Environmental Modelling & Software 66 (2015) 1–11

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

A computationally efficient approach for watershed scale spatial optimization

R. Cibin [a], I. Chaubey [b,*]

[a] Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, IN 47907, USA

[b] Department of Earth, Atmospheric, and Planetary Sciences, Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, IN 47907, USA

ARTICLE INFO

Article history:
Received 1 October 2014
Received in revised form
11 December 2014
Accepted 12 December 2014
Available online

Keywords:
Watershed scale optimization
Multi-level optimization
Residue removal
Biofuel production
SWAT model

ABSTRACT

A multi-level spatial optimization (MLSOPT) approach is developed for solving complex watershed scale optimization problems. The method works at two levels: a watershed is divided into small sub-watersheds and optimum solutions for each sub-watershed are identified individually. Subsequently sub-watershed optimum solutions are used for watershed scale optimization. The approach is tested with complex spatial optimization case studies designed to maximize crop residue (corn stover) harvest with minimum environmental impacts in a 2000 km^2 watershed. Results from case studies indicated that the MLSOPT approach is robust in convergence and computationally efficient compared to the traditional single-level optimization frameworks. The MLSOPT was 20 times computationally efficient in solving source area based optimization problem while it was 3 times computationally efficient for watershed outlet based optimization problem compared to a corresponding single-level optimizations. The MLSOPT optimization approach can be used in solving complex watershed scale spatial optimization problems effectively.

1. Introduction

Spatial optimization of land use and conservation practices under various objective functions/constraints can help sustainably manage limited resources available in a watershed. Spatial optimization of agricultural best management practices (BMP) has been done by many researchers to identify the best locations and practices within a watershed with minimum implementation cost and maximum economic and/or environmental returns (Srivastava et al., 2002; Bekele and Nicklow, 2005; Arabi et al., 2006; Maringanti et al., 2011; Lautenbach et al., 2013; among many others). However, most of these studies were limited to research problems with minimum practical implementation. In addition, most were conducted in relatively smaller watersheds or in simplified model representation where the search space for optimal solutions is relatively smaller resulting in efficient implementation of the optimization algorithms.

The most popular method of spatial optimization is dynamic linking of a watershed simulation model with an optimization algorithm (Srivastava et al., 2002; Bekele and Nicklow, 2005; Arabi et al., 2006; Lautenbach et al., 2013; Kalcic et al., 2014; among many others), wherein the simulation model outputs are used to estimate the objective functions for the optimization algorithm. A major limitation of this approach is the computational cost associated with model dynamic simulations. Generally, spatial optimization problems require tens of thousands of model simulations which can take several days or even weeks to complete (Arabi et al., 2006). Parallel computing could be one solution to reduce the computational time (Rouholahnejad et al., 2012; Wu et al., 2013; Zhang et al., 2013; Yalew et al., 2013; Joseph and Guillaume, 2013), but often parallel computing facilities available to model users are limited. Another solution would be to select computationally efficient watershed simulation models for objective function evaluations. However, spatial optimization requires distributed-parameter watershed models to simulate spatial variability of hydrologic/water quality processes and such models are generally computationally complex. Computational costs associated with use of complex models have resulted in innovative approaches of using surrogate models (Sreekanth and Datta, 2011) or lookup tables (Maringanti et al., 2009, 2011; Gitau et al., 2004) instead of direct usage of simulation model in optimization framework. In such applications a computationally simple surrogate model or look-up

* Corresponding author. Tel.: +1 7654943258.
E-mail address: ichaubey@purdue.edu (I. Chaubey).

http://dx.doi.org/10.1016/j.envsoft.2014.12.014
1364-8152/

table (also called pseudo-simulation models, Sudheer et al., 2011) is created using a few scenarios simulated from watershed models and these pseudo simulation models are linked with an optimization algorithm. This approach makes the optimization computationally efficient by considerably reducing the time to reach optimal solution (Maringanti et al., 2009; Sreekanth and Datta, 2011). However, a major limitation of this approach is that surrogate models can induce another level of uncertainty to the optimization results (Sreekanth and Datta, 2011) as they are much simpler representation of the behavior of complex natural systems.

Selection of an efficient optimization algorithm is also critical in spatial optimization for efficient solution convergence. Evolutionary optimization methods such as genetic algorithms (Holland, 1975; Goldberg, 1989) are popular in spatial optimization (Chatterjee, 1997; Srivastava et al., 2002; Veith et al., 2003; Gitau et al., 2004; Arabi et al., 2006; Maringanti et al., 2009, 2011; Lautenbach et al., 2013; among many others). Even efficient optimization algorithms may fail to converge when applied to large and complex watersheds. Testing of convergence is difficult since the true optimum solutions are often unknown. One method to test convergence is to perform multiple replications of the optimization using the same or different optimization algorithms and comparing their results. Comparing solutions from many optimization algorithms is more robust than multiple replicates using the same algorithm as the former approach can potentially reduce chances of converging to a local minimum. To the best of our knowledge no such efforts are reported in spatial optimization convergence testing, perhaps due to the computational cost of optimization. Multi-algorithm optimization methods are known to be more efficient than a single optimization algorithm. For example, Multi ALgorithm Genetically Adaptive Method (AMALGAM) (Vrugt and Robinson, 2007) is a multi-algorithm optimization method and is reported to be more efficient than a single algorithm optimization in watershed simulations (Vrugt and Robinson, 2007; Zhang et al., 2010). The method uses four widely used optimization algorithms, including the Non-dominated Sorted Genetic Algorithm II (NSGAII) (Deb et al., 2002), particle swarm optimization (PSO) (Kennedy and Eberhart, 2001), adaptive metropolis search (AMS) (Haario et al., 2001), and differential evolution (DE) (Storn and Price, 1997).

Our efforts to compare efficacy of single and multi-algorithm optimization methods for a complex spatial optimization case study indicated that all test cases converged to below optimum solutions and/or failed to search within the full search space. This may be primarily due to the complexity of the search space. With efforts to reduce search space complexity and drawing inspiration from the notion of dividing and reducing complexity, we introduce a new spatial optimization approach in this study. This novel optimization approach is developed for complex spatial optimization problems with a multilevel optimization concept, which we refer to as Multi-Level Spatial Optimization (MLSOPT). This method splits the optimization problem into more reasonably-sized sections by dividing a large watershed into small sub-watersheds. This manuscript presents the MLSOPT algorithm and compares the approach with multiple single-level spatial optimizations using complex spatial optimization case studies. The objectives of this study were to (1) evaluate performance of single-level spatial optimization test cases using NSGA-II, PSO, and AMALGAM for complex spatial optimization case study, (2) develop a computationally efficient optimization approach for watershed scale spatial optimization, and (3) evaluate performance of the proposed MLSOPT approach with single-level spatial optimization.

2. Methodology

The MLSOPT approach dynamically links a watershed simulation model with an optimization algorithm, where the simulation model estimates objective functions for the sample populations generated by the optimization algorithm. The proposed approach is tested with two complex case studies to spatially optimize corn stover removal rates for maximum biofuel production having minimum environmental impacts in a 2000 km^2 watershed (Wildcat Creek watershed, Fig. 1). Case study 1 was designed to minimize environmental impacts at source area scale with objective function to minimize erosion from the source agricultural fields. Case study 2 was designed to minimize pollutant loading at a specific point in the stream with objective function to minimize sediment loading at watershed outlet. The Soil and Water Assessment Tool (SWAT) was used in the study as the watershed simulation model to represent corn stover removal and to quantify biomass production and associated environmental impacts such as erosion from agricultural fields and sediment load at watershed outlet. The model is developed for the Wildcat Creek watershed with about 922 corn/soybean areas from where stover harvest is possible. The first optimization case study was done with single-level optimization using three popular optimization algorithms and resulting optimum solutions were compared. The three optimization algorithms included: (1) Non-dominated Sorting Genetic Algorithm-II (NSGA-II); (2) Particle Swarm Optimization (PSO); and (3) A Multi ALgorithm Genetically Adaptive Method (AMALGAM). The MLSOPT approach with AMALGAM optimization algorithm was then compared with these three test cases to evaluate the robustness of the proposed approach. Case study 2 compared single-level optimization and MLSOPT approach with AMALGAM as optimization algorithm.

2.1. *Spatial optimization approach: MLSOPT*

Spatial optimization at the watershed scale is inherently complex, computationally expensive, and can potentially fail to converge to an optimum solution in a large and complex search space. The proposed approach consists of two spatial levels of optimization that are performed sequentially. The first level divides the watershed into smaller sub-watersheds, each consisting of multiple field units. Optimum solutions for individual sub-watersheds are identified using the optimization algorithm and watershed simulation model. The complexity of the optimization problem is reduced significantly with sub-watershed level optimization. For example, if the watershed has 50 sub-watersheds and each sub-watershed has 20 field units, which can each have 4 decision options such as four stover removal rates, the complexity is reduced from 4^{1000} with watershed scale single-level optimization to 4^{20} with sub-watershed level optimization. The individual sub-watershed optimum solutions are further optimized in the second level of MLSOPT to identify watershed scale optimum solutions. At the second level only the optimal solutions from each sub-watershed is selected which considerably increases the optimization efficiency. If the size of individual sub-watershed Pareto-front is 100, then the complexity of second level is 100^{50}. Thus the total complexity of MLSOPT in two levels is sum of 4^{20} and 100^{50}, which is very small compared to single-level complexity. The approach is designed to (i) reduce the optimization complexity by splitting watershed in to smaller units, such as sub-watersheds, and identifying optimum solution individually for each sub-watershed, (ii) reduce the computational expense by parallel optimization of all sub-watersheds simultaneously, and (iii) identify watershed scale optimum solutions with the second level optimization using optimum solutions from individual sub-watersheds.

Fig. 2 depicts the flowchart of the MLSOPT spatial optimization approach. The approach begins with an initial population created from the search space, with Latin Hypercube Sampling in this study. Each sample in the population denotes a feasible spatial combination and is simulated using the watershed simulation model. Objective functions ($OF_{i\,=\,1:nObj,\,nsub}$) and constraints ($C_{i\,=\,1:nConst,\,nsub}$) are estimated for individual sub-watersheds (1:nsub) from model simulation. Initial sample and corresponding objective functions and constraints for each sub-watershed are linked with the individual optimization algorithm to create a next generation offspring sample for the sub-watershed. The same step is done for all sub-watersheds in parallel and the offspring samples ($Newsample_{j\,=\,1:nsub}$) are merged together to create a new sample population for the watershed, as shown in Fig. 3. In effect, one sample for 'nsub' sub-watersheds requires only one model simulation and this reduces the computational cost significantly. This process is continued until the user defined termination criteria are satisfied for this level. This provides optimum solutions for individual sub-watersheds as Pareto-optimal fronts (a set of compromised trade-off solutions with multiple conflicting objective functions) of objective functions.

For the second level of optimization, a lookup table is created with equally spaced optimal solutions from individual sub-watershed Pareto-optimal fronts generated from the first level of optimization. The optimization algorithm is then linked to this lookup table to find watershed level optimum solutions. This approach reduces the second level optimization search space to only combinations of best solutions from individual sub-watershed, thus improving the efficiency of optimization. For source area based optimization problems (e.g. to minimize erosion from all agricultural fields as in Case Study 1), a lookup table can be created with first-level optimal solutions and corresponding objective functions. Then the second level objective function can be evaluated as summation or average of sub-watershed objective function directly from this table without a need to run the watershed model again. For example, objective function of total erosion from watershed is cumulative of erosion from all sub-watersheds. For watershed outlet based