Climate Downscaling for Fire Management

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1 Introduction

Fires occur and re-occur on almost a third of the global landmass at different return intervals, with burned area averaging 4.5 million km^2 annually (Giglio et al. 2013; IUFRO 2018). Wildfires shape forest structure and composition; forests are dependent on, sensitive to, independent of, or influenced by fire (Myers 2006). Despite recent decreases in the annual area burned, catastrophic wildfires apparently are increasing in frequency globally (FAO 2001). For example, bushfires in Australia burned more than 16 million ha during the 2019–20 fire season, leading to losses of over 3,000 houses and 33 lives (Richards et al. 2020). Over 3 million ha were burned by wildfires during 2019 in Siberia (https://en.wikipedia.org/wiki/2019_Siberia_wildfires). The Amazon rainforest burned about 142,000 ha during the 2019 dry season with the highest fire count since 2012 (https://www.globalfiredata.org/updates.html). Extremely large fires occurred in the western United States (US) with burned areas of about 1.2 and 1 million ha in 2017 and 2018, respectively. The increased frequency of catastrophic wildfires, especially mega-fires (Stephens et al. 2014; Williams 2004; Williams and Hyde 2009) are due to multiple causes, including extreme weather events such as extended drought (Acácio et al. 2009; Dai 2011; González et al. 2018; Liu et al. 2010b). Climate is a primary driver for fire activity. Climate change that results in drier, warmer con-

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ditions potentially could increase fire occurrence and intensify fire behavior. These changes may already be occurring (Abatzoglou and Williams 2016; Flannigan et al. 2009; Reinhard et al. 2005; Westerling et al. 2006). Human factors also play central roles by increasing fuel loads due to years of suppression activity (DeWilde and Chapin 2006; O’Brien et al. 2017) and increasing wildland-urban interface (Hammer et al. 2009; Radeloff et al. 2005; Stewart et al. 2007). High intensity fires that occur outside the traditional fire season will exceed existing fire management capacities (IUFRO 2018; Jolly et al. 2015).

Climate information is necessary for understanding and predicting fire regimes, seasonal and inter-annual variability, and future wildfire trends. Fire risks are assessed daily for individual forests using tools such as the US National Fire Danger Rating System (NFDRS) (Deeming et al. 1977) and the Canada Forest Fire Danger Rating System (CFFDRS) (Van Wagner 1987). Weather conditions including temperature, precipitation, humidity, and wind are the major parameters used to assess fire occurrence, spread, and intensity. At broader spatial and long temporal scales, seasonal fire activity is predicted for geographical regions using dynamical and empirical planning tools. Future trends of fire regimes are projected mainly based on the projected climate change. Atmospheric variability, especially extremes such as droughts, is a major predictor.

Besides predicting wildfire activity, another response to the challenge of increased wildfire occurrence is to reduce hazardous fuel loads by prescribed burning (Bradstock et al. 2012; Fernandes et al. 2013; Tolhurst and McCarthy 2016; Wiedinmyer and Hurteau 2010). Frequent burning under mild fire weather conditions has been a common fire management practice in the southern US for decades (Fernandes and Botelho 2003; Waldrop and Goodrick 2012) and has been advocated in other regions of the US and as “indigenous fire treatments” in Australia (Eriksen and Hankins 2014; Gott 2005; Vigilante et al. 2009). Prescribed burning is not a panacea, however; managing smoke from intentional burning is critical to securing public acceptance (Hardy 2001). Additionally, climate change that alters fire weather may lengthen fire seasons (Liu et al. 2010a) and reduce the amount of time that burning may be conducted without significantly increasing the risk of escape (e.g., Sun 2006; Wonkka et al. 2015) or problems with smoke (McKenzie et al. 2014; O’Neill et al. 2017), thereby taxing management resources. The ability to project future climate conditions will assist managers in planning and efficiently allocating resources.

Climate change is projected mainly using global climate models (GCMs). Despite advances in complexity and the ability to resolve global climate, GCMs have limited ability to simulate regional climate. Significantly, most wildfires occur at spatial scales up to tens of kilometers in area, resulting in a significant size mismatch with GCM output. Nevertheless, the climate and fire communities have made great strides in developing and applying climate downscaling techniques to overcome the spatial deficiencies of GCMs. These techniques use either a dynamical approach by running regional climate models (RCMs) driven by GCMs or from measurements, or a statistical approach applying statistical tools to obtain relationships between historical meteorological conditions at local sites and global

GCM grids, for high-resolution (meters to tens of kilometers) climate information. Both approaches and their applications in various regions of the world have been documented and reviewed, for example, by Abatzoglou and Brown (2012), USAID (2014), Xue et al. (2014), Xu et al. (2019), and illustrated in recent publications by Kitoh et al. (2016), Li et al. (2019a), and Takhsha et al. (2018) for dynamical downscaling and Gebrechorkos et al. (2019), Jiang et al. (2018), and Navarro-Racines et al. (2020) for statistical downscaling. The downscaled climate provided necessary information for assessing the impacts of climate change on fires in various regions of the world, including Africa (e.g., Strydom & Savage 2017), Asia (e.g., Li et al. 2019b), Australia (e.g., Dowdy), Europe (e.g., Dupuy et al. 2020; Faggian 2018; Lozano et al. 2017), North America (e.g., Stambaugh et al. 2018), and South America (e.g., Silva et al. 2016).

The climate modeling community is advancing global climate change projections through implementing the Coupled Model Intercomparison Projects, Phase 6 (CMIP6). The CMIP6 projections use the Intergovernmental Panel on Climate Change (IPCC) new “Shared Socioeconomic Pathways” (SSPs) emission scenarios (Eyring et al. 2016; Meehl et al. 2016) and will be a part of the upcoming 2021 IPCC Sixth Assessment Report (AR6). Efforts have been underway to downscale the CMIP6 projections for impact assessment in various fields including wildfires. Here we introduce fire managers and researchers to climate downscaling techniques in this active field and their significance for fire management. First, we introduce dynamical and statistical downscaling approaches and compare their strengths and weaknesses. Second, available downscaling tools and products are described. Finally, some examples of actual fire applications are illustrated. The information provided in this paper is expected to provide managers with a basis for selecting the high-resolution climate products from both current resources and the coming new downscaling products of the CMIP6 projections, which are needed to achieve the specific fire management goals and to understand the connections of wildfires (including the recent large and mega-fires) to climate change.

2 Methodology

Each of the three topics of downscaling approaches, tools and products, and fire applications are presented with separate descriptions of dynamical and statistical downscaling (Fig. 1). The two essential tools for dynamical downscaling (that is, GCMs and RCMs) and their differences are first described. The GCM description focuses on the future global climate change projections made by GCMs through CMIP. The RCM description focuses on some classical models developed in various regions of the world. The methods and or models for statistical downscaling are then described. Finally, the strengths and weaknesses are compared between dynamical and statistical downscaling. The dynamical downscaling tools are described using the WCRP Coordinated Regional Climate Downscaling Experiment (CORDEX) (https://cordex.org) and its North America region as an

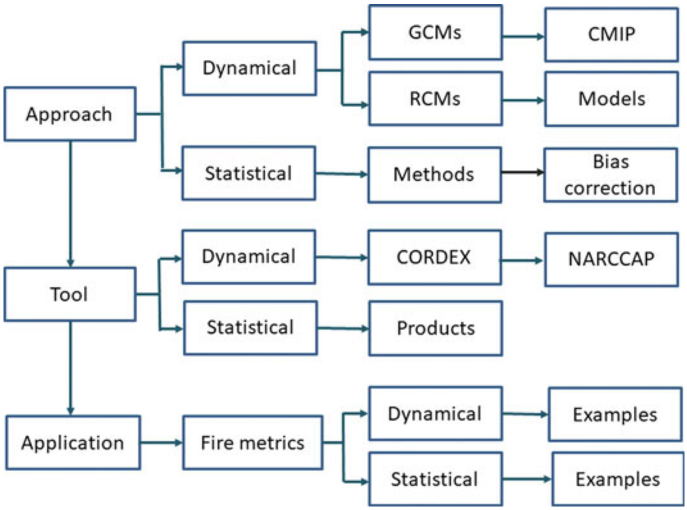

Fig. 1 A schematic diagram of topics (from top to bottom on left) and related issues (from left to right)

example. The statistical downscaling tools include a few major global and regional products. For fire applications, the need for downscaling climate for calculation of a metrics of fire weather indices is described, followed by examples of fire risk evaluation and projections under different downscaled regional climate change scenarios.

The information used to describe the above topics and issues was obtained from a number of sources. The GCMs and RCMs were based on our knowledge of climate modeling. The CMIPs and statistical downscaling methods were obtained from the literature. The downscaling tools were from online information. The fire applications were from literature, including studies by the authors.

3 Downscaling Approaches

3.1 Dynamical Downscaling

3.1.1 Approach

Dynamical downscaling utilizes RCMs with boundary conditions provided by GCMs or measurements to produce high-resolution regional climate change scenarios. A GCM is comprised of equations to describe atmospheric dynamics based on momentum, heat energy, mass, and moisture conservation and atmospheric physics to represent radiation, turbulence, cloud and precipitation, etc. In addition, GCMs also include other climate system components (ocean, ice, soil, vegetation, etc.) and gas and particle emissions. GCMs simulate and predict global climate, seasonal and inter-annual variability, and long-term change.

One of the important applications of GCMs is to project climate change due to the increasing atmospheric greenhouse gas concentrations, including carbon dioxide. A useful source for GCM projections is CMIP output. The CMIP provides a framework for coordinated climate change experiments for the major GCMs all around the world. The third (CMIP3) and fifth (CMIP5) phases of the project provided the major information for the scientific assessment of IPCC AR4 and AR5, respectively (Semenov and Stratonovitch 2010; Hausfather et al. 2020). About 25 GCMs participated in CMIP3 for the the Special Report on Emission Scenarios (SRES) emission scenarios (Nakicenovic et al. 2000). These scenarios distinct between strong economic values and strong environmental values and between increasing globalization and increasing regionalization. About 26 research centers participated in CMIP5 (Taylor et al. 2012) with some centers providing more than one GCM. The climate change projections were made based on the Representative Concentration Pathways (RCPs) (Van Vuuren et al. 2011). The pathways describe four possible climate futures, their likelihoods depending on the amount of greenhouse gases to be emitted in the years to come. The four RCPs (RCP2.6, 4.5, 6.0, and 8.5) are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively). About 100 GCMs are participating in CMIP6 for the emission scenarios defined in 8 SSPs, 4 of which correspond to the 4 RCPs.

Each GCM has a horizontal resolution, usually of hundreds of kilometers (Fig. 2). Global processes such as the El Niño and Southern Oscillation (ENSO) and synoptic systems such as cyclones and fronts can be identified at this resolution. However, regional climate and mesoscale processes such as convective storms are largely missed. The effects of local and regional forcing such as terrain, land cover variability, and aerosols emitted from local or regional natural and anthropogenic sources are often not well represented in GCMs.

RCMs are developed based on limited-area meteorological models (LAMs) to simulate regional climate and variability. LAMs are a primary tool for numerical

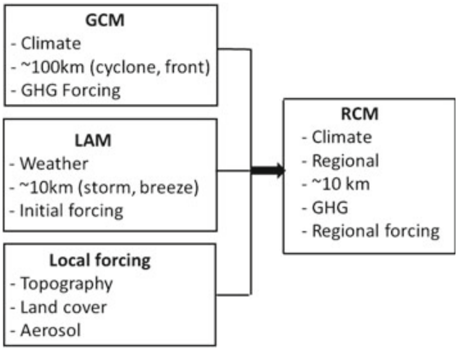

Fig. 2 Different features and relations among global climate models (GCMs), limited area models (LAMs), and regional climate models (RCMs)

weather simulation and prediction for a specific geographic region. They have similar components of dynamics and physics to GCMs, but with resolutions of tens of kilometers or higher and usually run for a short period such as a few days. They can identify storms and local circulations such as seas breezes. Initial conditions are very important in addition to internal dynamics, while lateral conditions and physical processes such as radiation and land-surface processes are less important.

An LAM is expanded into a RCM by including more detailed physical schemes for local and regional properties. Because RCMs are run over a longer period (months and years), initial conditions become less important while lateral conditions and forcing on the ground and inside the atmosphere become more important. The lateral boundary conditions of meteorological variables could be provided by a GCM, which makes RCMs a useful tool for climate downscaling of GCM simulations and projections. A RCM runs over the same or parts of the simulation period of GCM with frequently provided boundary conditions (e.g., once a day or a few hours).

The regional climate modeling technique was first developed in the US National Center for Atmospheric Research (NCAR) (Dickinson et al. 1989; Giorgi and Bates 1989) based on the standard NCAR/Penn State Mesoscale Model Version 4 (MM4) (Anthes et al. 1987). It has grown tremendously over the last three decades (Giorgi 2019) and become a powerful tool for climate downscaling (Tapiador et al. 2020). Table 1 lists some RCMs developed in the early time.

Table 1 Early developed regional climate models

RCM	Full name	Developer	Significance	Reference
CRCM	Canadian Regional Climate Model	UQAM	Regional version of Canadian GCM	Caya and Laprise (1999)
MM5	Mesoscale Model Version 5	PSU/NCAR	One of the widely used early US mesoscale models	Grell et al. (1994)
PRECIS	Providing REgional Climates for Impacts Studies	Hadley Centre	Easily applied to any area of the globe	Jones et al. (2004)
RAMS	Regional atmospheric modeling System	CSU	One of the widely used early US mesoscale models	Liston and Pielke (2000)
RegCM3	Regional Climate Model3	NCAR	First RCM	Giorgi and Bates (1989)
RSM	Regional Spectral Model	NCEP	Spectral model	Juang and Kanamitsu (1994)
WRF	Weather Research and Forecasting	NCAR/NOAA	For both research and operational forecasting	Liang et al. (2006)

UQAM, PSU, and CSU represent Université du Québec à Montréal, Pennsylvania State University, and Colorado State University

3.1.2 Evaluation and Bias Corrections

Evaluation is a process to assess a model's performance by comparing simulated historical averages, variability, and extremes of atmospheric as well as other climate system components to observed values. Although evaluation of a RCM is part of its development, its performance is dependent on the simulation region and time, and scheme and parameter setting. Thus, when more than one RCM is used for climate downscaling, it is useful to compare the performances of all models in the ensemble. Potential issues can be found and may need to be addressed before the model is used for climate downscaling. The evaluation process can also provide information on the uncertainty in the downscaled climate results.

RCMs can produce large biases in simulating present climate conditions. There are two ways to remove or at least reduce the biases. One way is to improve the models before they are used to predict regional climate (Jin et al. 2011). Xu and Yang (2012) used adjusted GCM climatology according to regional re-analysis to drive a RCM. Their results showed that the downscaled climatological means and extremes events were better than the downscaling without bias correction.

The other way to address bias is to correct the output of projected climate. For example, McGinnis et al. (2012) applied statistical bias correction to monthly mean surface air temperature and precipitation data from the North American Regional Climate Change Assessment Program (NARCCAP) regional climate change scenarios (Mearns et al. 2012) and examined the characteristics of the distributions of these fields on a regional basis. Appropriate statistical distributions (Gaussian for temperature and Gamma for precipitation) were used to fit RCM output for the monthly average of each climatic region. Quantile mapping (QM) was used in bias correlation through creating a transfer function to adjust the distribution of the simulated current climate so that they will match the cumulative distribution function (CDF) of observed climate. The same transfer function was then applied to output from the future climate projections.

3.2 *Statistical Downscaling*

3.2.1 Approach

Statistical downscaling is a technique developed based on the relationships between GCM predicted climate and historical weather observation data to produce high-resolution spatial and temporal climate at the regional level. Denoting GCM global and regional meteorological variables as X and Y with subscripts 0 and 1 for present and future conditions, the data for three of the four variables, X_0, X_1, and Y_0, are available. Y_1 is what statistical downscaling will provide. The procedure for statistical downscaling is as follows: (1) Building a relationship F between X_0 and Y_0 using a statistical method. (2) Correct X_0 based on Y_0 (optional). (3) Assume that F and correction are also applicable to future condition, thereby obtaining Y_1 using F and X_1.

3.2.2 Statistical Methods

The methods of statistical downscaling can be categorized into different types. One categorization (Wilby and Wigley 1997) classifies all methods into three types: (1) Transfer functions that relate large-area climate to local weather, or from upper air to the ground, (2) Weather typing that relates large-scale circulation systems or patterns to local weather, and (3) Weather generator that relates parameters from large- to local-scale. The transfer function type can be further classified as scaling methods and regression-based approaches (Schoof 2013).

1. *Transfer functions*

Transfer functions are developed using statistical techniques such as multiple linear regression, spatial pattern tools [e.g., empirical orthogonal functions (EOF), canonical correlation analysis (CCA), and singular value decomposition (SVD)], and artificial neural networks (ANN). These functions transfer information on large-scale meteorological variables provided by GCMs (predictors) to regional climate (responses) measured by direct meteorological variables such as temperature and precipitation. Transfer functions are computation efficient and therefore easily produce multiple scenarios for ensemble analysis. Large amounts of data and good correlations between predictor and response variables are the keys for successful applications.

Regressions develop linear relationships between individual variables. For example, Vasiliades et al. (2009) used multiple regressions between GCM variables and observed precipitation to downscale monthly precipitation values in order to estimate a meteorological drought index, the Standardized Precipitation Index (SPI) at multiple timescales. The validation indicated the accuracy of the methodology and the uncertainties propagated by the downscaling procedure.

The spatial pattern tools are similar to regressions but for relationships between spatial patterns of predictor and response fields. For example, SVD is a technique to identify coupled spatial patterns with the maximum temporal covariance between a variable from GCM and a variable from historical data. Uvo et al. (2001) developed linear regression models based on SVD analysis to downscale atmospheric variables to estimate average rainfall in a region in Japan. The results revealed that the Bai-u front was responsible for the majority of summer rainfall, the strong circulation pattern associated with autumn rainfall, and the strong influence of orographic lifting creating a pronounced east-west gradient across the local region.

The ANN approach can be used to build non-linear relationships between meteorological variables in a large network and variables within the network (Snell 2000). Trigo and Palutikof (1999) compared performances of linear models and non-linear ANNs in downscaling the site temperature at Coimbra, Portugal from large-scale atmospheric variables. Their results showed that even a simple configuration of a 2-layer non-linear neural network significantly improved on the performance of a linear model. Knowledge of complex spatial patterns and ANN are essential for downscaling with these tools.

2. *Weather typing*

Weather typing relates large-scale weather or circulation patterns to regional climate variations. Weather or circulation patterns can be selected based on the synoptic or statistical analyses of atmospheric systems responsible for local weather. Spatial analysis also can be used for weather typing. For example, the frequency distributions of regional climate variables can be derived by weighting the local climate conditions with the relative frequencies of the weather classes. Climate change then can be estimated by determining the change of the frequency of weather classes. Weather typing is based on understanding the physical processes of synoptic or planetary atmospheric systems and their connections with local climate. Knowledge of such systems is needed to apply the technique but may or may not exist for a specific location.

Abatzoglou and Brown (2012) used a weather type model, the Multivariate Adapted Constructed Analogs (MACA) that identifies commonality between the synoptic-scale field from a GCM and a catalog of observed synoptic-scale fields from observations to download weather for complex wildfire analyses in areas with diverse terrain. They found the model out-performed results obtained from direct interpolation of re-analysis. The MACA method was also found to be superior to the bias correction and spatial downscaling method for fire applications due to the improved spatial representation of analogs over interpolation and the MACA's multivariate approach that maintains the physical relationships among variables.

3. *Weather generators*

Weather generators are stochastic parameter models that generate synthetic time series of weather data based on historical weather at a location (Wilks 1999). Precipitation often is a primary weather field to be generated. There are two ways to create weather generators. One (Richardson 1981) first models wet day probability using a Markov procedure and then uses a frequency distribution to estimate rainfall amount. The other (Racsko et al. 1991) finds dry and wet day series and then estimates rainfall amount. The other variables such as temperature are then computed based on correlation relations under dry or wet conditions. Weather generators can create long-term series with less need for computation resources. However, the accuracy is likely low and depends on parameter specification.

The data produced by a weather generator can then be used to downscale a GCM. For example, Chen et al. (2006) used a first-order Markov chain as a weather generator to simulate wet day probability, the Gamma distribution function to describe variation of wet-day precipitation amounts, and statistical downscaling to transfer large-scale GCM (in both space and time) future precipitation series to station/local scales. The results showed the capacity of the technique to reproduce the observed mean daily amount and model parameters of the daily precipitation series at station/local scales in the study region.

3.2.3 Bias Correction

One feature of statistical downscaling is the use of large amounts of meteorological observations, Y_0. Bias correction uses this advantage in obtaining the differences between Y_0 and the present climate, X_0 simulated by GCM. The differences or biases are assumed to exist as well between the downscaled future local climate and the GCM projected climate. The downscaling was improved by applying the differences (bias correction) that could be obtained based on the cumulative distribution function or quantile instead of the original variable values.

Selection of the downscaling and bias correction methods depends on many factors, including the meteorological variables, seasons, regions, and time frequency (Maurer and Hidalgo 2008). Wood et al. (2004) found that the bias-correction and spatial disaggregation (BCSD) method was able to obtain the main features of the observed hydrometeorology based on the simulated climate sin the western US, while linear interpolation led to unacceptably biased hydrologic simulations and the spatial disaggregation result was not useful for hydrologic simulation purposes without bias-correction. However, performance of the bias correction method relative to other methods varies, depending on specific situations. Goodess et al. (2012) found that it was not possible to identify a consistently superior method for statistical downscaling of temperature and precipitation in the majority of 22 cases with a focus on extreme conditions in European regions. They therefore recommended the use of a range of the better statistical downscaling methods for the construction of scenarios of extremes.

3.2.4 Extremes

Two problems could arise when the statistical methods described above are used to download weather and climate extremes. First, extremes occur in the very far tail of both magnitude and frequency distributions and they may not meet the conditions required for the statistical distributions. There might be less reliable relationships connecting the extremes to their predictors. Second, the statistical downscaling technique is based on statistical relationships between large-scale fields or circulations and local weather and bias corrections of GCM projections using observations. They usually need a large number of sample data. Extremes, however, are rare events and there are much fewer observations for extremes than normal values. In addition, rainfall extremes often occur under circulation anomalies at much larger spatial scale and longer duration. The downscaling techniques for normal or mean conditions may only consider circulation at more local area and shorter periods.

Recently new statistical tools have been applied to solve these problems. Extreme value theory (EVT) is one of these widely used tools. Different from regular statistical tools that describe mean, variance and skewness (the first, second, and third moment of a probability distribution function), EVT describes the tail (fourth moment). EVT uses the generalized extreme value (GEV) distribution to model the frequency of extremes such as a series of maxima or minima. The GEV is a cumulative exponential distribution function with location, scale, and shape parameters and depending on the parameters is a general form for one of the three special cases of Gumbel, Fréchet and Weibull distributions. Using the generalized Pareto distribution (GPD) the EVT can model the magnitude of extremes such as the abnormal values exceeding a high threshold or very high quantiles.

There have been an increasing number of EVT applications to statistical downscaling. Friederichs (2010) assessed the potential of using EVT for statistical downscaling of the re-analysis of daily extreme precipitation events to German weather stations. The results from two approaches (a Poisson point process representation with non-stationary parameters using defined constant threshold and parameters, and the peak-over-threshold representation using the GPD with defined threshold) indicated that both approaches led to reliable estimates of high quantiles. It also showed that the EVT application produced less uncertain quantile estimates than the censored quantile regression. Another study by Mannshardt-Shamseldin et al. (2010) fit the GEV distribution to the right tail of the distribution of both rain gauge and gridded events and developed regressions to connect them. They found that return values computed from rain gauge data were extremely higher than those computed from gridded data and that it was possible to project future changes in precipitation extremes at the point-location level based on results from climate models.

3.3 Comparisons of Two Approaches

3.3.1 Strengths and Limitations

The major strengths and limitations of the dynamical and statistical downscaling approaches are compared in Table 2. Dynamical downscaling is physically consistent between RCMs and GCMs and among meteorological elements to be downloaded. The RCMs have almost the same components of dynamics and physics as GCMs. In contrast, statistical downscaling has to develop separate relationships for each of the variables and therefore the physical relationship between variable may be weak or lacking.

Dynamical downscaling provides a wide range of variables with high frequency, while statistical downscaling mostly provides temperature and precipitation although humidity and wind are also available from some datasets. Dynamical downscaling products can provide daily or even hourly temperature and precipitation. Daily data is required in calculating some fire weather indices such as the Keetch-Byram Drought Index (KBDI) (Keetch and Byram 1968). Hourly data is useful for estimating some atmospheric and fuel properties whose values at certain

Table 2 Comparisons of the strengths and limitations with dynamical and statistical downscaling approaches

Feature	Dynamical	Statistical
	Strength	Weakness
Consistence	Physically consistent	Inconsistent among variables
Variable	Multiple variables	Limited variables
Forcing	Local interactions	Not included
Vertical	Yes	No
Data need		Observations, sparse in some areas
Assumption		Empirical relations applied to future
	Weakness	Strength
Computation	Need in large capacity	Efficient
Resolution	Lower (but more frequent)	Higher (but lower frequency)
Scenario	Limited number	Multiple no. for assembling
Bias	Passed over from GCMs	Control with observations
	Common features	
Extreme	Included	EVT used to downscale extremes
Dependence	Model dependent	Method dependent

periods of a day are important to fire behavior modeling and fire management. For example, prescribed burning is conducted mostly between 9 am and 3 pm when wind, fuel moisture, and atmospheric stability during this period are key for burn prescriptions. Wind and humidity are useful for estimating the Fosburg fire weather index and many NFDRS indices (Deening et al. 1977). Dynamical downscaling also provides many energy and water fluxes and soil temperature and moisture conditions that are needed for fuel condition and change modeling.

RCMs include many physical interactions and feedbacks important for projections of climate change, which are largely missed in GCMs due to coarse grid spacing. The snow-radiation-warming feedback is an example. The summits of mountains are often covered by snow; due to global warming, part of that snow is melting. This leads to reduced albedo and more absorption of solar radiation. As a result, warming becomes more significant. With finer spatial resolution, RCMs are better than GCMs to represent topography and therefore the feedbacks. Dynamical downscaling provides data at multiple atmospheric layers, which are needed, for example, for calculation of the Haines Index (Haines 1988; Winkler et al. 2007).

Dynamical downscaling requires present and future, large-scale climate projections from GCMs. Besides GCM outputs, statistical downscaling also needs a large amount of observational data to build empirical relationships with the present climate simulated by a GCM. Such relationships may not exist for a particular variable at a specific location. Also, it is especially difficult to develop such relationships in complex terrain such as mountains where data are spatially sparse and may lack representativeness. Another major limitation with statistical downscaling is that the relationships developed using the current data are assumed applicable in the future, which may be not a valid assumption.

One of the major strengths with statistical downscaling is that fewer computation resources are needed in comparison with dynamical downscaling. Because of this, statistical downscaling for a specific region can be conducted using multiple GCMs, emission scenarios, and statistical methods, importantly allowing inter-comparisons and uncertainty analyses. More importantly, it allows obtaining ensemble results, thereby permitting use of higher spatial resolution for statistical downscaling, although this is limited by the resolution of observations. The resolution of statistical downscaling could be as high as meters, while the spatial resolution of dynamical downscaling is usually at tens of kilometers, or a few kilometers if using multiple-nesting techniques. Further, it is relatively easy to update statistical downscaling products using the most recent GCM projections. For example, there are already many downscaling studies using the CMIP5 GCM projections (Brekke et al. 2013). These advantages of statistical downscaling are very difficult to do with dynamical downscaling.

Both downscaling approaches can produce large errors. Those for dynamical downscaling may arise from the errors passed over from GCMs to RCMs and from internal dynamics of a particular RCM. One strength with statistical downscaling, however, is the bias correction procedure using observational data. For statistical downscaling, errors may arise from inaccuracy in observations and empirical relationships.

Extreme events present a challenge for both approaches. Because RCMs include all physical processes needed to simulate mesoscale weather systems and better represent topography and other local forcing for convective precipitation, dynamical downscaling is able to directly produce weather and climate extremes. Many studies, however, have so far indicated limited capacity of RCM simulations of weather and climate extremes. The regular tools useful for statistical downscaling, on the other hand, are unable to deal with the extreme issue. However, the development and application of the extreme value theory may provide a useful solution to this problem.

The regional climate change scenarios depend on which RCM or method is used and on the selection of GCMs and emission scenarios. Specific RCMs and statistical methods have been compared in various geographic regions. Haylock et al. (2006) found that the differences in the future changes of the seven downscaled precipitation indices in England among six statistical and two dynamical downscaling models were no smaller than the differences between the emission scenarios for a single model, emphasizing the importance of including multiple types of downscaling techniques, global prediction models, and emission scenarios. Tryhorna and DeGaetanoa (2011) found that two statistical models (BCSD and the Statistical DownScaling model-SDSM) and a regional climate model (HadRM3) simulated reasonable estimates of extreme rainfall across the northeastern US. The SDSM matched observed extreme climatology the best, while HadRM3 tended to overestimate mean precipitation and extremes. Ayar et al. (2015) showed that the occurrence and intensity of rain were better simulated by stochastic and re-sampling-based statistical downscaling, whereas spatial and temporal variability were better modeled by RCMs and re-sampling-based statistical downscaling. Tang et al. (2016) found that WRF driven by two GCMs tended to underestimate the surface temperature over most of China. Both approaches required further work to improve their ability to downscale precipitation. Zhang et al. (2020) found that PRECIS driven by 20 GCMs better represented temperatures in China than the GCMs alone. Kreienkamp et al. (2019) found that the grid cell bias for yearly values was mostly less than 0.1 °C for temperature and 10% for precipitation totals.

3.3.2 Hybrid Approach

The two approaches of dynamical and statistical downscaling have been used together in some modeling efforts. This hybrid approach aimed to maximize advantages while minimizing the limitations of each approach. For example, dynamical downscaling could be used first to get physically based climate at moderate-resolutions of tens of kilometers. The data can then be used with observations using statistical models to obtain climate at high-resolution of kilometers or higher. Yoon et al. (2012) indicated that a hybrid forecast system has the potential to maximize prediction skill. Walton et al. (2015) described another method for hybrid downscaling. Dynamical downscaling was first applied to five GCMs among the entire 32 CMIP5 GCMs. A simple statistical model was then built relating the GCM input and the dynamically downscaled output. This statistical model was used to approximate the warming patterns of the remaining GCMs.

4 Climate Change Downscaling Tools and Products

4.1 Dynamical Downscaling

4.1.1 CORDEX

CORDEX was initiated in 2009 to evaluate and benchmark model performance and design a set of experiments to produce climate projections for use in impact and adaptation studies (Giorgi et al. 2009; Giorgi and Gutowski 2015). One of the goals of CORDEX is to produce coordinated sets of regional downscaled projections worldwide. The domains of the current 14 regions cover essentially all land areas of the globe at a grid spacing of about 50 km. Dynamical downscaling has been conducted using a large number of RCMs under the forcing from CMIP3 and CMIP5 outputs. The downscaled climate data are provided through the Earth System Grid Federation (ESGF), a geographically distributed archiving system. CORDEX also provides statistical downscaling products.

4.1.2 NARCCAP

NARCCAP (Mearns et al. 2012) is one of the CORDEX regions covering North America. The GCMs used were the Community Climate System Model (CCSM), the Coupled Global Climate Model, version 3 (CGCM3), the Geophysical Fluid Dynamics Laboratory climate model (GFDL), and the Hadley Centre Climate Model, version 3 (HadCM3) for the SRES A2 emissions scenario. The GCM-RCM combinations are listed in Table 3. Simulations were conducted for the present period of 1971–2000 and the future period of 2041–2070 at a spatial resolution of 50 km. The NARCCAP projections provide 3-hourly, 2-D surface meteorological variables (air temperature, precipitation, humidity, winds, pressure), fluxes (radiation, heat, water, momentum) and soil variables, daily 2-D variables (maximum and minimum air temperature, 10-m wind speeds and sea ice), and 3-hourly 3-D atmospheric variables at multiple vertical levels. Constant parameters such as land-cover type, latitude and longitude of grid points, capacity of soil water, surface altitude, root depth etc. are also included. The RCMs were evaluated by running these models during 1980–2004 with the boundary conditions provided by the NCEP/DOE re-analysis data.

Using the projections driven by CCSM3 as an example, the GCM projected strong winter warming in northern Central Canada by about 7 °C. The large warming area extended southward to the Great Lakes by about 5 °C and further to the Deep South by about 4 °C. There is a small isolated warming area by about 4 °C in the Intermountain Region of the western US. Three RCMs projected a similar warming pattern, with a comparable strong warming with WRF, weaker in the Deep South with CRCM, and weaker in both the Great Lakes and Deep South with MM5. The summer warming projected by CCSM3 was the largest in the western US centered on the Intermountain Region by about 5 °C, and extended north towards southwest Canada and northeast towards the Northern Plains. However, warming was only about 1.5 °C in some areas in the South and Southeast US. The RCM projections were much different. The warming center in the western US was weaker, but warming in the eastern US was larger with WRF. The warming in Canada was much weaker. Two other RCMs go to opposite extremes. CRCM projected strong warming by about 5 °C across the continental US, while weaker warming by 2.5 °C was projected by MM5 for the southern US with a value of 3.0 °C in the Southern Plains.

Table 3 RCM-GCM combinations used in the NARCCAP dynamical downscaling simulations (https://www.narccap.ucar.edu/about/plan.html#rcm-gcm)

	GFDL	HADCM3	CGCM3	CCSM
RegCM3	X		X	
ECPC	X	X		
PRECIS	X	X		
CRCM			X	X
WRF			X	X
MM5		X		X

Projections of precipitation were also different between RCMs and the driven GCM. The CCSM3 projected drying summer in the Pacific Coast of the US and southern Canada by 20–50%, and wetting in Southwest US by more than 60% and in the Northern Rocky Mountains by about 40%. The RCM projections were overwhelmingly drier in the US. Although the Pacific Coast remained dry and the Northern Rockies wet, the Southwest turned to weak wetting or even strong drying, together with drying in most of the eastern US.

4.2 Statistical Downscaling

In comparison with dynamical downscaling, statistical downscaling applies multiple methods, covers greater ranges of spatial resolution, and demands much less computational resources. As a result, a larger number of the tools and products for statistical downscaling are available. Many of them are online that provides more power for user involvement and visualization. The major features of a number of tools and products for statistical downscaling summarized below are obtained from their websites. Some of these tools and products also come with dynamical downscaling.

(1) *Climate Wizard* (http://www.climatewizard.org)

This tool provides global maps of past and projected future temperature and precipitation trends, based on user-selected climate models and emissions scenarios, time steps, and regional boundaries (e.g., country or state). There is an associated tool of Climate Wizard Custom Extremes, which outputs include 23 temperature and precipitation variables at daily time steps, summary statistics, figures of statistical trends, and optional GIS data downloads. Resolution of outputs varies, ranging from 4 to 50 km depending on the datasets used. The first version of Climate Wizard Basic launched in 2009 using CMIP3. There are plans to update the database for both tools using CMIP5.

(2) *WorldClim* (https://www.worldclim.org)

WorldClim is comprised of a set of global historical and future climate conditions. The spatial resolution is about 1 km. The data can be used for spatial GIS mapping and numerical modeling. The data are provided for use in research and related activities; and some specialized skill and knowledge is needed to use them. More easily available data for the general public will be available soon.

(3) *Earth Exchange Downscaled Climate Projections (NEX-DCP30)* (https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-dcp30)

NEX-DCP30 was developed by NASA. It applied a statistical technique to downscale maximum and minimum air temperature and precipitation from 33 of the CMIP5 climate models to a very fine, 800-m grid over the contiguous United States

(CONUS). The full dataset covers the historical period (1950-2005) and 21st century (2006-2099) under the four RCPs.

(4) *National Climate Change Viewer (NCCV)* (https://www2.usgs.gov/landresources/lcs/nccv.asp)

The NCCV was provided by US Geological Survey. It includes the historical and future climate projections from 30 of the downscaled models for RCP4.5 and RCP8.5 from NEX-DCP30. The NCCV allows users to visualize projected changes in climate (maximum and minimum air temperature and precipitation) and the water balance (snow water equivalent, runoff, soil water storage and evaporative deficit) for any US state, county and USGS Hydrologic Units (HUCs, a hierarchical classification of hydrologic drainage basins).

(5) *MACA Datasets* (https://climate.northwestknowledge.net/MACA)

The datasets were obtained using the MACA method to downscale the model output from 20 CMIP5 GCMs for historical GCM forcing (1950–2005) and RCP 4.5 and RCP8.5 (2006–2100) from the native resolution of the GCMs to either 4 km or ~6 km in CONUS.

(6) *1/8 degree-CONUS Daily Downscaled Climate Projections* (https://cida.usgs.gov/thredds/catalog.html)

This dataset was provided by USGS using an advanced statistical downscaling method, asynchronous regional regression model. The method combines high-resolution observations with outputs from 16 different GCMs based on four AR3 emission scenarios to generate the most comprehensive dataset of daily temperature and precipitation projections. The gridded dataset covers CONUS, southern Canada and northern Mexico at one-eighth degree resolution and Alaska at one-half degree resolution. The data period is January 1, 1960–December 31, 2099.

(7) *ENSEMBLES Regional Scenario Web Portal* (https://crudata.uea.ac.uk/projects/ensembles/ScenariosPortal)

The ENSEMBLES project is coordinated by the Hadley Centre for Climate Prediction and Research at the UK Met Office. It is one of the CORDEX regions, covering Europe. The ENSEMBLES portal provides statistical downscaling techniques and simulations, which allows users to choose a statistical downscaling method. Downscaling is performed through selecting predictors, and predictand, and downscaling method.

5 Fire Applications of Climate Downscaling

5.1 Climate Downscaling Needs for Fire Applications

While not intended as an exhaustive review, this section describes some applications of downscaling to investigations of changes in wildland fire potential. How one utilizes downscaled climate information to evaluate future wildland fire conditions depends on the scale of the analysis and the weather data needed to describe fire conditions. At the global scale, changes in fire potential can be directly addressed from GCM data without downscaling (Liu et al. 2010a). Analyses at the continental scale can also utilize GCM data directly, for example for Canada by Wotton et al. (2010) with the realization that there may be issues in areas of complex terrain due to the large grid size. As the scale of analysis becomes more refined, downscaling becomes more important and the choice of downscaling method will be driven by the complexity of weather data required for describing fire conditions for a given analysis as not all methods will supply the required information. For some descriptions of fire conditions, precipitation and temperature data may be sufficient as is the case for applications using an index such as the KBDI (Liu et al. 2013). Other descriptions can also involve more detailed indices such as those comprising a fire danger rating system which will require a broader range of weather inputs, often collected at a specific time. Table 4 provides a list of metrics used to describe fire conditions in a number of downscaling studies along with the weather data required for their calculation.

Table 4 Fire metrics used in downscaling studies and weather inputs required for calculation

Fire metric	Weather inputs
KBDI	Daily surface high temperature, daily and annual average precipitation
Fosberg Fire Weather Index	Surface temperature, relative humidity, wind speed
Haines Index	Temperature and dew point depression at two atmospheric pressure levels which are determined by the elevation. Elevation: 950 & 850 hPa (low), 850 & 700 hPa (mid), 700 & 500 hPa (high)
US NFDRS Indices	Surface temperature and relative humidity (daily max/min and 1,300 local time), surface wind speed, and precipitation amount and duration for the previous 24-h from the observation time
Canadian Fire Weather Index	Maximum temperature, relative humidity, wind speed at 10 m above ground, and precipitation
McArthur Forest Fire Danger Index	Surface temperature, relative humidity, wind speed and precipitation

5.2 Applications of Dynamically Downscaled Climate

Dynamic downscaling has been employed for fire studies. Liu et al. (2013) estimated fire potential for the contiguous US using KBDI and a modified form of the Fosberg Fire Weather Index (mFFWI; Goodrick 2002). The study used a NARCCAP dynamical downscaled regional climate change scenario from the HadCM3 GCM with the PRECIS. Findings were expected increased fire potential across the Southwest, Rocky Mountains, northern Great Plains, Southeast, and Pacific coastal regions driven mainly by future warming trends. Rocco et al. (2014) draw upon the climate projections of Liu et al. (2013) for their study of climate change impacts on fire regimes and key ecosystem services in Rocky Mountain, US forests. Rather than relying solely upon a metric such as KBDI for their assessment, they employed a conceptual model of fuel dynamics and fire regimes that relied on current knowledge of climate-fire regime relations combined with literature on future climates to allow for the projection of how climate change is likely to alter both short- and long-term fire regimes in each of the four forest types studied within the region.

Bedel et al. (2013) conducted a similar study to Liu et al. (2013) targeted at the southeastern US but used a different set of GCM/RCM pairings available from NARCCAP. In addition to looking at changes in KBDI, Bedel et al. (2013) also explored changes in the Haines Index that is often related to the potential for large, plume-driven wildfires to grow and exhibit unpredictable behavior (Haines 1988; Winkler et al. 2007). Calculation of the Haines Index involves temperature and specific humidity from different levels in the atmosphere. For the low elevation version of the index appropriate for the southeastern US, that data came from the 950 and 850 hPa pressure levels. The ability to utilize more than just surface data is an advantage of dynamically downscaled over statistical methods.

Other studies have used dynamical downscaling and focused on specific countries and regions. For example, Carvalho et al. (2011) examined the impact of climate change on fire danger at the regional scale using Portugal as a case study. They used the MUGCM with MM5. Canadian Fire Weather Index (FWI) System components were estimated from the MM5 outputs, at 10 km resolution. They found higher FWI values in 2050 at the beginning of summer and increased total area burned. Fox-Hughes et al. (2014) used data from six dynamically downscaled CMIP3 climate models for 1961–2100 to estimate daily values of the McArthur Forest Fire Danger Index (MFFDI) at 10 km resolution over Tasmania, Australia. The MFFDI was developed in the 1960s by CSIRO to measure the degree of danger of fire in Australian forests. Model projections showed a broad increase in fire danger across Tasmania, but with substantial regional and seasonal variation. Days of elevated fire danger increased in frequency during the simulated twenty-first century. They concluded that dynamically downscaled model data were useful projections of future fire danger for landscape managers and the community.

5.3 Applications of Statistically Downscaled Climate

Abatzoglou and Brown (2012) used the MACA statistically downscaled data to analyze fire conditions in the western CONUS (west of 104° W longitude) with the complex meteorology inherent to its heterogeneous landscape. The desired description of fire conditions focused on two daily fire danger metrics widely used in operational fire management, the Energy Release Component (ERC) and the Fosberg Fire Weather Index (FFWI; Fosberg 1978). The ERC is a widely used metric from the US NFDRS (Deeming et al. 1977) that provides a cumulative drying index that responds on multiple time scales tied to fuel size classes based on previous daily temperature, precipitation and humidity. In contrast, the FFWI is not tied to fuel conditions and reflects short-term, weather-driven impacts on wildfire potential that are a function of temperature, wind speed and relative humidity.

The MACA methodology and the more general constructed analog (CA) approach have been used in other fire related studies. Abatzoglou and Kolden (2011) used MACA data in their analysis of the role of climate change and invasive annual grasses on wildfire potential in the deserts of the western United States. Stavros et al. (2014) and Barbero et al. (2015) employed the MACA data in their assessments of the potential for very large fires in the western US and the CONUS, respectively. In these assessments, the MACA data and derived fire danger indices were used as inputs to regional relationships predicting changes in potential for very large wildfires, adding another layer to the description of future fire conditions.

In an examination of climate change and population growth impacts on California wildfires, Westerling et al. (2011) developed daily climate data from six realizations of future climate by downscaling to a 1/8-degree grid usings the CA method following the work of Maurer and Hidalgo (2008). The monthly probability of large (>200 and >8,500 ha) wildfires was modeled using generalized linear models driven by land-surface characteristics, human population, and climate on a 1/8-degree grid. Most scenarios signaled increases in wildfire burned area across much of California, although the range of outcomes was large and increases with time.

6 Concluding Remarks

Climate change under various emission scenarios are projected by GCMs with a typical resolution of a few hundreds of kilometers. The size of most wildfires, on the other hand, is less than tens of kilometers. Downscaling fills the space gap between GCM output and fire applications. Dynamical downscaling is especially valuable for assessing the impacts of climate change on fires at regional and continental scales, in mountains where RCMs are able to capture amplified climate change due to topography-atmosphere interactions and feedbacks, and for estimating fire indices that need atmospheric conditions of multiple variables, at hourly scale, and at atmospheric levels above the ground. Statistical downscaling is especially valuable for assessing the impacts of climate change on fires at local scale, with long and dense meteorological observations, for ensemble analyses, and active involvement of users due to relatively easy applications of the models and low requirements of computing resources.

The CIMP6 GCMs are providing updated global climate change projections under the new SSPs emission scenarios. The corresponding downscaling products are becoming available from, for example, WorldClim (https://www.worldclim.org/data/cmip6/cmip6climate.html) and EURO-CORDEX (Jacob et al. 2020). The CMIP6 projections provide improved simulations of historical climate and higher spatial resolutions with many GCMs, outputs from more GCMs and scenarios for future, and considerations of socioeconomic factors. The downscaled regional and local climate change scenarios of CMIP6 global projections are expected to provide more accurate and climate information and more ensemble products for wildland fire managers to improve decision support. In addition, there is an increasing number of Earth System Models (ESMs) with the CMIP6 projections. ESMs project not only atmospheric but also vegetation conditions, which are important for fires. The vegetation condition themselves are expected to change in future due to climate change, which would change future wildland fires. Thus, the climate change scenarios from CMIP6 would be specifically valuable for assessing the impacts of forest fuel change on wildland fires under changing climate.

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