numbers. With respect to drainage area, White (1988) recommended that the use of curve numbers be limited to watersheds of

2.6 km<sup>2</sup> (1 mi<sup>2</sup>) or less where land use was uniform and unchanging. In standard hydrograph calculations, a constant *CN* is used to separate rainfall excess and losses. However, the conditions of a watershed vary over the duration of a storm event, and the time variation of the processes affects runoff characteristics of actual events.

A proposal is made herein to relax the requirement of the *CN* being temporally constant. Then the temporal nature of watershed processes will be better reflected in the value of a curve number at any point in time. The temporally varying *CN* will be referred to as a dynamic curve number. The hypothesis is that, since watershed processes vary over the duration of a storm, then the *CN* should be allowed to vary with time when separating losses and rainfall excess. If this hypothesis is correct, then prediction accuracy using a dynamic *CN* should be better than when a static, non-time varying *CN* is used. A constant curve number for temporally varying runoff processes is not flexible and can limit prediction accuracy.

The goal of the study was to develop and test the concept of a dynamic curve number. The objectives were to: (1) demonstrate that a dynamic *CN* could be used to more accurately separate rainfall excess from the total rainfall, (2) assess the accuracy of the dynamic *CN* technique using actual rainfall-runoff data, (3) compare the accuracy of the dynamic *CN* with that of the static *CN* method, and (4) use the dynamic curve number to improve understanding of the initial abstraction and infiltration conceptual problems. The accuracy of both the static *CN* and the dynamic *CN* are assessed based on how well the observed hydrographs are reproduced.

## 2. STATIC CN TECHNIQUE

The static curve number technique separates rainfall into an initial abstraction, losses, and precipitation excess (see Fig. 1). The curve number is used to determine the retention *S* (in.):

$$S = 1000/CN - 10 \quad (1)$$

where the initial abstraction (*I<sub>a</sub>*, in.) is:

$$I_a = 0.2 S \quad (2)$$

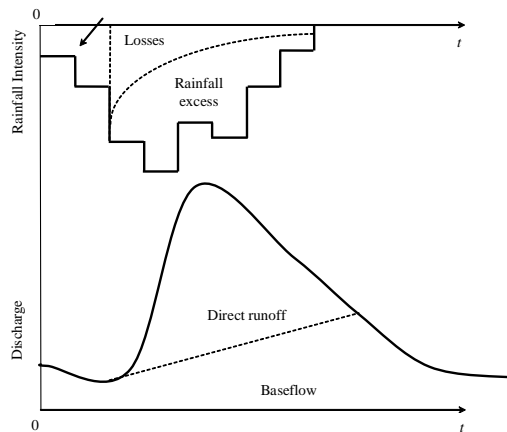


Figure 1: Separation of a Rainfall Hyetograph and Runoff Hydrograph into Component Parts

All rainfall that occurs to a depth of  $Ia$  is removed before any rainfall excess occurs. The remainder of the rainfall is separated into rainfall excess and other losses. The cumulative rainfall excess,  $\sum Q(t)$ , depends on the cumulative rainfall,  $\sum P$ , to any point in time  $t$ , and the total retention,  $S$ , to any point in time:

$$\sum Q(t) = \frac{(\sum P(t) - 0.2S)^2}{(\sum P(t) + 0.8S)} \quad (3)$$

where  $\sum P(t)$  is the cumulative rainfall from the start of the storm to any time  $t$  during the storm. The rainfall excess  $Q(t)$  for any time interval during the storm is a function of time and is computed from the cumulative excess  $\sum Q$ . In essence, Eq. 3 acts as an infiltration or loss function model, which has been widely documented (Aron *et al.*, 1977; Hawkins, 1978; Chen, 1982; Hjelmfelt, 1980). Hawkins (1978) points out that as time goes to infinity, the infiltration rate based on the basic model with a static  $CN$  goes to zero, rather than a finite value as indicated by standard infiltration formulas, such as the Horton (1937) equation. While this is not generally of concern, analyses of long-duration storm events could result in higher than expected loss rates at the start of the storm and lower than expected loss rates at the end of an event. This temporal bias would lead to lower prediction accuracy.

The recent concern about the initial abstraction coefficient of 0.2 in Eq. 2 (Jain *et al.*, 2006) and the asymptotic behavior of the imbedded loss function are not independent of each other. When applied to the analysis of a rainfall hyetograph, the relatively high initial abstraction coefficient of 0.2 suppresses immediate rainfall excess, and therefore, the computed depth of direct runoff. The embedded loss function inherent to Eq. 3 then allows more rainfall excess at the end of the storm, which essentially allows the losses to approach zero. Holding the  $CN$  constant for the duration of the storm allows these two limiting conditions of the  $NRCS$  method to decrease the accuracy of hyetograph separation.

### 3. DYNAMIC $CN$ ANALYSIS

The dynamic  $CN$  procedure accomplishes separation of losses and rainfall excess in much the same way as the static  $CN$  except that the magnitude of the  $CN$  varies over the duration of the storm. At the start of the storm, the curve number has an initial value  $CN_0$  that changes with time by amount  $dCN/dt$ . In this exploratory analysis, a linear relation was used to relate  $CN$  and time ( $t$ ):

$$CN_t = CN_0 - bt \quad (4)$$

in which  $CN_t$  is the  $CN$  at storm time  $t$  and  $b$  is the slope of the relation (with units of per minute), which represents  $dCN/dt$ . Equations 1, 2, and 3 are applied just as with the static  $CN$  except the value of  $CN$  is varied over the duration of the storm, which causes  $S$ ,  $Ia$ , and  $\sum Q$  to vary with time. The  $CN$  coefficients,  $CN_0$  and  $b$ , are optimized by minimizing the standard error of the differences between the ordinates of the computed and observed runoff hydrographs. Thus, the value of  $Ia$  is also optimized rather than computed from the standard  $Ia = 0.2S$ . The

static  $CN$  requires the constraint that  $\sum P > Ia$ . This constraint would also apply to the dynamic  $CN$ . The initial value of the dynamic  $CN$  is higher than that of the static  $CN$  that was calculated using the depth of precipitation and runoff.

A dynamic curve number circumvents the individual problems of the initial abstraction coefficient  $\lambda$  and the non-Hortonian infiltration function while allowing the depth of direct runoff to equal the depth of rainfall excess. Specifically, the higher initial  $CN$  causes the initial abstraction to decrease, which essentially reduces the  $Ia$  parameter  $\lambda$ . Then as the storm progresses, the lower curve number produces a progressively higher loss rate than produced by the traditional static  $CN$ . Thus, the dynamic  $CN$  yields loss rates that reflect a more Hortonian infiltration form that levels off to a constant rate.

The dynamic curve number analysis procedure follows the standard rainfall-runoff analysis steps. First, the base flow is separated from the direct runoff using the constant slope method in which the low point on the rising limb is connected with a straight line to the inflection point on the hydrograph recession (McCuen 2005). After removing the base flow, the volume of direct runoff is determined from the direct runoff hydrograph. The initial abstraction is removed from the total rainfall hyetograph. The rainfall excess and other losses can be separated by the same technique as for the static  $CN$  method, specifically Eq. 3 is used.

To test the feasibility of using a dynamic  $CN$ , eight storm events from Pennsylvania to Oklahoma watersheds were analyzed. The drainage areas ranged from 0.6 ha to 717 ha. The total rainfall depths ranged from 23 mm to 89 mm. The static curve numbers calculated from rainfall and runoff depths varied from 53 to 96. The validity of the dynamic  $CN$  method was assessed by the extent to which measured runoff hydrographs were reproduced. The accuracy was assessed using the relative bias ( $Rb$ ) and the relative standard error ( $Re$ ), which are measures of the systematic and nonsystematic error variations, respectively:

$$Rb = \sum_{i=1}^n \frac{\hat{q}_i - q_i}{n \bar{q}} \quad (5)$$

$$Re = \frac{\sum_{i=1}^n \frac{(\hat{q}_i - q_i)}{n - 2}}{\sum_{i=1}^n \frac{(\hat{q}_i - \bar{q})^2}{n - 1}} \quad (6)$$

in which  $n$  is the number of ordinates on the runoff hydrograph,  $\hat{q}_i$  is the predicted discharge, and  $\bar{q}$  is the mean measured discharge. The resulting goodness-of-fit statistics are included in Table 1. The two statistics will also be used to assess the ability of the static  $CN$  to reproduce the observed runoff hydrograph, which can provide a means of comparison and the extent to which the dynamic  $CN$  concept is an improvement over the static  $CN$ . A positive bias indicates over prediction while a negative value indicates under prediction of the predicted direct runoff hydrograph ordinates when compared with the measured hydrograph ordinates. The standard

**Table 1**  
**Storm Characteristics, Drainage Area, Total Rainfall ( $P$ ), Rainfall Wxcess ( $PE$ ), Static and Dynamic Curve Numbers, and Goodness-to-fit Statistics ( $Rb$  = Relative Bbias,  $Re$  = Relative Standard Error) for Each Storm Event; for Each Watershed, The Upper and Lower Rows are for the Static and Dynamic CNs, Respectively**

<i>Watershed</i>	<i>Date</i>	<i>Area (ha)</i>	<i>P (mm)</i>	<i>PE (mm)</i>	<i>CN</i>	<i>Rb (%)</i>	<i>Re</i>
Chickasha, OK 5145	4/12/67	102.3	77.0	19.8	71.1 80.2	2.708 0.965	0.925 0.783
Chickasha, OK 5143	4/12/67	196.6	52.8	6.2	69.1 79.0	0.450 0.517	0.645 0.411
Oxford, MS WC-2	7/9/67	0.6	46.7	30.0	93.2 97.7	0.463 0.289	0.388 0.364
Chickasha, OK 612	9/21/69	227.8	89.1	7.4	53.3 57.1	0.062 0.000	0.389 0.399
Waco, TX W-1	4/16/77	70.4	22.6	14.1	96.3 93.3	5.383 0.357	0.286 0.244
Monticello, IL 1A	8/7/77	33.2	49.3	27.7	90.7 96.2	0.518 0.518	0.772 0.600
Monticello, IL 1B	8/7/77	18.4	49.3	24.5	88.8 98.5	0.383 0.152	0.763 0.454
Klingerstown, PA WE-38	2/24/77	717.5	19.3	11.1	96.3 99.0	0.296 -12.250	0.421 0.365

error ratio indicates nonsystematic scatter, or error variation, between the predicted and measured direct runoff hydrographs.

The coefficients of the dynamic  $CN$  model (Eq. 4) were fitted with measured rainfall hyetograph and runoff hydrograph data. The procedure commonly used to separate losses (see McCuen, 2005) using a constant  $CN$  was applied, but the coefficients of Eq. 4 were calibrated using least-squares fitting of the hydrograph ordinates. The sum of the squares of the differences between the measured ( $Q_i$ ) and computed ( $\hat{Q}_i$ ) runoff hydrograph ordinates

**Table 2**  
**Comparison of Initial Abstraction Depths (mm) for Analysis with Static and Dynamic Curve Numbers**

<i>Watershed</i>	<i>Static analysis</i>				<i>Dynamic analysis</i>				
	<i>CN</i>	<i>S</i>	<i>Ia</i>	$\lambda$	$CN_0$	<i>So</i>	<i>Ia</i>	$\lambda$	<i>b</i>
Chickasha 5145	71.09	103	12	0.12	80.2	63	4	0.06	-0.0476
Chickasha 5143	69.07	114	17	0.15	79.0	68	5	0.07	-0.0666
Oxford WC-2	93.15	19	4	0.21	97.7	6	1	0.17	-0.0467
Chickasha 612	53.26	223	53	0.24	57.7	186	28	0.15	-0.0116
Waco	96.30	10	2	0.18	93.3	18	2	0.13	-0.0248
Monticello 1A	90.68	26	5	0.19	96.2	10	1	0.10	-0.0288
Monticello 1B	88.79	32	6	0.19	98.5	4	<1	0.00	-0.0513
Klingerstown	96.31	10	2	0.20	99.0	3	<1	0.00	-0.0172

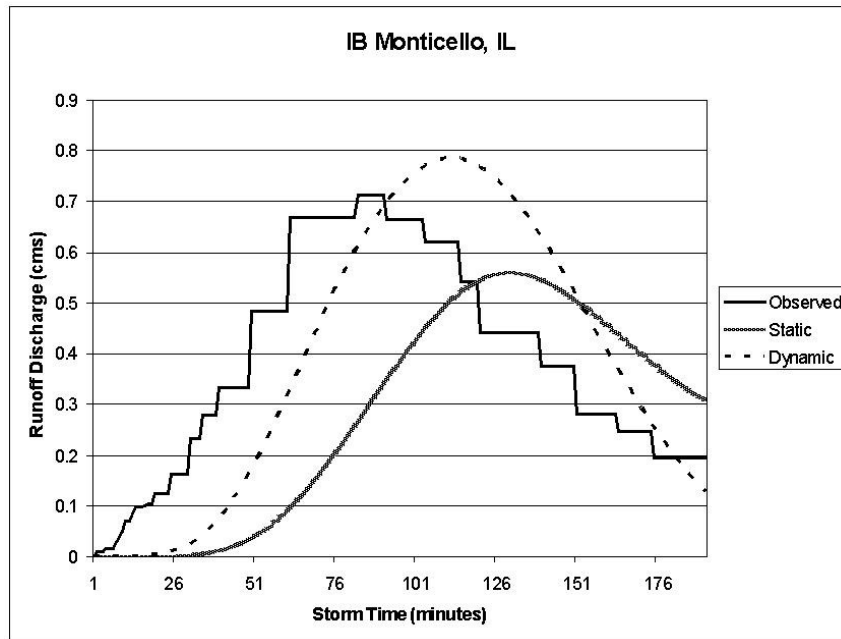
was minimized. The initial curve number  $CN_0$  and the slope coefficient are given in Table 2 for each of the eight storm events analyzed.

#### 4. ANALYSES OF RAINFALL-RUNOFF EVENTS

For all eight events, the dynamic curve number analysis resulted in an overall better fit to the observed runoff hydrograph than that provided by the static curve number analysis. In some cases, the relative standard errors were essentially the same, but the dynamic  $CN$  analysis was less biased and often provided better agreement of the rising limbs of the runoff hydrographs. For example, the event on watershed 612, Chickasha, *OK*, produced an insignificantly larger standard error ratio (0.399 vs 0.389 for the static  $CN$ ), but the dynamic curve number model was much less biased (0.000 vs 0.062), where a relative bias of 6.2% is considered significant over prediction. In six of the eight analyses, the accuracy of the dynamic  $CN$  was substantially better than that of the static  $CN$  as evident from the lower  $Re$ . For example, the  $Re$  for the event on watershed 1B in Monticello, *IL*, was more than 30% lower than for the static  $CN$  (0.76 vs. 0.45) and also had a smaller bias (38.3% for the static  $CN$  vs. 15.2% for the dynamic  $CN$ ).

From a conceptual standpoint, a dynamic  $CN$  seems more realistic than a static  $CN$  as watershed processes vary with time and space. A high initial  $CN$  will produce less initial abstraction ( $I_a$ ) at the start of the storm, but the abstraction decreases proportionally just as it would in an actual storm event. The static  $CN$  technique with the traditional  $I_a$  coefficient of 0.2 has been criticized in the past for producing more initial abstraction than is realistically needed (e.g., Hawkins *et al.*, 2009). The high initial  $CN$  for the dynamic  $CN$  approach allows the initial runoff to be more responsive to rainfall intensity. With the dynamic  $CN$  method, the initial infiltration would not be overwhelmed by intense rainfall, with infiltration losses at the start of the storm being lower than with the static  $CN$ . This essentially reduces the initial abstraction parameter  $\lambda$ . The relatively low  $CN$  at the end of the storm yields greater losses at that time, which better reflects the response of other infiltration formulas.

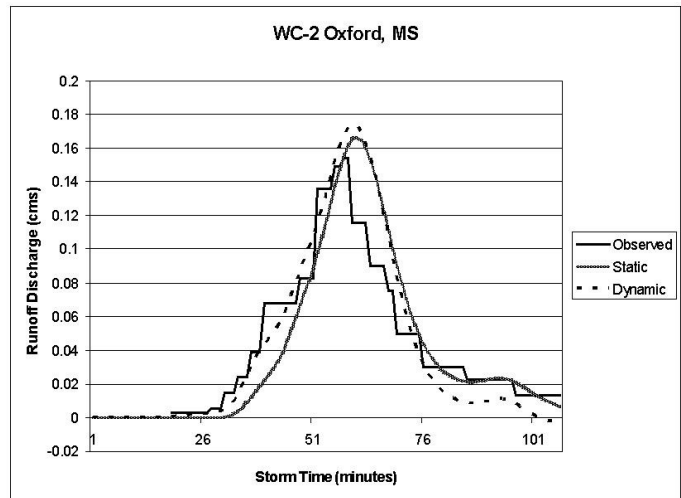
For watershed 1B at Monticello, *IL*, the relative bias for both models was less than 1%, and the relative standard error improved from 76% for the static  $CN$  to 45% for the dynamic  $CN$ , which is a significant change of 31% (see Fig. 2). However, the times to peak of both the static and dynamic hydrographs are later than that of the observed runoff. The observed peak runoff rate of 0.665 cms occurred at a storm time of 92 minutes. The static  $CN$  underpredicted with a computed peak discharge of 0.560 cms at a storm time of 131 minutes. The dynamic  $CN$  analysis overpredicted the peak discharge with a computed value of 0.785 cms at 112 minutes. The dynamic  $CN$  method provided an estimate of the time of the peak discharge that is better than the static  $CN$  estimate, but both times to peak are significantly late. This was due to the characteristics of the rainfall, which had its peak intensity near the start of the storm. The important observation to make from Fig. 2 is the much better fit produced by the dynamic  $CN$  on both the rising and falling limbs of the computed hydrograph. By having a higher  $CN$  at the start of the event, the smaller initial abstraction allowed the computed runoff to more nearly match the observed runoff rates on the rising limb. The lower dynamic  $CN$  at the end of the storm provided for greater losses, which again resulted in a better fit of the hydrograph recession.



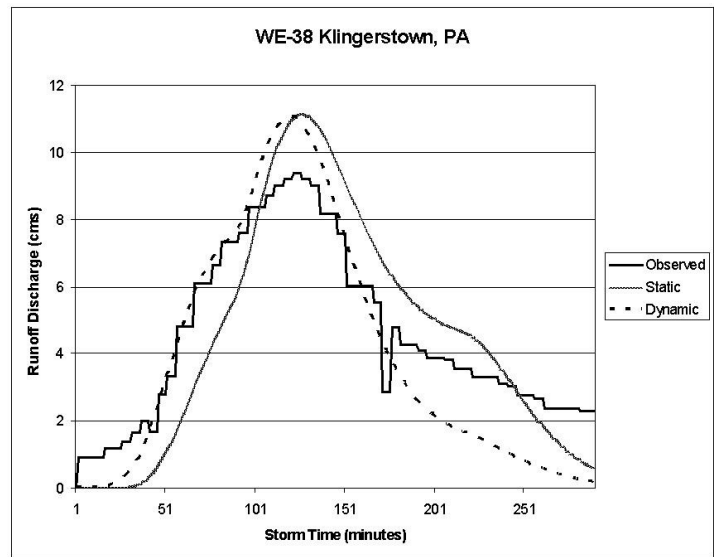
**Figure 2: Measured Hydrograph for Monticello Watershed 1B and the Computed Hydrographs for Static and Dynamic Curve Numbers**

In watershed WC-2 in Oxford, MS, the dynamic *CN* method did not show significant improvement in the two goodness-of-fit statistics when compared to the results of the static *CN* analysis, but did show a much improved fit of the observed hydrograph (see Fig. 3). The relative bias improved by only 0.17% and the relative standard error improved by 2.35%. The peak discharge of the observed runoff was 0.154 cms and occurred at a storm time of 59 minutes. The static *CN* overpredicted the peak discharge with a computed value of 0.166 cms at 60 minutes. The dynamic *CN* also overpredicted the peak discharge with a computed value of 0.174 cms also at 60 minutes. Both methods accurately predicted the time to peak. The important difference between the two *CN* approaches that is not evident from the goodness-of-fit statistics is the better fit of the rising limb provided by the dynamic *CN*. This indicates that single-valued indices such as the relative bias and the relative standard error can not always summarize the goodness-of-fit of computed hydrographs.

For watershed WE-38 in Klingerstown, PA, the dynamic *CN* method provided mixed results as assessed using the goodness-of-fit statistics. The dynamic *CN* method resulted in a significant under prediction of 12% but the relative standard error for the dynamic *CN* was 5.6% better than that of the static *CN*. Figure 4 shows the observed runoff hydrograph for both the static *CN* method and the dynamic *CN* method. A comparison reveals that the dynamic *CN* provided improvement in the overall fit. The shape of the runoff hydrograph of the dynamic *CN* method more closely resembles that of the observed runoff hydrograph especially on the rising limb and the early part of the recession.



**Figure 3: Measured Hydrograph for Oxford Watershed WC-2 and the Computed Hydrographs for Static and Dynamic Curve Numbers**



**Figure 4: Measured Hydrograph for Klingerstown Watershed WE-38 and the Computed Hydrographs for Static and Dynamic Curve Numbers**

The other five events showed similar findings. In general, the dynamic curve number approach provided better goodness-of-fit, especially on the rising limbs of the hydrographs. This is the result of the flexibility provided by a time-varying *CN*. In some cases, the two single-valued goodness-of-fit indices were not able to reveal the better reproduction of the observed hydrograph provided by the dynamic *CN* approach.



## 5. IMPLICATIONS TO INITIAL ABSTRACTION

The higher initial curve number  $CN_0$  using the dynamic  $CN$  approach yields a lower initial abstraction, which would reflect a smaller abstraction coefficient  $\lambda$ . A lower  $\lambda$  has both an empirical and conceptual basis (Mishra and Singh 1999). A lower initial abstraction would allow the computed runoff to be characterized by a higher rising limb. This is evident in Figs. 2, 3, and 4. Table 2 shows the static and initial dynamic  $CNs$  and the initial abstractions for each of the eight events. In most cases, the optimum dynamic  $CN_0$  was higher than the static  $CN$ , thus the lower initial abstractions. The use of a time varying  $CN$  allows for greater flexibility in the initial abstraction, and from the results shown herein better estimation of the runoff hydrograph. The lower depths of initial abstraction enabled the rising limbs of the observed hydrographs to be fitted more accurately. Based on the initial abstractions computed from the rainfall hydrographs and the computed start times of direct runoff, the  $Ia$  coefficients  $\lambda$  were computed (see Table 2). The dynamic  $CN$  approach produced smaller values of  $\lambda$  such that they more closely agreed with the values reported in the literature. It is important to note that the value of the initial abstraction coefficient should not be changed without adjusting the  $CN$ . Otherwise, the use of Eq. 3 would result in higher values of the rainfall excess and, therefore, the direct runoff volumes.

## 6. CONCLUSIONS

Given the wide use of the curve number method in planning and design, methods that can increase the accuracy of design estimates need to be considered. For example, the proposals to change the initial abstraction coefficient of 0.20 to 0.10 or 0.05 show some improvement in accuracy. These are exploratory studies that show promise. The dynamic  $CN$  is another alternative that has a basis in the physical processes and appears to improve prediction accuracy. In some cases, it provided a similar level of goodness of fit as the static  $CN$  but still showed a better reproduction of the rising limb of the hydrograph. The dynamic  $CN$  cannot have prediction accuracy that is less than the static  $CN$  as the slope coefficient of Eq. 4 could be zero. The improvement in accuracy can be slight or substantial, as was shown in the eight case studies presented herein.

It may seem irrational that the  $CN$  would decrease over the duration of a storm event. After all, high  $CNs$  are supposed to reflect impervious or saturated conditions, which should suggest a high  $CN$  at the end of the storm. While this is true, this concept relates to the total storm depth, not the time dependency of a temporally distributed rainfall. However, this issue is the product of one of the basic conflicts identified by Hawkins *et al.*, (2009). Specifically, they point out that Eq. 3 was not designed to be used in a time dependent manner, as it is when used to separate losses and rainfall excess; however, anytime that a time dependent analysis is made with Eqs. 1, 2, and 3, the losses are computed with the static  $CN$  method. It is important to recognize the effect that Eq. 3 has on computed losses, namely an over estimation of initial abstractions and an under estimation of losses late in the storm event. When Eq. 3 is used in the static  $CN$  mode, it fails to provide a rational depiction of both the initial abstraction and the infiltration functions. Use of the dynamic curve number approach enables Eq. 3 to provide a reasonable reflection of the physical processes. Specifically, including the dynamic curve number model of Eq. 4 provides corrections for the failure of Eq. 3 to properly model the initial abstraction and infiltration losses.

## References

- [1] Aron G., Miller Jr. A. C., and Lakatos D. F., (1977), "Infiltration Formula Based on SCS Curve Number", *J. Irr. Drain. Div.*, **103**(4), 419-427.
- [2] Chen C.-L., (1982), "Infiltration Formulas by Curve Number Procedures", *J. Hydro. Div.*, **108**(7), 823-829.
- [3] Capece J. C., Campbell K. L., and Baldwin L. B., (1986), Estimation of Runoff Peak Rates and Volumes from Flatwoods Watersheds, *Ag. Eng. Dept., Univ. FL*, Gainesville.
- [4] Hawkins R. H., (1978), Discussion of "Infiltration Formula Based in SRS Curve Number", *J. Irr. and Drainage Div.*, **103**(4), 464-467.
- [5] Hawkins R. H., (1979), Runoff Curve Numbers from Partial Area Watersheds, *Journal of The Irrigation and Drainage Division*, **105**(IR4), 375-389.
- [6] Hawkins R. H., (1982), "Interpretations of Source Area Variability in Rainfall Runoff Relations", In *Rainfall Runoff Relationship*, Water Resources Publications, Littleton, Colorado, 303-324.
- [7] Hawkins R. H., (1993), "Asymptotic Determination of Runoff Curve Numbers from Data", *J. Irr. Drng.*, **119**(2), 334-345.
- [8] Hawkins R. H., Ward T. J., Woodward D. E., and Van Mullem J. A., (2009), *Curve Number Hydrology: State of the Practice.*, ASCE Press, Reston, VA.
- [9] Hjelmfeldt A. T. Jr., (1980), "Curve Number Procedure as Infiltration Method", *J. Hydraulics. Div.* **106**(6), 1107-1111.
- [10] Horton R. E., (1937), "Determination of Infiltration Capacity for Large Drainage Basins", *Trans. Amer. Geophys.*, Union, **18**, 371-385.
- [11] Jain M. K., Mishra S. K., Babu P. S., Venugopal K., and Singh V. P., (2006), "Enhanced Runoff Curve Number Model Incorporating Storm Duration and a Nonlinear *Ia-S* Relation", *J. Hydrol. Eng.*, **11**(6), 631-635.
- [12] McCuen R. H., (2005), *Hydrologic Analysis and Design*, Pearson/Prentice Hall, Upper Saddle River, NJ.
- [13] Mishra S. K., and Singh V. P., (1999), "Another Look at SCS-CN Method", *J. Hydrologic Eng.*, **4**(3), 257-264.
- [14] Price M. A., (1998), "Seasonal Variation in Runoff Curve Numbers", *M.S. Thesis*, Univ. of Arizona, Tuscon.
- [15] Rallison R. E., and Cronshey R. C., (1979), Discussion of "Runoff Curve Number with Varying Site Moisture", *J. Irr. Drng.* **105**(4), 439-441.
- [16] Rallison R. E., and Miller N., (1982), *Past, Present, and Future SCS Runoff Procedure*, From the Book: *Rainfall-Runoff Relationship*, Water Resources Publications, Littleton, Colorado.
- [17] Simanton J. R., Renardi K. G., and Sutter N. G., (1973), Procedure for Identifying Parameters Affecting Storm Runoff Volume in a Semiarid Environment, *ARS-W-1*, Agricultural Research Service, Southwest Range Watershed Research Center, Tuscon, AZ.
- [18] Simanton J. R., Hawkins R. H., Moheni-Saravi M., and Renard K. G., (1996), Runoff Curve Number Variation with Drainage Area, Walnut Gulch, Arizona, *Transactions of the ASAE*, **39**(4), 1391-1394.
- [19] White D., (1988), "Grid-Based Application of Runoff Curve Numbers", *J. Water Resources Planning and Management*, **114**(6), 601-602.
- [20] Woodward D. E., (1973), "Runoff Curve Numbers for Semiarid Range and Forest Conditions", Paper Presented at the 1973 Annual Meeting of ASCE, Lexington, KY.



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