20 The Future of Soil Erosion Modelling

M.A. NEARING[1] AND P.B. HAIRSINE[2]

[1]*USDA-ARS, Southwest Watershed Research Center, Tucson, AZ, USA*
[2]*CSIRO Land and Water Division, Canberra, Australian Capital Territory, Australia*

Niels Bohr reputedly commented that 'Prediction can be very difficult, especially about the future' (Rosovsky, 1991). Certainly that statement is true for prediction of processes in nature, including soil erosion. It also may hold true when attempting to predict the future direction of a field of research. In 1990 Nearing *et al.* published a paper in the *Soil Science Society of America Journal* entitled 'Soil Erosion Prediction Research Needs'. A retrospective assessment of that paper indicates that it was largely unsuccessful in outlining the important advances and changes in this field of science since it was published. One might want to keep that in mind when reading this chapter.

The Nearing *et al.* (1990) review of research needs was written during a time when the development of process-based soil erosion models was at the forefront of the science. This was a line of research that began sometime in the late 1960s and early 1970s (Meyer & Wischmeier, 1969), and was near its peak of effort at the time. A team of scientists from the USDA was developing the Water Erosion Prediction Project (WEPP) model (Nearing *et al.*, 1989; Laflen *et al.*, 1997), which relied on a numerical, steady-state solution of the sediment continuity equation, and which focused heavily on modelling inter-storm variations in the determinant system properties such as soil erodibility, soil moisture, soil surface conditions, plant canopy and ground cover. Another team from Europe, in a project funded by the European Union, developed a model called EUROSEM (Morgan *et al.* 1998), which used a dynamic solution to the sediment continuity equation driven in part by a hydrological model based on the kinematic wave equation (Woolhiser *et al.*, 1990). EUROSEM is a single storm model that focuses on infiltration, runoff and erosion from individual storms, and allows the user to define initial system conditions for storms. In Australia, Hairsine and Rose (1992a,b) developed a dynamic solution to the sediment continuity equation that encompassed what were at that time novel and important descriptions of fundamental erosion mechanics not explicitly included in other models. These were based on the concept of balancing simultaneous entrainment, deposition and re-entrainment of particles rather than relying on an independent sediment transport equation. A simplified product from this line of research was later introduced as the GUEST model (Misra & Rose, 1996; Yu *et al.*, 1997). In the Soviet Union, Larionov (1993) had been working on yet another process-based description of soil erosion for the purposes of prediction.

Certainly there has been a great deal of value derived from the development of process-based soil erosion models, both in terms of practical application and advancement of the science. The engineers who worked on the clean-up of the Rocky Flats Superfund site in Colorado claimed

Handbook of Erosion Modelling, 1st edition. Edited by R.P.C. Morgan and M.A. Nearing. This chapter © 2011 M.A. Nearing. Published 2011 by Blackwell Publishing Ltd.

to have saved 600 million dollars by using the WEPP model for remediation design (Clark *et al.*, 2006), which was undoubtedly by any estimation a greater sum than had been spent in the development of the model itself. Hundreds of scientific studies have been conducted over the last two decades related to applying and improving process-based erosion models, including EUROSEM, WEPP, LISEM (DeRoo *et al.*, 1996), the Hairsine-Rose models, GUEST, and so on, the sum of which has resulted in a greatly improved understanding and quantification of soil erosion and sediment yields.

The four major conclusions of the Nearing *et al.* (1990) research-needs review paper were that the future of erosion modelling research would follow the paths of advancing: '…(i) fundamental erosion relationships, (ii) soil and plant parameters and their effects on erosion, (iii) databases, user interfaces, and conservation system design, and (iv) model development and analysis.' They further stated that 'Development of process-based erosion prediction technology has required the delineation and description of fundamental erosion processes and their interactions. Further improvement in prediction technology will require further delineation and mathematical descriptions.' These statements generally represent reductionist science, which was the norm at least in this area of science at the time. Both the advantages and limitations of this approach were discussed by Govers (1996), who concluded in part stating:

> 'The selection of priority subjects for process studies should be driven by the deficiencies between model predictions and field observations: the construction of an alternative, more sophisticated model to include an additional effect is only meaningful if a strategy can be devised which allows a validation of the model so that its presumed superiority can be proved.'

Many of the realised advances in soil erosion science and modelling over the last two decades have arisen coincidentally with our increased understanding of the limitations of the process-based soil erosion models, and many of those limitations centre around variability and uncertainties of many different types. These include issues related to, but not limited to: (a) natural variability in rates of soil loss from replicated soil erosion plots; (b) temporal variability, the importance of extreme erosion events and vulnerable site conditions, and the associated problems of interpreting short-term data records; (c) extreme spatial variability of erosion on the landscape, our lack of measured data to quantify that variability, and our limited ability to model the variability correctly; and (d) the effects of input data variability on model projections, particularly relative to cumulative model output uncertainty. The reader will find that variability and uncertainty have been common themes throughout this book, which represents a significant shift in thinking from two decades ago.

An eminent European scientist once stated that if there were to be a Nobel Prize for Soil Erosion Science, it would have to go to the study published by Wendt *et al.* (1986). In that study the authors reported soil erosion rates for 40 cultivated, fallow, experimental plots located in Kingdom City, MO, in 1981. All of the 40 plots were cultivated and in other ways treated identically. The coefficients of variation between plots for the erosion rates measured for each of 25 storms ranged from 18% to 91%. Based on the data from that study, they calculated that the 95% confidence interval for quantifying the mean erosion rate of two replicated plots for a given storm was plus or minus 175% of the mean value. In other words, the confidence interval for the mean erosion from the two plots would range from essentially zero to nearly twice the mean measured value. Also, the results of the study indicated that 'only minor amounts of observed variability could be attributed to any of several measured plot properties, and plot differences expressed by the 25 events did not persist in prior or subsequent runoff and soil loss observations at the site.' The study was suggesting that replicated plots may give greatly

different measures, and variable trends, of soil erosion for all conditions being equal.

Nonetheless, a survey of the literature will show that when scientists attempt to test a new soil erosion model or the application of a model in a new environment, they almost invariably rely upon measured data for comparison with model output results. Also, invariably, the documented fact that the data have enormous natural variability is ignored: the measured data are assumed to be correct. If one were to model, for example, the 40 replicated plots from the Wendt *et al.* (1981) study, with essentially the same soil, cover and rainfall conditions, the input parameters for the model would be nearly or exactly the same for all the plots. Given that the models are essentially all deterministic in nature, the output of the model would be a single value. In that case one could see where the modelled value falls within the distribution of the 40 measured values. However, if one only has a single (or two at best) measured erosion values with which to compare, one has no idea where that measured value lies within the distribution associated with the natural measurement variability. In most cases that variability would be much larger than recognized. Nearing *et al.* (1999) provided a more universal scheme for characterizing replicated plot variability, and Nearing (2000) attempted to develop a procedure for using that information in model validation studies, but those concepts have been neither widely recognized nor implemented.

A major limitation that erosion modellers face in quantifying and comparing soil erosion rates is the lack of long-term data. The paradigm the world over for funding scientific research is the two- to five-year grant, which is a serious problem in terms of collecting long-term data. A study by Edwards and Owens (1991) found that soil erosion measurements on nine small watersheds in Ohio over 28 years were dominated by a few large storms. The five largest erosion-producing events out of more than 4000 accounted for 66% of the total erosion. On one watershed, one storm caused more than half of the 28-year total. Nearing *et al.* (2007) looked at 11 years of data from six small watersheds in the Walnut Gulch Experimental Watershed in southeastern Arizona. In each case the single largest storm on the record contributed between 9% and 11% of the total sediment yield for the 11-year period of record, and approximately 50% of the sediment yield came from between six and ten events during the 11 years. Lane and Kidwell (2003) looked at data from four small watersheds in the Santa Rita Experimental Range in southern Arizona measured over 16 years. They found that the year with the largest erosion event accounted for between 18% and 26% of the total measured sediment. This temporal variability is one reason why we need soil erosion models. Appropriately constructed, a process-based model may have the ability to extrapolate a short record of measured erosion to a longer time frame. Nonetheless, the problem is that models developed and parameterized from short records that do not contain the extreme event probably will not effectively represent the extreme event. The most likely scenario will be that the impact of the extreme event will be under-predicted. This is one area obviously ripe for further research.

Jetten *et al.* (2003) published a review on the application of models in terms of spatial distributions of erosion rates within watersheds. Not surprisingly they found that the models were able to characterize sediment yields from watershed outlets only moderately well, a result they attributed to 'the high spatial and temporal variation of erosion and sediment transport and our inability to assess and/or describe this variability in terms of the input parameters normally used in erosion models.' The models performed even more poorly in terms of characterizing the spatial erosional patterns within the watersheds: 'The application of the LISEM tested here shows that accurate predictions at the grid-cell resolution at which the model is run are impossible.' They found that the finer and more detailed the resolution for the model inputs and grid, the worse were the spatial predictions. Obtaining good spatial predictions of measured erosion requires extensive and detailed spatial datasets (van Oost *et al.*, 2004). The number of scientific papers in the literature

related to modelling spatial distributions of soil erosion is relatively large, particularly with the increasing use of GIS in modelling, but studies that make any attempt to evaluate the spatial predictive capability of the models using measured data are very few.

If we have learned anything over the past two decades it is that increased model complexity does not correspond to improved capability to predict soil erosion rates and sediment yields. It is important to keep in mind, however, that improved prediction capability, in terms of improved ability to quantify erosion rates and amounts as a function of system properties and inputs, is not the only goal for the models. Models also form a structure for integrating our understanding of soil erosion processes. Complex models may also play a role in addressing some problems that simple models cannot – climate change, for example. Govers (1996) noted this in his review paper on soil erosion models, as did Williams *et al.* (1996) in discussions of modelling climate change impacts on soil erosion. Also, complex models do not necessarily need to remain complex in the application phase. A good example of this was the evolution of the Hairsine-Rose model framework (Hairsine & Rose, 1992a,b) to that of the GUEST model described in Chapter 11. Another example was the use of the framework of the WEPP model (Laflen *et al.*, 1997) to the simpler, more targeted-use, and less data-intensive Rangeland Hydrology and Erosion Model (Wei *et al.*, submitted), as well as the web-based WEPP Climate Assessment Tool (Bayley *et al.*, in preparation).

Model complexity can lead to increased prediction uncertainty. Chapter 4 addressed the issue of model uncertainty in a great deal of detail. The most mathematically accurate, and hence common, manner to assess the propagation of input errors is with the use of Monte Carlo simulations using distributions of input parameter variation (e.g. Wei *et al.*, 2008). Conceptually, however, the first-order error (FOE) framework (Wu *et al.*, 2006) allows one easily to visualize error summation in the models as a function of complexity. Every input parameter for a model carries with it some degree of uncertainty, which can be expressed using FOE by using a coefficient of variation (CV). Prediction uncertainty associated with parameter definition will propagate through all models to generate some level of uncertainty in the model response, which within the FOE analysis is expressed as a CV of the model response. The degree to which the error propagates is directly proportional to the sensitivity of the model output to the model input parameter and to the input uncertainty (CV). First-order errors sum with each additional input parameter, so the decision on whether to add an additional input parameter to a model is whether or not the new process described by the equations that use the parameter adds more to prediction capability than is lost through the additional error propagated due to the uncertainty in the value of the input parameter. This is more or less equivalent to the statement attributed to Govers (1996) above.

Hairsine and Sander (2009) recently provided a further description of the trade-offs in the development of models of soil erosion by water. Figure 20.1 shows the conceptual trade off between data availability, model complexity and model performance as proposed by Grayson and Bloschl (2000) for hydrological prediction. For any application with a given level of data available, there will be an optimum level of model complexity that will allow one to reach optimum predictive performance (see bold solid line in Fig. 20.1). In order to move forward with increasing model predictive performance, model complexity must move forward hand-in-hand with data availability. To make progress, we should be constantly moving in the direction of the solid arrow in Fig. 20.1. When one is using a model that is parameter-rich and informed by a relatively small amount of data, predictive performance deteriorates due to parameter identifiability problems because the model is too complex. We contend that this is the current situation for most existing models of soil erosion and related sediment transport in most predictive environments. Thus these models plot in the bottom right-hand corner of Fig. 20.1, in which case the path to greater predictive capability is along the bold

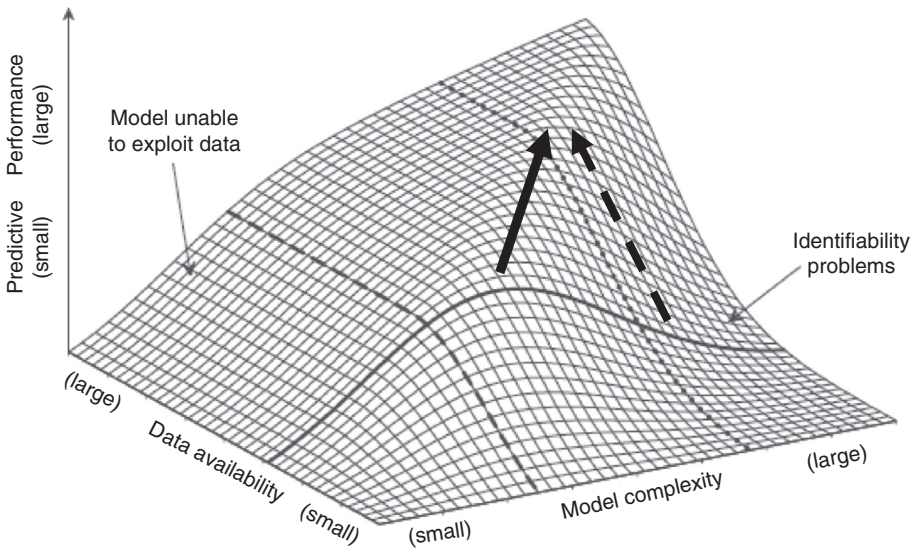

Fig. 20.1 Schematic diagram of the relationship between model complexity, data availability and predictive performance (reproduced with permission from Grayson & Bloschl, 2000). The added arrows are: the full line which is the ideal path of model development where added complexity is supported by new data; and the dashed line which is the more common scenario where new data acts to better constrain existing models.

dashed arrow: more often than not we need more and better data rather than more complex models to improve erosion predictions.

And so we come back to the subject of the chapter and ask: 'In what direction will the future of soil erosion modelling go?' The 1950s to the 1970s was the period of empirically-based erosion equation development, culminating in the second Universal Soil Loss Equation release in 1978 (Wischmeier & Smith, 1978). The 1970s to the 1990s was a period of development of process-based erosion models facilitated by computer simulation modelling. As discussed above, much of the progress during the 1990s and 2000s has focused on understanding and representing uncertainty associated with model applications. In most recent years we have seen, and (we predict) into the future we will continue to see, advances in spatial modelling and up-scaling, interfaces that utilize GIS, the increased use of remotely sensed data, and web-based delivery systems tied to large databases for soils, topography, land use and weather. This does not mean that we will not also see advances in other aspects of the modelling. Empirical modelling has continued, for example, as evidenced by the publication of the Revised Universal Soil Loss Equation in 1997 (Renard *et al.*, 1997), and there is much work yet to be done on solving the problems associated with model and data uncertainty, as discussed above. Uncertainty will continue to play a large role in our thinking on erosion, and ideally will lead to new ways of both modelling soil erosion and thinking about how we manage land for purposes of conservation. Nonetheless, practical goals associated with management decisions will require a set of model requirements that stress data reliability and availability, ease of use, capability for routing water and sediment through watersheds, and ability to delineate primary trends in erosion rates as a function of management practices and changing climate.

The material in this book goes a long way to pointing to the probable future of soil erosion modelling. A perusal of the applications chapter of this book indicates that watershed- and basin-scale assessments have become a dominant interest to modellers (see chapters 9, 13, 14, 16, 18 and 19). As we look to larger areas and up-scaling soil erosion models (chapters 6 and 19), spatial interfaces complete with GIS will continue to play a big role in new model development. The use of the Internet as a delivery mechanism for erosion models will certainly also be important in the future (chapters 16 and 17).

Continued data collection for supporting erosion modelling will be critical. Paucity of data remains a major limitation to the development of reliable models. The types of data needed will correspond to the new emphases in the model applications. Whereas in the past, plot studies have been the basic data of the erosion modeller, in the future modellers will increasingly need spatial data on erosion patterns and sources (Walling, 2005). Fortunately, there is a wide range of sediment sourcing tools now available to test models that accumulate sediment across complex environments. Motha *et al.* (2004) applied a combination of minor and major element chemistry and sediment magnetic properties to assess the proportion of sediment reaching a river from different sources, including gravelled and ungravelled roads and hillslope erosion from different soil types. Rhoton *et al.* (2008) performed similar work in the Walnut Gulch Experimental Watershed in southeastern Arizona. On a smaller spatial scale, Polyakov *et al.* (2004) used rare earth element oxides to measure the erosion, redistribution and deposition of sediment in a small agricultural watershed in Ohio. Sediment tracers that differentiate between surface and subsurface soil have been used widely to assess the proportion of river sediment coming from hillslope, stream bank and gully erosion (see review by Mabit *et al.*, 2008). In some instances these techniques have been extended to assess the contributions of rill and sheet to hillslope erosion (Wallbrink & Murray, 1993). Sediment tracers that differentiate between soil and sediment that was sourced from land uses with specific vegetation types are under active research (Gibbs, 2008).

Sediment that is deposited can be used as an accumulated record of the transport history. Where this history is well defined, it can serve as a testing ground for predictive models run retrospectively. A key element in this approach is the association of the deposited sediment with events in the rainfall record. A wide range of evidence has been used to establish the age of recent (within the past 100 years) layers of sediment deposition. These include charcoal layers from known fires, and labelling by atmospheric events including the atmospheric testing of nuclear weapons (e.g. ^{137}Cs as reviewed by Walling and He (1999) and Walling *et al.* (1999), and plutonium as introduced by Everett *et al.* (2008)). Until recently, many of the sediment dating techniques used in geochronology and anthropology were not applicable to the last 100 years. The advent of optically stimulated luminescence and other techniques has enabled the assessment of the age of modern deposited sediment and residence times of sediment in fluvial systems (Gale, 2009). Sediment dating data are now available for recent agricultural history (Olley *et al.*, 1998). The application of single-grained, optically stimulated luminescence has now extended this development to small samples and ages greater than 2 years (Gale, 2009; Pietsch, 2009).

Each of these forms of sediment dating and tracing techniques serve to provide further data to our models of sediment transport. Specifically, we can test the question of 'Are we getting the right answer for the right reason?' in terms of when the sediment was transported, from what soil type it was sourced, what were the eroding processes (sheet, rill or gully), and what land use was in place at the source of the sediment.

Integrating the use of remote-sensing data into the erosion modelling process has the potential to offer an opportunity to verify independently and provide initial conditions to models, but also to change the way we conceptualize modelling of erosion. Two key methodologies include the determination of effective vegetative soil cover and the direct sensing of sediment concentration

in surface waters. Remote sensing has long been used to assess vegetative cover at regional to global scales. There is increasing use of libraries of time series of images to assess time variations in cover (Lu *et al.*, 2003). These time series permit assessment of spatial and temporal variations of cover inputs to models and the evaluation of hindcast predictions from crop and pasture models. Limitations in the classifications of some forms of cover, specifically bleached dead vegetation, have been resolved by Guerschman *et al.* (2009). Remotely sensed interpretations of soil moisture and soil surface roughness could also be important mechanisms for informing erosion models (Rahman *et al.*, 2008). At the catchment scale there are some prospects for the use of remote sensing in estimating the concentration of surface water sediment concentrations directly. A further form of remote sensing with ramifications for erosion modelling is the development and availability of rainfall radar data (Steiner *et al.*, 1995). These data could be made useful in providing more spatially and temporally realistic inputs of rainfall rates than do conventional and often sparse networks of rain gauges. Where all of these techniques could have the advantage of providing a spatial-rich source of data for evaluation and identifying the initial conditions of models, near real-time remote sensing combined with models also opens up the prospects of data–model fusion where initial conditions for models, rainfall rate inputs and parameter estimation are continuously and automatically updated. These techniques have been extensively developed in terrestrial and ocean biogeochemical models (e.g. Barrett *et al.*, 2005).

Ultimately, the model builder must combine lines of evidence to assess and improve models. To do this well the product should track the ridge indicated by the solid arrow in Fig. 20.1. The use of multiple lines of evidence will result in more robust models that engender more confidence for use in predictive environments. A case study of adaptive changes to a model and the consequent prediction of spatial erosion processes was provided by Rustomji *et al.* (2008). This study showed that default parameters from a national assessment could be significantly improved by local information so as to give a progressive refinement of sediment source maps used to target management actions.

Underlying the discussion above is also the increasing understanding that 'Stationarity is Dead' (Milly *et al.*, 2008). We live in a rapidly changing world with respect to both land use and climate (Chapter 15). As population increases, stresses on land resources will continue to increase, often in those areas of the world that are already severely stressed. When we add to that trends of increasing rainfall amounts (Karl & Knight, 1998), rainfall intensities (Groisman *et al.*, 2005), and rainfall erosivity (Nearing, 2001), it becomes evident that our erosion models must be able to represent a world of changing land use and a changing climate.

References

Barrett, D.J., Hill, M.J., Hutley, L.B., *et al.* (2005) Prospects for improving savanna biophysical models by using multiple-constraints model-data assimilation methods. *Australian Journal of Botany* **53**: 689–714.

Bayley, T.W., Nearing, M.A., Guertin, D.P., *et al.* (In preparation) The Water Erosion Prediction Project Climate Assessment Tool: predicting soil erosion in the face of changing precipitation regimes.

Clark, D.L., Janecky, D.R. & Lane, L.J. (2006) Science-based cleanup of Rocky Flats. *Physics Today* **59**(9): 34–40.

De Roo, A.P.J., Wesseling, C.G. & Ritsema, C.J. (1996) LISEM: A single-event physically based hydrological and soil erosion model for drainage basins. 1: Theory, input and output. *Hydrological Processes* **10**: 1107–17.

Edwards, W.M. & Owens, L.B. (1991) Large storm effects on total soil erosion. *Journal of Soil and Water Conservation* **46**: 75–8.

Everett, S.E., Timsa, S.G., Hancock, G.J., *et al.* (2008) Comparison of Pu and ^{137}Cs as tracers of soil and sediment transport in a terrestrial environment. *Journal of Environmental Radioactivity* **99**: 383–93.

Gale, S.J. (2009) Quaternary dating the recent past. *Geochronology* **4**: 374–7.

Gibbs, M.M. (2008) Identifying source soils in contemporary estuarine sediments: A new compound-specific

isotope method. *Estuaries and Coasts* **31**: 344–359. DOI 10.1007/s12237-007-9012-9

Govers, G. (1996) Soil erosion process research: a state of the art. *Academiae Analecta* 58(1). Mededelingen van de Koniklijke Academie voor Wetenschappen, Letteren en Schone Konsten van België, Brussels.

Grayson, R. & Bloschl, G. (2000) Spatial processes, organisation and patterns. In Grayson, R. & Bloschl, G. (eds), *Spatial Patterns in Catchment Hydrology: Observations and Modelling*. Cambridge University Press, Cambridge.

Groisman, P.Y., Knight, R.W., Easterling, D.R., *et al*. (2005) Trends in intense precipitation in the climate record. *Journal of Climatology* **18**: 1326–50.

Guerschman, J.P., Hill, M.J., Renzullo, L.J., *et al*. (2009) Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. *Remote Sensing of the Environment* **113**: 928–45.

Hairsine, P.B. & Rose, C.W. (1992a) Modeling water erosion due to overland flow using physical principles: I. Sheet Flow. *Water Resources Research* **28**: 237–43.

Hairsine, P.B. & Rose, C.W. (1992b) Modeling water erosion due to overland flow using physical principles: 2. Rill flow. *Water Resources Research* **28**: 245–50.

Hairsine, P.B & Sander, G.C. (2009) Comment on "A transport-distance based approach to scaling erosion rates": Parts 1, 2 and 3 by Wainwright *et al*. *Earth Surface Processes and Landforms* **34**: 882–5. DOI: 10.1002/esp.1782

Jetten, V., Govers, G. & Hessel, R. (2003) Erosion models: quality of spatial predictions. *Hydrological Processes* **17**: 887–900.

Karl, T.R. & Knight, R.W. (1998) Secular trend of precipitation amount, frequency, and intensity in the United States. *Bulletin of the American Meteorological Society* **79**: 231–42.

Laflen, J.M., Elliot, W.J., Flanagan, D.C., *et al*. (1997) WEPP-Predicting water erosion using a process-based model. *Journal of Soil and Water Conservation* **52**: 96–102.

Lane, L.J. & Kidwell, M.R. (2003) Hydrology and soil erosion. *USDA Forest Service Proceedings* RMRS-P-30: 92–100.

Larionov, G.A. (1993) *Erosion and Wind Blown Soil*. Moscow State University Press, Moscow, 200 pp.

Lu, H., Raupach, M.R., McVicar, T.R. & Barrett, D.J. (2003) Decomposition of vegetation cover into woody and herbaceous components using AVHRR NDVI time series. *Remote Sensing of the Environment* **86**: 1–18.

Mabit, L., Benmansour, M. & Walling, D.E. (2008) Comparative advantages and limitations of the fallout radionuclides Cs-137, Pb-210(ex) and Be-7 for assessing soil erosion and sedimentation. *Journal of Environmental Radioactivity* **99**: 1799–1807.

Meyer, L.D. & Wischmeier, W.H. (1969) Mathematical simulation of the process of soil erosion by water. *Transactions of the American Society of Agricultural Engineers* 12: 754–8, 762.

Milly, P.C.D., Betancourt, J., Falkenmark, M., *et al*. (2008) Stationarity is dead: whither water management. *Science* **319**: 573–4.

Misra, R.K. & Rose, C.W. (1996) Application and sensitivity analysis of process-based erosion model GUEST. *European Journal of Soil Science* **47**: 593–604.

Morgan, R.P.C., Quinton, J.N., Smith, R.E., *et al*. (1998) The European Soil Erosion Model (EUROSEM): a dynamic approach for predicting sediment transport from fields and small catchments. *Earth Surface Processes and Landforms* **23**: 527–44.

Motha, J.A., Wallbrink, P.J., Hairsine, P.B. & Grayson, R.B. (2004) Agricultural lands and unsealed roads as sources of suspended sediment in a predominantly agricultural water supply catchment in south-eastern Australia. *Journal of Hydrology* **286**: 1.

Nearing, M.A. (2000) Evaluating soil erosion models using measured plot data: accounting for variability in the data. *Earth Surface Processes and Landforms* **25**: 103–43.

Nearing, M.A. (2001) Potential changes in rainfall erosivity in the United States with climate change during the 21st century. *Journal of Soil and Water Conservation* **56**: 229–32.

Nearing, M.A., Foster, G.R., Lane, L.J. & Finkner, S.C. (1989) A process-based soil erosion model for USDA-Water Erosion Prediction Project technology. *Transactions of the American Society of Agricultural Engineers* **32**: 1587–93.

Nearing, M.A., Lane, L.J., Alberts, E.E. & Laflen, J.M. (1990) Prediction technology for soil erosion by water: status and research needs. *Soil Science Society of America Journal* **54**: 1702–11.

Nearing, M.A., Govers, G. & Norton, L.D. (1999) Variability in soil erosion data from replicated plots. *Soil Science Society of America Journal* **63**: 1829–35.

Nearing, M.A., Nichols, M.H., Stone, J.J., *et al*. (2007) Sediment yields from unit-source semi-arid watersheds at Walnut Gulch. *Water Resources Research* **43**: W06426. DOI: 10.1029/2006WR005692

Olley, J.M., Caitcheon, G. & Murray, A.S. (1998) The distribution of apparent dose as determined by

Optically Stimulated Luminescence in small aliquots of fluvial quartz: implications for dating young sediments. *Quaternary Geochronology* **17**: 1033–40.

Pietsch, T.J. (2009) Optically stimulated luminescence dating of young (<500 years old) sediments: testing estimates of burial dose. *Quaternary Geochronology* **4**: 406–22.

Polyakov, V.O., Nearing, M.A. & Shipitalo, M. (2004) Tracking sediment redistribution in a small watershed: implications for agro-landscape evolution. *Earth Surface Processes and Landforms* **29**: 1275–91.

Rahman, M.M., Moran, M.S., Thomas, D.P., *et al*. (2008) Mapping surface roughness and soil moisture using multi-angle radar imagery without ancillary data. *Remote Sensing of the Environment* **112**: 391–402.

Renard, K.G., Foster, G.R., Weesies, G.A., *et al*. (1997) *Predicting soil erosion by water – a guide to conservation planning with the revised universal soil loss equation (RUSLE)*. Agricultural Handbook No. 703, US Government Printing Office, Washington, DC.

Rhoton, F.E., Emmerich, W., DiCarlo, D.A., *et al*. (2008) Identification of suspended sources using soil characteristics in a semiarid watershed. *Soil Science Society of America Journal* **72**: 1102–12.

Rosovsky, H. (1991) *The University: an Owners Manual*. Norton & Co., New York, 312 pp.

Rustomji, P., Caitcheon, G., & Hairsine, P.B. (2008) Combining a spatial model with geochemical tracers and river station data to construct a catchment sediment budget. *Water Resources Research* **44**: W01422. DOI: 10.1029/2007WR006112

Steiner, M., Houze, R.A. & Yuter, S.E. (1995) Climatological characterization of 3-dimensional storm structure from operational radar and rain-guage data. *Journal of Applied Meteorology* **34**: 1978–2007.

Van Oost, K., Beuselinck, L., Hairsine, P.B. & Govers, G. (2004) Spatial evaluation of a multi-class sediment transport and deposition model. *Earth Surface Processes and Landforms* **29**: 1027–44.

Wallbrink, P.J. & Murray, A.S. (1993) Use of fallout radionuclides as indicators of erosion processes. *Hydrological Processes* **7**: 297–304.

Walling, D.E. (2005) Tracing suspended sediment sources in catchments and river systems. *Science of the Total Environment* **344**: 159–84.

Walling, D.E. & He, Q. (1999) Improved models for estimating soil erosion rates from cesium-137 measurements. *Journal of Environmental Quality* **28**: 611–22.

Walling, D.E., He, Q. & Blake, W. (1999) Use of Be-7 and Cs-137 measurements to document short- and medium-term rates of water-induced soil erosion on agricultural land. *Water Resources Research* **35**: 3865–74.

Wei, H., Nearing, M.A., Stone, J.J. & Breshears, D.D. (2008) A dual Monte Carlo approach to estimate model uncertainty and its application to the Rangeland Hydrology and Erosion Model. *Transactions of the American Society of Agricultural and Biological Engineering* **51**: 515–20.

Wei, H., Nearing, M.A., Stone, J.J., *et al*. (Submitted) A Rangeland Hydrology and Erosion Model. *Rangeland Ecology and Management*.

Wendt, R.C., Alberts, E.E. & Hjelmfelt, A.T. Jr. (1986) Variability of runoff and soil loss from fallow experimental plots. *Soil Science Society of America Journal* **50**: 730–36.

Williams, J., Nearing, M.A., Nicks, A., *et al*. (1996) Using soil erosion models for global change studies. *Journal of Soil and Water Conservation* **51**: 381–5.

Wischmeier, W.H. & Smith, D.D. (1978) *Predicting rainfall erosion losses: a guide to conservation planning*. USDA Agriculture Handbook No. 537. USDA-SEA, US Government Printing Office, Washington, DC.

Woolhiser, D.A., Smith, R.E. & Goodrich, D.C. (1990) *KINEROS: a Kinematic Runoff and Erosion Model: Documentation and User Manual*. USDA Agricultural Research Service ARS-77.

Wu, J.R., Zou, Z. Rui & Yu, S.L. (2006) Uncertainty analysis for coupled watershed and water quality modeling systems. *Journal of Water Resources Planning and Management ASCE* **132**: 351–61.

Yu, B., Rose, C.W., Ciesiolka, C.A.A., *et al*. (1997) Toward a framework for runoff and soil loss prediction using GUEST technology. *Australian Journal of Soil Research* **35**: 1191–1212.