ADVANCES IN FOREST FIRE RESEARCH

Edited by DOMINGOS XAVIER VIEGAS LUÍS MÁRIO RIBEIRO

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Towards real-time predictions of large-scale wildfire scenarios using a fully coupled atmosphere-fire physical modelling framework

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Keywords

Wildfires, Coupled fire-atmospheric modelling, High-performance computing, Large-scale fire simulations

Abstract

With the changing climate, fire-exclusion, and expansion of wildland-urban interfaces, the frequency and severity of wildfires are expected to increase, putting substantial stress on fire management and authorities to mitigate the risk of wildfires. Improved physical models in conjunction with advanced high-performance computing resources offer new opportunities for operational use in examining potential fire-spread scenarios and planning. This work presents an opensource, high-fidelity modelling framework for simulating large-scale wildfire scenarios, taking into consideration atmospheric/fire coupling, complex terrain, and heterogeneous fuel loading. The framework is implemented using the TensorFlow programming environment on tensor processing units (TPUs). TPUs are a dedicated high-performance computing architecture to accelerate machine-learning applications and high-performance scientific computing. This framework solves the Favre-filtered reacting Navier-Stokes equations and the unclosed terms describing turbulence/chemistry interaction and turbulence transport are modelled using large-eddy simulation (LES) closures. Wildfire dynamics is described by a one-step solid-fuel pyrolysis/combustion model that is coupled to atmospheric flow dynamics using a Boussinesq-type approximation. A second-order finite-difference discretization is employed in a variable-density, low-Mach number formulation to discretize the governing equations, and an immersed-boundary method is adapted to represent complex terrain. In conjunction with the coupled atmosphere/fire model and physical models for turbulence/atmosphere/fire interaction, the resulting simulation framework enables high-resolution simulations (with spatial resolution below 2m) of large-scale fires that cover up to ~100,000 acres. Following the summary of validation results against a prescribed fire experiment to assess the overall accuracy at well-controlled conditions, we employ this coupled atmosphere/fire modelling framework to simulate a large-scale wildfire scenario that is representative of the 2017 California Tubb's fire. To this end, we extract the terrain of the North Bay region of Calistoga and Santa Rosa, spanning an area of 20 × 20 km², and consider a North-Eastern wind. The simulation results illustrate the rapid fire-spread dynamics and the coupling of the fire with the terrain and atmosphere. With relevance to operational and research applications that include parametric studies to examine effects of wind, fuel-density, other environmental factors, and fire-management strategies, we discuss the scalability and further extensions of the physical fidelity towards enabling real-time applications on TPU-compute architectures.

1. Introduction and Motivations

Wildfires can threaten livelihood and properties and impact the environment and health [Kollanus et al., 2016; van der Werf et al., 2017]. Over the last few decades, wildfire management has changed profoundly, facing longer fire seasons and more severe fires with more acres burned on average each year [Westerling et al., 2006]. Now, extreme fire events are becoming the norm rather than the exception [Zhongming et al., 2020], with some of the most destructive wildfires in California's history occurring over the last ten years [Khorshidi et al., 2020]. While the number of total fires in the United States has stayed the same, the scale of these extreme fires and subsequently the cost to suppress them and the devastation they cause on forests and communities has grown [Hazard HQ Team, 2021]. In addition, wildfires significantly impact the climate and are estimated to contribute to 10% of the CO2 emissions per year worldwide. Main issues in reliably predicting wildfires are variability in atmospheric conditions, fuel loading, moisture content, and uncertainties in physical models. Therefore, ensemble simulations are required, which provide a statistical representation of the effects of wildfire behaviour

and the prediction of extreme-fire dynamics, ultimately to improve early-detection, prevent, and mitigate impacts [Brillinger et al., 2003].

By leveraging emerging computing architectures, the objective of this work is to develop a scalable highperformance simulation tool that enables the reliable prediction of realistic wildfire scenarios under consideration of representative terrain topographies, fuel distribution, and atmospheric conditions. Here, we will present recent progress toward the development of such a simulation framework using the TensorFlow programming environment. The underlying combustion-physical models and the key features of this solver to efficiently run on Tensor Processing Units (TPU) are presented. The application of this solver is demonstrated by performing simulations of a wildfire scenario that is representative of 2017 Tubbs fire.

2. Numerical Methods

2.1. Governing Equations and Discretization

In this work, we present a simulation framework that solves the three-dimensional Navier-Stokes equations in a low-Mach formulation. The physical model describes the interaction between wildfire spread behaviour and atmospheric flow dynamics. The combustion of the fine-grained fuel is described using a single-step reaction that accounts for solid-fuel pyrolysis and combustion. The states of the solid fuel, including the fuel density, moisture content, and solid temperature, are modelled with a set of ordinary differential equations. The fire behaviour is represented by two prognostic variables, namely the potential temperature and the oxygen mass fraction. The evolution of these variables is modelled by two transport partial differential equations in conjunction with the Navier-Stokes equations, which couples the fire dynamics with the hydrodynamics of air flows using a Boussinesq formulation [Linn & Cunningham, 2005]. Effects of turbulence are considered using eddy-diffusivity-based subgrid models through LES filtering. Specifically, the Smagorinsky-Lilly model [Lilly, 1962] is used as the sub-grid scale closure to represent small-scale turbulence in atmospheric flows.

The governing equations are discretized using a finite-difference formulation with a time-explicit iterative scheme. This simulation framework was examined through benchmark simulations for non-reacting and turbulent conditions [Wang et al., 2022], confirming second-order temporal and spatial accuracy, and excellent weak and strong scalability thanks to the graph-based computing architecture and the optimization through the accelerated linear algebra compiler for TPUs.

To consider complex terrains, we employ the immersed boundary method with feedback-force [Zhang & Zheng, 2007]. In this method, an additional forcing term is added to the momentum and scalar transport equations for the potential temperature and oxygen mass fraction. With this method, the ground is represented as a non-slip isothermal interface. The boundary conditions were tested in canonical flow configuration to confirm expected solution accuracy.

2.2. Tensor Processing Unit

A main contribution of this work is the implementation of the wildfire simulation framework on TPU platforms using the TensorFlow programming interface. The TPU architecture is an application-specific integrated circuit that specifically targets accelerated dense matrix multiplications for machine-learning applications and high-performance scientific computing. The simulation framework is based on a recently developed CFD-solver [Wang et al., 2022] that was developed for high-fidelity reacting and non-reactions fluid-flow applications.

To provide context, we briefly summarise salient features of the TensorFlow TPU implementation. The TPU architecture consists of a TPU board with four independent chips. Each chip contains two tensor compute cores that are optimised for vectorized operations and dense-matrix operations. Up to 1024 chips are connected through a dedicated high-speed inter core interconnect network, forming a TPU pod [Jouppi et al., 2017, 2021]. Main benefits of this computer architecture, making it particularly interesting for large-scale wildfire simulations, are high-peak performance, the flexible programming environment, and the compilation of the executable taking into consideration data management, memory allocation, hardware execution, and inter-chip communication.

3. Results

3.1. Validations for prescribed fire experiments

We validate our wildland fire simulation framework against the FireFlux II experiment [Clements et al., 2019], which is a prescribed grassland fire over a flat ground with homogeneous fuel distribution. Extensive parametric studies have been performed and will be published in a forthcoming study [Wang et al. 2022], and this presentation focuses on illustrating key results from this study. Simulations were performed in a Cartesian domain of size $1 \ km \times 0.5 \ km \times 0.6 \ km$ along the wind-direction, lateral, and height. The domain is discretized using a structured regular mesh with resolution $2 \ m \times 2 \ m \times 0.5 \ m$ along the three respective directions. The atmospheric boundary layer is prescribed by a logarithmic velocity profile with a bulk-velocity of 5 m/s and neutrally stratified atmosphere [Clements et al., 2019], and is modelled by the Monin-Obukhov similarity theory [Porté-Agel et al., 2000]. We consider a homogeneous grassland that is 1.5 m tall, having a fuel density of 0.4 kg/m³. The simulation is advanced over a total of 200 s at a time-step size of 0.01 s, which corresponds to a CFL number of 0.4. The simulation is performed using 128 TPU cores, taking 0.15 s wall-clock time to complete one temporal iteration. Considering the scaling to a full TPU-pod with 1024 cores and linear scalability, suggest that these simulations can be performed at near real-time conditions, opening unique opportunities for operational services.



Figure 1- Time sequences of the temperature profile. The first row shows results from the experiment [13], and the second row is results from the simulation at the corresponding time.

Quantitative comparison of simulation results against published measurements for temperature fields are presented in Figure 1, with the top row showing experimental data (taken from LIDAR) and the bottom row showing temperature fields at a fuel-bed height of 0.5 m above the ground. Results for three different time instances are shown, indicating overall good agreement in predicting the head-fire spreading rate and lateral extent of the fire. The perimeter and key topology of the fire are captured by the simulation. Additionally, the overall good agreement in peak temperature suggests that the heat release and corresponding fire intensity is well captured by the simulation. Differences are evident for the backfire, with the simulation overpredicting the fire residence time. We attribute these differences to the ignition and variability in the fuel load [Wang et al. 2022].

3.2. Large-scale wildfire simulation

Following the validation of the wildfire simulation framework against a prescribed fire experiment, we proceed by considering a large-scale fire scenario. For this, we consider a fire scenario that is representative of the Tubbs fire [Martinez et al. 2017]. The domain for this simulation takes a size of $20 \text{ km} \times 20 \text{ km} \times 2 \text{ km}$, as shown

in Fig. 2, with the x-axis aligned with the north-eastern wind direction [Martinez et al. 2017]. The mesh resolution is 20 m horizontally and 4 m in vertical direction. The elevation map is obtained from the USGS database [The National Map-Data Delivery, n.d.] with the latitudes and longitude coordinates sampled in the selected area, which are then interpolated onto the computational mesh. We assume that the ground is covered by homogeneously distributed tall grass of height 1.35 m with a bulk density of 1 kg/m^3 , which corresponds to a fuel load of 1.35 kg/m^2 . The velocity field is initialised with a Blasius boundary layer that conforms with the terrain. The inflow velocity profile is set to a bulk flow of 10 m/s on which we superimpose turbulence fluctuations that are generated with a digital filter [Klein et al., 2003] with a turbulence intensity of 20%. A convective outflow boundary condition is applied at the downstream exit of the domain. The two boundaries at the lateral sides are set as free-slip walls. A Reighley damping layer is applied at the top boundary, covering 10% of the domain. Within this layer, we prescribed values for all velocity components and prognostic variables. Before ignition, the flow is advanced for one flow-through time (corresponding to 2000 s) to establish a fully developed atmospheric boundary layer. Following this initialization period, we ignite a square region of size 500 m^2 at the location where the fire was first spotted. The solution is advanced for another 4000 s until the fire reaches the end of the domain (near the region of Santa Rosa).



Figure 2- Simulation domain over $(20 \text{ km})^2$ area covering the spread of the Tubbs fire in the first 2 hours.

300+0

Santa

Rosa

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(b) time: 2000 s

(a) time: 1000 s

© time: 3000 s

Figure 3- Simulation of large-scale wildfire behaviour over (20 km)² area in Northern California near Santa Rosa, representative of the Tubbs fire, showing time-sequence of fire front (colored by temperature at a height of 6 metres above the ground) over the topography (with elevation map shown in green, scaled by a factor of 2.5). The red square in (a) indicates the ignition location.

Ignition site

2km

A time-sequence at three instances after the ignition is shown in Fig. 3, together with an enlarged view of the fire front. This transient fire sequence illustrates the coupling of the fire plumes with approaching wind. The fire front exhibits severe corrugation due to the conforming terrain and increasing spreading rate on uphill slopes. It can be seen that after 1000 s (~15mins) the fire completely traversed the valley and approached the mountain ridge to Santa Rosa. We note that our current simulations consider homogeneous fine grassland, which is not representative of the vegetation in this area. Because of these important differences in the vegetation and time-dependent wind, we note that these results are not fully representative of the Tubbs fire scenario, but illustrate the capability in predicting large-scale fire events at affordable computational cost.

4. Conclusions

High-fidelity numerical simulations for realistic wildfires are helpful for physical analyses of atmosphere/fire coupling yet too expensive to generate. In this study, we demonstrate that these simulations are within reach using advanced HPC architectures by showing simulations of two realistic fire scenarios. The first scenario considers a prescribed grassland fire over a flat ground. Validations with the experimental results show good predictability of the simulation framework regarding fire statistics including rate of spread, perimeter, and fire intensity. The second scenario considers a historical fire in California 2017. This simulation covers an area of $400 \ km^2$ with 0.5 billion mesh points. With the current simulation setup and partition, we simulate the 1 hour duration of the fire that propagates from Calistoga to Santa Rosa in a 12-hour wall-clock period. The performance of this simulation can be further improved by optimising the time step size and refining the partitioning strategy, which makes the simulation close to real time.

5. Acknowledgment

We thank Rod Linn from Los Alamos National Laboratory for helpful discussions on the model development. Craig Clements is acknowledged for sharing the Fire-Flux II validation data. We also thank Mark Finney from the United States Forest Services for helpful discussion on the wildfire dynamics.

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