Research Article

A Comparison of Rangeland Monitoring Techniques for Modeling Herbaceous Fuels and Forage in Central Arizona, USA

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ABSTRACT

While fire and rangeland managers frequently have different land management roles and objectives, their data needs with regards to herbaceous biomass (fuel loads and forage) often overlap, and can be served with a single sampling protocol for both rangeland and fuels management. In this study, we examined how two herbaceous sampling methods compare in measuring species richness, ground cover, and standing herbaceous biomass for range and forestry management using the Phytomass Growth Simulator (Phygrow). Phygrow is an herbaceous vegetation growth model used to simulate rangeland plant production for herbivory, drought, and wildfire severity early warning systems. The Point-frequency protocol has been used for 10 years to

RESUMEN

Aunque los gestores de áreas naturales y aquellos involucrados en el manejo del fuego tienen diferentes roles y objetivos, sus necesidades en cuanto a datos relacionados con la biomasa herbácea (carga de combustible o biomasa forrajera) frecuentemente se superponen y podrían ser usados, para su determinación, basados en un mismo protocolo de muestreo. En este estudio examinamos como dos métodos de muestreo pueden compararse para medir riqueza de especies, cobertura, y biomasa herbácea en pié para determinar tanto forrajes como carga de combustible, usando el simulador Phytomass Growth Simulator (Phygrow). Phygrow es un modelo de crecimiento que simula la producción de plantas para forraje, sequías, y un sistema de alerta temprana de severidad de incendios. El protocolo de puntos de frecuencia ha sido usado por 10 años para coleccionar parámetros de la comunidad para collect plant community parameters for Phygrow. The Common Non-Forested Vegetation Sampling Protocol (CNVSP) is a commonly used rangeland assessment protocol in the southwestern United States. Data from both methods were used to parameterize the Phygrow model to examine their similarities and differences, and to see if data collected from the CNVSP methodology could be used to model herbaceous fuel loads. We determined that the data collected in the CNVSP protocol met the needs for Phygrow model validation of standing herbaceous fuels, but data was insufficient for modeling surface dead fuel loads.

Phygrow. El llamado Protocolo Común para Muestrear Vegetación de Áreas no Forestadas (Common Non-Forested Vegetation Sampling Protocol; CNVSP) es un protocolo de muestreo de vegetación comúnmente utilizado en el sudoeste de los EEUU. Datos de ambos métodos fueron usados para parametrizar el modelo Phygrow, para examinar sus similitudes y diferencias, y ver si los datos colectados con la metodología del CNVSP pueden usarse para modelar cargas de combustible herbáceo. Determinamos que los datos colectados mediante el protocolo CNVSP cumplen con los requisitos para validar el modelo Phygrow para los combustibles herbáceos en pié, pero son insuficientes para modelar la carga de combustibles superficiales muertos.

Keywords: fine fuels, frequency, fuel load, grass, modeling, non-forested areas, Phygrow, rangeland

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INTRODUCTION

The risk of wildfire ignition in grasslands, shrublands, and other non-forested areas is related to the spatial and temporal condition of weather and vegetation variables within an ecological community (Simard and Main 1982). When compared to fire modeling and mapping procedures in forested ecosystems, scientific knowledge in the characterization and interpretation of fine herbaceous and shrub land fuels is lacking (Russell and Tompkins 2005, Stephan *et al.* 2010, Thaxton *et al*. 2012, Hummel *et al.* 2013, Overholt *et al.* 2014). Herbaceous fuel quantity and moisture content is quite dynamic and sensitive to growth rate, seasonality, weather, herbivory, and anthropogenic manipulation (Dale *et al.* 2001), and can be difficult to account for in fire behavior models. Due to the high heat capacity of water, vegetation with high moisture content can act as a heat sink that impedes fire growth, while vegetation with low moisture content may accelerate fire propagation and intensity (Schroeder and Buck 1970, Pyne *et al.*1996). Presently, the dynamic nature of the Standard Fire Behavior Fuel Models (Scott and Burgan 2005) allows for changes in fuel availability based on fuel moistures. However, the choice of a fuel model or the development of a custom fuel model can be difficult given seasonal and daily fuel quantity and moisture fluctuations. Furthermore, data to support analyses of fire effects on herbaceous systems is insufficient. Models such as the Forest Vegetation Simulator (FVS; Dixon 2010) and the Fire and Fuels Extension of FVS (FFE-FVS; Rebain 2013) are capable of simulating total surface fuel loads. However, Hummel *et al*. (2013) found that the FFE-FVS model performed poorly for estimating fine fuels. The need to accurately evaluate and model understory fuels is increasing as expectations for quantitative risk assessments grow, and the infrastructure, habitat, recreational, and other values on these lands are increasingly recognized.

In non-forest areas such as rangelands and shrublands, and within forested understories, near real-time estimations of herbaceous fuel composition, loads, and moisture are necessary for better planning, implementation, and improvement of prescribed fire and wildfire management. The excessive accumulation of fuels and extreme weather conditions in recent years have been the key contributors to extreme wildfires (USDA Forest Service 2000, Schoennagel *et al.* 2004, and Westerling *et al.* 2006). With growing demands from the general public regarding safety and management of fires on public lands, especially near wildland-urban interfaces, methodologies to accurately monitor and estimate dynamic fuel characteristics and effects are vitally important.

The need to accurately evaluate and model understory fuels has increased interest in the use of rangeland simulation models that have historically been used to estimate forage production for livestock, but could be modified for estimating fine fuels. Simulation models on rangelands, shrublands, and non-forested areas can be useful for simulating hydrology, soil erosion, plant growth, or combinations thereof (Bouraoui and Wolfe 1990). Models that have the ability to predict plant biomass on rangelands include the Simulation of Production and Utilization of Rangelands (SPUR) model (Wight and Skiles 1987, Carlson and Thurow 1992, Carlson and Thurow 1996), Ekalaka Rangeland Hydrology and Yield Model (ERHYM-II) (Wight and Neff 1983), Water Erosion Prediction Project (WEPP) (Flanagan and Nearing 1995), Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) (Kiniry *et al*. 2002), Ecological Dynamics Simulation Model (EDYS) (Childress *et al.* 2002), and the Phytomass Growth Simulator Model (Phygrow; Stuth *et al*. 2003*b*)

The Phygrow model estimates aboveground plant growth (fuel addition), forage consumption (fuel reduction) by livestock or wildlife, and hydrologic processes on a daily time-step basis (Stuth *et al*. 2003*b*). Phygrow has been used as part of bioeconomic studies for climate change (Butt *et al.* 2005), optimal grazing management strategies (Souza-Neto *et al.* 2001), brush control investment and hydrology policy analysis (Lee *et al.* 2001, Lemberg *et al.* 2002), and forage forecasting (Alhamad *et al.* 2007), and has been the foundation of drought early warning systems on rangelands in East Africa (Stuth *et al.* 2003*a*, Ryan 2005, Stuth *et al.* 2005), Mongolia (Angerer 2008, 2012), and Afghanistan (GLEWS 2013). In recent studies, it has been used to estimate fine fuel loads on the Fort Hood Military installation in Texas (CNRIT 2013*a*), and on the Lincoln, Coronado, Prescott, and Coconino national forests in New Mexico and Arizona, USA (CNRIT 2013*b*). When properly calibrated, Phygrow can provide daily estimations of total herbaceous biomass, live and standing dead herbaceous biomass, and live-dead fuel moisture.

In order to represent plant growth correctly in the model, the rangeland model needs to be parameterized with field-collected data on the proportional composition of plant species within the plant community being modeled. For Phygrow, a field sampling protocol has been developed to collect this data for model parameterization (Ryan 2005; Angerer 2008, 2012) that is a modification of the Point frequency method (Levy and Madden 1933). However, many natural resource management agencies already have data collection protocols in place that may or may not be similar to the Phygrow method. Therefore, an evaluation of whether current data collection protocols used by natural resource management agencies could be extended for use in parameterizing simulations models to predict fine fuel loads could provide a dual application of the field monitoring data to fulfill both the land management and fire management objectives.

In June of 2008, a workshop was organized at the University of Arizona's V Bar V Ranch on the Coconino National Forest. The workshop was attended by managers, scientists, and administrators from the University of Arizona, Texas A&M AgriLife Research, and USDA Forest Service (USFS) Southwestern Region to demonstrate the Phygrow model and to evaluate current USFS vegetation data collection methods to determine if they could be used for Phygrow model parameterization, or if modifications would need to be made to the existing protocol to gather the required parameterization data. One result of the meeting was the development of the Common Non-Forested Vegetation Sampling Protocol (CNVSP) that used existing USFS sampling procedures and the addition of biomass data and ground basal cover measurements (USDA Forest Service 2013*a*). This protocol would integrate field sampling procedures into a single methodology that would provide the USFS with rangeland and fire monitoring data while also delivering Phygrow data input. Adoption of methods in use by, and familiar to, USFS personnel was important for continuity with historical data sets, management goals, and training procedures.

The purpose of our study was to compare the CNVSP to the Point-frequency procedure traditionally used to gather the field data used to parameterize plant communities in the Phygrow model. Our hypothesis was that the CNVSP method would provide acceptable data in order to calibrate the Phygrow model, thus providing the USFS with value-added enhancements to improve fine fuel monitoring.

METHODS

Study Area

Field data collection occurred in central Arizona on the Coconino National Forest, USA. The Coconino National Forest was established in 1908 and encompasses over 730 000 ha of both forested and non-forested areas, varying from 800 m to 3850 m in elevation. The forest includes an assortment of grassland, desert shrubland, pinyon-juniper (*Pinus edulis* Engelm, *Juniperus osteosperma* [Torr.] Little, and *J. deppeana* Steud.), and ponderosa pine (*Pinus ponderosa* Lawson and C. Lawson) dominated plant communities (USDA Forest Service 2013*b*). Mean yearly precipitation across all study sites was 47.44 cm in 2008, 19.42 cm in 2009, and 52.11 cm in 2010 (NOAA 2013).

Phygrow Model

The Phygrow model estimates plant growth based on the species proportion in the plant community (as estimated from the CNVSP and PF [Point-frequency; Ryan 2005] methods) and soil water availability (Stuth *et al*. 2003*a*, Angerer 2008). Water balance is calculated from the interaction of four main components: climate, soil, vegetative growth, and herbivory (Stuth *et al.* 2003*b*). The soil profile acts as a water repository that is replenished by precipitation and depleted by vegetation transpiration and evaporation. Soil parameters include depth of each horizon, percent rock, saturated hydraulic conductivity, bulk density, infiltration, and water holding capacities. Plant communities may be parameterized in the model as individual species, or lumped into functional groups. Plant community composition parameters include initial standing crop, basal cover of grasses, frequency of forbs, and canopy cover of woody and succulent plants. Individual plant species are characterized with up to 27 parameters. The basic required parameters are minimum, optimum, and maximum plant growth temperatures; leaf area index; dry matter to radiation ratio (radiation use efficiency); leaf and wood turnover (i.e., proportion of biomass that transfers from standing green to standing dead to surface litter); leaf and wood decomposition rate; and plant rooting depth (Angerer 2008).

Field Sampling Protocol

Site selection. We chose 14 locations on or near previously established USFS rangeland monitoring transects. Sites were chosen based on the availability of USDA Natural Resources Conservation Service (NRCS) Soil Survey Geographic (SSURGO) data (USDA NRCS 2013). SSURGO-level soil data is commonly used in hydrologic and agricultural models to simulate soil water retention and runoff (Drohan *et al.* 2003, Wang and Melesse 2006, Mednick 2010), allowing us to quickly identify basic soil characteristics for model parameterization.

Eight of the sites had a juniper overstory with an understory composed primarily of side-oats grama (*Bouteloua curtipendula* [Michx.] Torr.), blue grama (*B. gracilis* [Willd. ex Kunth] Lag. ex Griffiths), threeawns (*Aristida* sp. L.), and broom snakeweed (*Gutierrezia sarothrae* [Pursh] Britton and Rusby). Five sites were dominated by a ponderosa pine overstory, with blue grama, junegrass (*Koeleria macrantha* [Ledeb.] Schult.), western wheatgrass (*Pascopyrum smithii* [Rydb.] A. Love), and broom snakeweed as the predominant understory species. One site was a grassland site dominated by tobosagrass (*Pleuraphis mutica* Buckley), with no woody overstory.

General site attributes collected were date of collection, latitude and longitude coordinates, aspect, transect bearing, and slope. We chose transect bearings that were perpendicular to the slope and stayed within the soil boundary. Two transects, one for each sampling protocol, were established parallel to each other at a distance of 10 m apart at each site location. Basal ground cover and quadrat frequency data were collected in the summers of 2008 and 2009 (Table 1). Standing herbaceous biomass was collected in the summers of 2008 and 2010 (Table 1).

Table 1. Summary of data collection dates for the Common Non-Forested Vegetation Sampling Protocol (CNVSP), and the Point-frequency protocol (PF).

Year	CNVSP	PF	Biomass
2008: Jul	X	X	X
2009: Aug	X	X	
2010: Jul to Sept			X

Point-frequency protocol. The Phygrow model is usually parameterized via data collected from a one-meter wide Point-frequency (PF) frame (Ryan 2005; Angerer 2008, 2012) (Figure 1A). The PF frame consists of five pins spaced equidistant that are used to measure basal ground cover characteristics: bare ground, rock, surface fuel (identified as 1-hr herbaceous and woody surface fuels, or 10-hr, 100-hr, and 1000-hr dead surface fuels [Fosberg 1970, Pyne *et al.* 1996]), and perennial grass. Centered on each of the five pins is a 5 cm × 5 cm quadrat used to record annual grass, perennial forb, and annual forb rooted frequency. Woody plant cover is measured by laying a small mirror with a point in the center on each quadrat. If the point is intercepted by a woody plant canopy, a hit is recorded. In the case of multiple overlapping canopies, the species of the first canopy encountered is recorded. The PF frame is placed once every five footsteps along a linear transect for a total of 50 times, yielding a total of 250 possible pins and frequency quadrats per transect.

Common Non-Forested Vegetation Sampling Protocol. The CNVSP frame consists of a 40 cm × 40 cm quadrat, with a 10 cm × 10 cm nested quadrat (Figure 1B). In order to capture ground basal cover needed for fuels monitoring and Phygrow simulation, three basal hit pins were added to the perimeter of the larger quadrat at the 1, 6, and 11 o'clock positions. Bare ground, rock, surface fuel, and perennial grass basal cover were observed with pin hits at these positions. For this study, we only used forb and annual grass frequency within the 10 cm × 10 cm quadrat, given that the 40 cm × 40 cm quadrat would result in much higher forb and annual grass frequency estimates, which would inflate the proportions of these species in the Phygrow model parameterization. Data collected in the 40 cm × 40 cm quadrat was collected and retained for other USFS purposes. Woody plant hits were re-

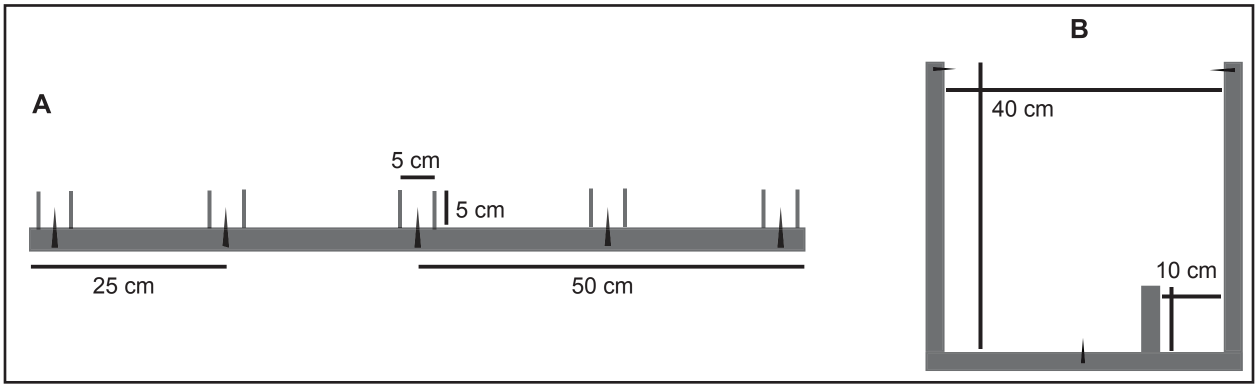

Figure 1. Vegetation sampling frames used in this study. The Point-frequency frame (A) has been the standard for the Phygrow model. The Common Non-Forested Vegetation Sampling Protocol (B) is part of the USFS Southwest Region's monitoring methodology.

corded if the canopy intersected a hypothetical vertical extension of the 10 cm × 10 cm quadrat, counting only the first species' canopy that was encountered. The CNVSP frame was placed every two footsteps, 100 times, for a total of 300 possible pin hits and 100 quadrats per transect.

Cover and frequency. For each sampling protocol in this study, cover was defined as percent ground basal cover as measured from the tip of a pin. If the pin tip contacted the base of a plant, a hit for that species was recorded. If no plant was hit, then the hit was recorded as bare ground, rock, or surface fuel. Frequency for both protocols was simply a binary absence or presence measure of each rooted species (forbs and annual grasses) within a quadrat. Cover and frequency were then calculated as a function of observed hits divided by the maximum possible hits from each transect.

Woody species characterization. In attempting to model herbaceous fuel production, it was important that we parameterized the woody plant components within each plant community to properly account for competition and soil water use by woody plants. As the Phygrow model is driven by hydrological processes (precipitation, infiltration, runoff, evaporation, and plant water use), the structural dimensions of an average specimen of each woody species was recorded for each transect location. Parameters recorded include total plant height, maximum crown width, height at maximum crown width, crown base width, and crown base height (Figure 2). This information was recorded at each of the 14 sites and was used in Phygrow simulations for both methodologies.

Herbaceous biomass. In order for us to calibrate the plant growth parameters within the Phygrow model, for fine fuel biomass estimation, herbaceous biomass data was also collected. This involved the harvest of live herbaceous vegetation and standing dead biomass, drying for 48 hr at 70 °C, weighing, and converting into kg ha^{-1}. The PF sampling protocol utilized 10 circular 0.25 m^2 quadrats in which herbaceous biomass was clipped from the quadrat (leaving 1 cm stubble). The clipping quadrat was placed at every fifth reading of the point frame along the transect. For the CNVSP protocol, we clipped herbaceous biomass from the 40 cm × 40 cm (0.16 m^2) frame after every tenth reading of the frame, for a total of 10 clippings per transect. Herbaceous surface fuels (i.e., detached plant fragments not part of standing biomass) and 1-hr woody surface fuels (woody material <0.62 cm) were

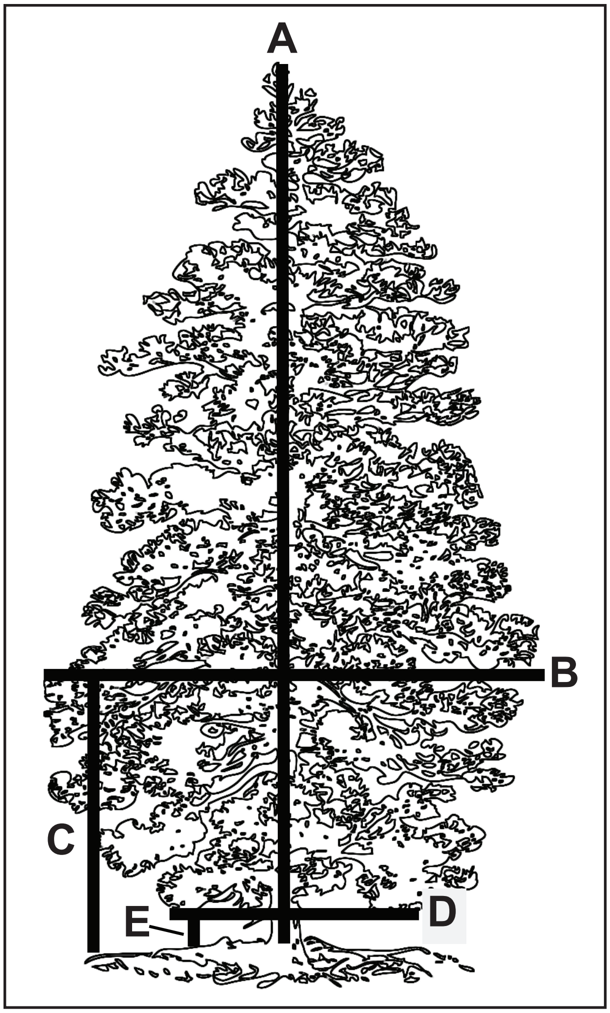

Figure 2. Woody plant characteristics collected for the Phygrow model include: total height (A), maximum crown width (B), height at maximum crown width (C), crown base width (D), and crown base height (E). All measurements are entered in the Phygrow model in centimeters.

also collected at the second and eighth clipping station on each transect. As we did not have data on livestock numbers and rotations for every monitoring location, we visually estimated the percent grazing use of each frame before clipping (Smith *et al.* 2012), thus allowing us to estimate total potential production with the Phygrow model. Biomass data were collected in the summers of 2008 and 2010 (Table 1) in order to provide two temporally spaced biomass data records for model calibration adjustments (Angerer 2012).

Model input. Following field data collection, the Phygrow model was parameterized for each site and sampling protocol using the plant community data collected in 2008. For site-specific soil parameters, we used the Map Unit User File (MUUF) tool to perform pedotransfer regressions on the SSURGO data to obtain hydraulic conductivity and water holding variables (Rawls *et al.* 2001). The model was then calibrated using the 2008 and 2010 herbaceous biomass data. Phygrow calibration requires temporally spaced biomass measurements (here 2008 and 2010) in order to model production across multiple points in time. Calibration proceeds by adjusting plant growth curves, growth, and turnover rates until the output falls within one standard error of the field observed biomass.

Statistics

Field data comparison. We estimated the relationship between basal ground cover (bare ground, surface fuels, rock, and perennial grass; Table 2), species richness (total and by functional group; Table 3), and biomass from the PF and CNVSP protocols using Pearson's correlation coefficient (Galton 1888, Pearson 1896, Zou *et al.* 2003). Also known as Pearson's *r*, it is used to test for linear correlation between two values. Pearson's *r* is defined by

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad , \qquad (1)$$

where $\bar{X}$ and $\bar{Y}$ are the sample of means of X_i and Y_i sample values, and n is the number of data pairs.

Pearson's r ranges from −1 to +1, where +1 is complete correlation, and −1 represents total inverse correlation. Where r is equal to zero, then there is no correlation. Each r statistic has a corresponding P value expressing the significance of the correlation.

Frequency was not directly compared between sampling methods as it is a function of

Table 2. Pearson's *r* correlation coefficients for ground cover characteristics measured using the Point-frequency (PF) protocols versus the Common Non-Forested Vegetation Sampling Protocol (CNVSP), and their associated significance values (*P*).

	CNVSP		PF			
	Mean	**SE**	**Mean**	**SE**	**Pearson's *r***	***P***
Perennial grass	5.31	0.71	4.63	0.79	0.74	<0.001
1-hr fuel	45.40	2.76	47.87	2.37	0.81	<0.001
10-hr fuel	0.86	0.17	0.88	0.18	0.43	0.02
100-hr fuel	0.33	0.07	0.26	0.10	0.48	0.01
1000-hr fuel	0.23	0.08	0.31	0.12	0.22	0.25
Combined fuel	46.82	2.65	49.32	2.32	0.79	<0.001
Bare ground	26.19	3.48	25.06	3.13	0.92	<0.001
Rock	21.68	2.64	20.99	2.64	0.96	<0.001

Table 3. Mean species richness by plant functional group and standard error (SE) for Common Non-Forested Vegetation Sampling Protocol (CNVSP) and Point-frequency (PF) sampling protocols with Pearson's *r* correlation coefficient and significance values (*P*).

	CNVSP		PF			
	Mean	**SE**	**Mean**	**SE**	**Pearson's *r***	***P***
Perennial grass	2.32	0.98	2.29	1.21	0.54	0.003
Annual grass	0.50	0.79	0.50	0.96	0.68	<0.001
Perennial forb	5.29	2.52	4.36	2.75	0.65	<0.001
Annual forb	2.50	1.82	2.57	2.11	0.57	0.002
Woody	2.32	1.76	2.11	1.42	0.13	0.500
Succulent	0.25	0.44	0.14	0.36	0.00	1.000
Total richness	13.18	5.03	11.96	5.04	0.59	0.001

quadrat size relative to species density and dispersion (Mosley *et al.* 1989). Due to each frequency protocol having differing quadrat sizes, spatial placement, and number of quadrats, direct comparisons of frequency were not practical. Rather, we relied on model calibration as a metric of sampling effectiveness.

Phygrow calibration. We plotted the simulated and observed means of herbaceous biomass in a linear regression to inspect predictive strength of the Phygrow model (r^2) (Carlson and Thurow 1996). However, r^2 values alone are not sufficient in the assessment of model goodness of fit, as it is extremely sensitive to outliers and variability in magnitude (Willmott 1981, Willmott *et al.* 1985, Kessler and Neas 1994, Legates and Davis 1997). Therefore, to further explore model performance, we also relied upon root mean square difference and index of agreement (Angerer 2008).

Root mean square difference (RMSD; also referred to as root mean square error) measures model performance by describing the average magnitude of the difference between field observations and model outputs. RMSD is much more sensitive to extreme values in the data, and is used to complement r^2 values (Willmott 1981, 1982; Legates and McCabe Jr. 1999). It is calculated as

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \quad , \qquad (2)$$

where P_i is the i^{th} predicted value, and O_i is the i^{th} observed value, and n is the number of data pairs (Willmott 1981).

Finally, we complemented the r^2 and RMSD with the index of agreement (d; also known as Willmott's d), which is a measure of the tightness perceived between observed and simulated values (Willmott 1981, 1982; Andales *et al.* 2005). It is used to test the degree to which a model's simulations are error free, and is calculated as

$$d = 1.0 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \ . \qquad (3)$$

Values of d vary from 0 to 1, with higher numbers representing more agreement between observed and simulated outcomes.

RESULTS

Field Sampling

Perennial grass, 1-hr surface fuel, total surface fuel, bare ground, and rock were all strongly correlated between ground cover sampling methods ($P < 0.05$; Table 2). Two fuel classes, 10-hr and 100-hr ground cover, displayed a weak correlation between sampling methods, and 1000-hr fuels were poorly correlated.

Species richness was moderately correlated between sampling protocols for perennial grass, annual grass, perennial forbs, annual forbs, and total combined richness (Table 3). Woody plant species richness was poorly correlated (r = 0.13), with the CNVSP capturing slightly more woody plants, while succulent richness showed no correlation between the two sampling protocols.

We found that herbaceous standing crop was positively correlated between the two sampling methods for both sampling periods (Table 4). Surface fuels biomass, however, was very poorly correlated between sampling protocols (Table 4).

Phygrow Model Calibration

We were able to satisfactorily calibrate the model with herbaceous standing crop data from each sampling protocol. In 2008, we calibrated 100 % of the sites within one standard error. With the addition of the 2010 data, we were able to maintain calibration on 85.71 % of the CNVSP model runs, and 92.85 % of the PF runs. Of the three model runs that we were not able to calibrate in 2010 (two CNVSP and one PF), all were within two standard errors of calibration.

Table 4. Pearson's r correlation coefficient and significance level (P) for herbaceous standing crop and 1-hr fuel.

	2008					
	CNVSP		PF			
	Mean	**SE**	**Mean**	**SE**	**Pearson's r**	**P**
Herbaceous standing crop	801.39	214.18	840.52	224.64	0.56	0.047
1-hr surface fuel crop	704.24	115.58	1496.45	855.91	0.05	0.874
	2010					
Herbaceous standing crop	1227.79	328.13	1127.99	301.47	0.86	<0.001
1-hr surface fuel crop	1299.87	264.02	867.14	187.13	0.18	0.540

As evidenced by r^2 and index of agreement (d) values, our herbaceous model simulations provided a good fit with low error (Table 5). When using data collected with the CNVSP, the Phygrow model, on average, over-predicted standing crop by 69 kg ha^{-1} and 1-hr surface fuels by 43 kg ha^{-1} during 2008, but under-predicted these variables by 206 kg ha^{-1} and 590 kg ha^{-1}, respectively, in 2010 (Table 5). Using data from the PF method, the Phygrow model under-predicted standing crop and 1-hr surface fuels by 10 kg ha^{-1} and 4 kg ha^{-1}, respectively, in 2008. In 2010, the model under-predicted standing crop by 107 kg ha^{-1} and over-predicted 1-hr surface fuels by 665 kg ha^{-1} with the PF inputs (Table 5).

Model performance for 1-hr surface fuels in 2010 was poor for both the CNVSP and PF methods (Table 5). The large RMSD for 1-hr surface fuels in both methods indicates a large degree of variability in model predictions and field data, and is further evidenced by poor r^2 and d values (Table 5).

DISCUSSION

Our ability to sufficiently model herbaceous production gives us confidence to further explore the Phygrow application for fuel and standing crop modeling in southwestern US ecosystems. Output from the Phygrow model is spatially and temporally explicit and

Table 5. Observed and simulated results for standing crop and 1-hr fuel (herbaceous and woody) for each sampling method by year. Pearson's r correlation coefficient, significance values (P), and goodness of fit measures (r^2 and index of agreement, d) are provided for the observed versus simulated results. Means, standard deviation (SD), and root mean square difference (RMSD) are all reported in kg ha^{-1}.

	2008			
	Standing crop		**1-hr surface fuel**	
	CNVSP	**PF**	**CNVSP**	**PF**
Observed mean	801.39	840.52	704.24	1496.45
Observed SD	481.47	400.14	432.45	2961.67
Simulated mean	870.67	830.42	747.36	1492.33
Simulated SD	492.11	402.37	435.02	2948.95
RMSD	122.29	157.61	107.97	42.23
r^2	0.96	0.84	0.95	0.99
Index of agreement (d)	0.98	0.96	0.98	0.99
Sample size (n)	14	14	14	14
	2010			
Observed mean	1227.79	1128.00	1299.87	867.14
Observed SD	590.99	727.12	987.86	700.16
Simulated mean	1022.12	1020.77	709.28	1532.31
Simulated SD	665.38	570.55	521.14	3202.54
RMSD	417.01	194.77	1372.91	3342.29
r^2	0.68	0.99	0.16	0.03
Index of agreement (d)	0.88	0.98	0.02	–0.03
Sample size (n)	14	14	14	14

can be entered into fire behavior and spread models to provide early warning and information for risk management. The success of the herbaceous model calibration leads us to believe that the frequency measurements from the CNVSP are compatible with current Phygrow data needs.

When parameterizing the plant communities in the Phygrow model, we chose to use only the 2008 transect data. We did this in part due to it being a more representative year weather-wise, and because we did not have corresponding herbaceous biomass data for 2009 (Table 1). More research is needed on the effects of using plant community data from a drought year versus a wet year in herbaceous fuels modeling.

Our inability to match 1-hr surface fuel production in Phygrow is most likely an issue with sampling protocol and quadrat quantity. During the workshop at which the CNVSP was written, there was much concern over time constraints for field crews if data collection for model parameters became too extensive. Retaining 10 vegetation and 10 1-hr surface fuels samples for every site that would require drying and weighing later could place a substantial work load on crews that are already required to collect large amounts of data at each site. A compromise was made to only collect two 1-hr surface fuels samples per location, which, through the analyses presented here, appears to be insufficient for model calibration. In the future, a more rapid estimation of 1-hr surface fuels, such as the comparative yield method (Haydock and Shaw 1975) or a modified double sampling technique (USDA NRCS 2003), could possibly be utilized in order to obtain a larger sample size without substantially increasing work load.

Additionally, there was a poor to moderate correlation between large surface fuels cover (10-hr, 100-hr, and 1000-hr fuels) for the two methods. Woody plant overstory on our study sites was light to moderate, allowing us to move freely through the sites without obstruction. These larger fuels tend to make up a small, and non-uniform, portion of the total fuel load in non-forested and moderately forested areas (<1% average cover across all study sites and dates). It is possible that this is due to transects being parallel to each other, and random placement along a line that is measured in footsteps that can vary from one individual to the next.

The Phygrow model includes an optional herbivory simulation that was not used in this study. When herbivore species' daily intake and plant preferences are known, then daily herbage removal estimates are possible. The ability to model wildlife and livestock reduction of fuel loads through consumption of biomass by herbivory may prove useful for mapping dynamic fuel fluctuations and warrants further exploration.

Overall, the data provided by the CNVSP was sufficient for model parameterization and demonstrated that the CNVSP can be used for modeling herbaceous plant growth, and therefore fine fuel production, in the Phygrow model. The addition of the basal cover assessment to the USFS protocol provides us with the data necessary for building simulation modeling scenarios, and gives land managers additional descriptive information about fuel and herbage cover. Ground cover characteristics can be a good indicator of site hydrologic function, soil stability, and general health of a landscape (Pellant *et al.* 2000, Pyke *et al.* 2002), while species richness can be used to relate to niche differentiation and is instrumental to understanding and preventing exotic species invasion (Tilman *et al.* 1997, 2001).

Knowledge of field conditions is of paramount importance for rangeland and fire management planning. Whether a land manager is viewing the herbaceous biomass from a grazing or a fuels standpoint, the fact remains that, in order to make an informed decision, one must have data on the structure, use, and trends present in the field. Time and resources are often limited, which makes the use of computer model simulations more appealing. With the aid of nearest neighbor interpolation methods (Lister *et al.* 2004, Crookston and Finley 2008) and geographical information systems (GIS), model simulated plant growth can provide near real-time maps of fuel and forage conditions over a much broader area. Moving forward, long term model simulation validation studies using the CNVSP are of primary concern, as well as exploration of other 1-hr surface fuels sampling protocols, fuel moisture validation, and GIS applications such as wildfire behavior modeling to improve risk management decision making.

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