1 Whether restored wetland hydrology improves wetland function often goes unstudied
2 I investigate if reduced groundwater pumping enhances wetland soil carbon (C) storage
3 Monte Carlo methods propagate error through 3 relationships linking pumping to soil C
4 Less pumping enhances soil C, but C gains are uncertain at severe pumping cutbacks
5 The dynamic response of soil C to soil inundation time accounts for most uncertainty
6

**Response of wetland soil carbon to groundwater conservation: probabilistic outcomes from
error propagation**

David Bruce Lewis

Department of Integrative Biology

University of South Florida

Tampa, FL 33620, USA

davidlewis@usf.edu

1-813-974-8108

Abstract

Water loss compromises functions performed by wetland ecosystems. Efforts to rehabilitate wetland function typically begin with attempts to reestablish hydrology. These activities are often not monitored, so tools to extract information from them could partly offset the lost opportunity to learn from whole-ecosystem hydrological manipulation. In 2002, groundwater abstraction was lessened by 35% throughout 1,700 km² of west-central Florida (USA). I assembled a pathway of correlations to project how this hydrological manipulation affected water levels and soil carbon (C) storage in overlying wetlands. Parameter values and residual error in these statistical models were resampled from known variances, thereby propagating uncertainty through the pathway of relationships, and expressing the response of soil C probabilistically. Projected soil C probability distributions were most distinguishable between full and moderate (30% less) abstraction. With more severe abstraction cutbacks, gains in projected soil C became more marginal and uncertain, suggesting that wetland soil C pools are not notably impacted by low-volume groundwater abstraction. Reducing uncertainty in projected soil C will require better understanding the dynamic response of soil C to increases in the amount of time that wetland soil is inundated. The step-by-step error propagation routine presented here is a platform for assimilating information from diverse sources in order to project probabilistic responses of ecosystem function to wetland restoration attempts, and it helps identify where further certainty is most wanted in a pathway of cause-effect relationships.

47 **Keywords:** cypress swamp, decomposition, groundwater abstraction, Monte Carlo, soil organic
48 matter, uncertainty

1. Introduction

Wetland structure and function are defined by wetland water balance, meaning that water loss poses a threat to wetland conservation (NRC, 1996). Wetland water loss occurs for several reasons, including climate change (Klein et al., 2005; Roulet et al., 1992), land reclamation (Baldock et al., 1984; McCorvie and Lant, 1993), and water appropriation (Rains et al., 2013). Water appropriation is a growing concern because groundwater abstraction is now faster than aquifer recharge (Gleeson et al., 2012; Richey et al., 2015), which dictates falling water tables. This syndrome of wetland dewatering presents the restoration question of whether reestablishing wetland hydrologic regimes will rehabilitate wetland ecosystem structure and function (Acreman et al., 2007; Zedler, 2000).

One prominent function of wetland ecosystems is the storage of carbon (C) in soil organic matter (Ahn et al., 2009; Marín-Muñiz et al., 2014). Wetlands store 9-19% of the C contained in the terrestrial plus surface-ocean biosphere, mostly in their soils, yet cover $\leq 1\%$ of the planet surface (Bridgham et al., 2006; Mitra et al., 2005). Such massive C storage supports several ecosystem services: it mitigates global climate by sequestering carbon away from the atmosphere, it supports secondary productivity by supplying abundant energy for heterotrophic organisms, it benefits water quality by fueling the removal of pollutants from hydrologic flowpaths, and it supports primary production by releasing a steady supply of plant nutrients bound to soil organic C (SOC).

These SOC-mediated services are vulnerable to water loss because the preservation of wetland soil C depends on frequent soil saturation. Soil organic C accumulates in wetlands

because soil enzyme activity and decomposition are slowed by prolonged soil saturation and anoxia (Day and Megonigal, 1993; Freeman et al., 2004; Lewis et al., 2014; McLatchey and Reddy, 1998; Skopp et al., 1990). Conversely, water loss triggers C export from wetlands by stimulating the oxidation of organic matter (Bridgham et al., 1998; Fenner and Freeman, 2011; Updegraff et al., 1995) and by inducing export of dissolved organic matter in outflowing water (Pastor et al., 2003; Strack et al., 2008). By accelerating organic matter efflux from wetlands, dewatering shrinks the standing stock of C in wetland soils (Bridgham et al., 2008; Craft and Richardson, 1993; Lewis and Feit, 2015; Pitkänen et al., 2013).

A pressing question is therefore whether wetland SOC stocks can be recovered by reestablishing high water tables. Indeed, several studies (mostly in peatlands) generally find that rewetting dewatered wetlands can cause C exports to slow within months of implementing restoration measures, and cause wetlands to become net C importers within months to years (Cagampan and Waddington, 2008a,b; Tuitilla et al., 1999; Waddington and Price, 2000). Soil C stocks in rewetted wetlands can reach levels found in intact reference systems within a decade (Gao et al., 2014), although a meta-analysis of diverse wetland types reveals that carbon stocks in restored wetlands reach only 50% of natural levels even 20 years after restoration efforts (Moreno-Mateos et al., 2012). In situ studies such as these, where hydrology is manipulated at the whole-wetland extent, are valuable, yet they are unfortunately expensive and rare. In many instances of hydrological manipulation, adequate data are not collected to determine if ecosystem services have recovered in turn. The failure to monitor ecosystem response to attempted restoration is a missed opportunity to learn from the widespread management practice of whole-system manipulation, and it diminishes return on investment in these expensive activities (Alexander and Allen, 2006; Bernhardt et al., 2005). Accordingly, methods to extract

information from unmonitored restoration activity could return some of this lost value (Berkowitz, 2013).

One such method is to aggregate information that links hydrological manipulation with ecological responses such as soil C storage. For instance, it may be feasible to combine information from multiple studies to assemble a step-by-step pathway of relationships ($X_1 \rightarrow \dots \rightarrow X_n \rightarrow Y$) that connects the mechanism of wetland water loss (e.g., groundwater abstraction) with water table elevation, wetland inundation time, and ultimately wetland soil C storage. This approach, known as step-by-step prediction, sequentially links multiple empirical models such that the predictor (X_n) of one variable (Y) is itself predicted by at least one other (X_{n-1}) (Håkanson and Peters, 1995). This approach is illustrated in a step-by-step model that predicts mercury (Hg) concentrations in piscivorous game fish (Hg_{pi}) in boreal cool-summer lakes. In this illustration, Håkanson (1999) identifies an empirical regression model of Hg_{pi} as a function of Hg concentrations in planktivorous prey fish (Hg_{pe}), a model of Hg_{pe} as a function of several variables including bioavailable reactive Hg concentrations in water (RHg), and a model of RHg as a function of lake color and tributary discharge. A step-by-step model is then assembled to predict Hg_{pi} from lake color and discharge. This approach is used in place of a sole multiple regression model that might predict Y from all X_1 - X_n in cases where causal relations truly are sequential and in cases where each empirical relationship is fit using a different dataset. Error is introduced at every step, inflating confidence limits around the final predicted variable, Y (Håkanson 1999).

An analogous sequence of relationships could inform how wetland soil C storage might respond to lessened groundwater abstraction. However, uncertainty would accumulate across such a sequence of relationships. Consequently, some projected outcome (soil C storage) has a

probability distribution, rather than a discrete value, given a manipulation such as lessened groundwater abstraction (Carpenter, 1998). The important question is whether projected increases in soil C are sufficiently large, relative to uncertainty, for probabilities to be distinguished between dewatered vs. hydrologically restored wetlands.

Soil C (or any predicted response variable) can be expressed probabilistically by incorporating parameter uncertainty in models that relate it to its predictor variables, or by adding residual error (ϵ) to model output ($\hat{Y}$). Uncertainty in parameter estimates can be incorporated by resampling from known parameter variances, so parameter values are different every time a model projects a response variable (Crowley, 1992). Likewise, the ϵ added to $\hat{Y}$ can be resampled from a known distribution of residuals. Using a resampling approach in each relationship will propagate error through a step-by-step pathway. For example, Blukacz et al. (2005) compute annual lake zooplankton production from directly measured variables through several intermediate calculations. They incorporate statistical error at each step by resampling from raw data or from probability distributions, thereby better estimating the full magnitude of error in their final computed variable (zooplankton production). Treating ecological outcomes as probabilistic takes advantage of pre-existing information, such as quantified parameter variance (Holtgrieve et al., 2010). It also avoids the unrealistic expectations conveyed by discrete model predictions, which in turn may result in more easily defended decisions about implementing management strategies (Olson et al., 1998).

Here, I propagate statistical error through relationships linking groundwater abstraction, wetland hydrology, and soil C storage in order to project a probability distribution for wetland soil C when groundwater abstraction is lessened. This procedure is applied to west-central Florida (USA), where wetlands sit over a groundwater aquifer that is abstracted to serve the

Tampa Bay region. In late 2002, groundwater abstraction volume was lessened in order to mitigate harm to surface waters (TBW, 2009). My objectives here are to propagate error through statistical relationships that link groundwater abstraction to soil C in order [1] to determine whether soil C probability distributions can be distinguished between scenarios with restoration (lessened groundwater abstraction) and without restoration (historically intense groundwater abstraction), and [2] to identify where to reduce error in order to best tighten these soil C probability distributions. An additional objective was [3] to corroborate whether wetland hydrology actually was rehabilitated when groundwater abstraction was lessened.

2. Methods

2.1. Study region

Freshwater mineral-soil wetlands cover about 14% of west-central peninsular Florida, and commonly form in depressional basins. Most basins are cypress forest swamps characterized by pond cypress (*Taxodium ascendens*, sometimes considered a variety of *T. distichum*) (Haag and Lee, 2010). They are colloquially referred to as cypress domes, as the tallest trees are found in the basin center, creating a dome-shaped canopy. These basins are fed by an unconfined surficial aquifer and are seasonally inundated even in a hydrologically unimpaired state. These wetlands are interspersed throughout an upland landscape of pine flatwoods habitat, which is composed of *Pinus* species and the shrub saw palmetto (*Serenoa repens*). This low-elevation (15 m) coastal region along the Gulf of Mexico has little topographic relief and receives 1,353 mm/y of precipitation. Average temperatures are 15 °C in January and 28 °C in August, with a mean humidity of 73% (National Climatic Data Center, 1981-2010).

This wetland complex overlaps the 1,700-km² Northern Tampa Bay water management zone (Rochow, 1998). Within this management zone, groundwater from the confined Floridan Aquifer (which lies beneath a clay confining layer and the unconfined surficial aquifer) is abstracted to meet the demands of 2.87 million people in the Tampa Bay metropolis, and associated agricultural and extractive industries. In 2012, water was abstracted from the Floridan Aquifer at 681 ML day⁻¹ and delivered to urban (76%) and agricultural (24%) users (Ferguson, 2014). Of this volume, 298 ML day⁻¹ was taken from a consolidated network of 13 wellfields. This magnitude of groundwater abstraction has been sustained for decades, as abstraction from the wellfield network has exceeded 250 ML day⁻¹ (running 12-month average) since 1975 (data, Southwest Florida Water Management District). The wellfield network comprises a collection of distinct land parcels (each a wellfield) that are generally distal to the built urban environment (Fig. 1). This network is operated by Tampa Bay Water, a public water utility consisting of county and municipal member governments.

Pumping the confined Floridan Aquifer has a spatially heterogeneous impact on the overlying unconfined surficial aquifer. The elevation of the unconfined water table varies as a function of distance from abstraction points, heterogeneity among abstraction points in abstraction volume, and discontinuities in the clay confining layer (Lopez and Fretwell, 1992; Sinclair, 1982; Stewart and Stedje, 1990; TBW, 2009). Spatial variation in the elevations of the unconfined water table and the land surface is manifest as variation among groundwater-fed wetlands in hydroperiod (Nilsson et al., 2013), with hydroperiod (percent time soil is inundated) then partially regulating soil C accumulation in cypress swamp wetlands (Lewis and Feit, 2015). Groundwater abstraction is thus linked to wetland soil C through a pathway of relationships that each has error. By propagating this error, I project probability distributions for soil C values that

might be expected from cutbacks in abstraction. This routine is specific to soil C in depressional-basin cypress swamps of west-central Florida. These wetlands typically have poorly developed (Inceptisols and Entisols) sandy, hyperthermic, siliceous soils (Soil Survey Staff 2014) with a 0-6-cm thick soil organic horizon underlain by a 4-30-cm thick A horizon, in turn followed by either an E or B horizon containing 0.2-1.1% organic matter by mass (*unpublished data*). Table 1 shows soil organic matter, nutrient, and texture characteristics (from Lewis and Feit, 2015) integrated over the top 30.5 cm of the soil profile.

2.2. Error propagation routine

The error propagation routine links three relationships: [1] the influence of reduced groundwater pumping (*ppr*) on a change in water level (*dWL*); [2] the influence of *dWL* on wetland hydroperiod (*hp*); and [3] the influence of *hp* on wetland soil C (C_s). Each relationship has been empirically documented by studying a population of locations throughout the study region, and is described with a least-squares statistical model. A single application of the error propagation routine consists of 50,000 iterations. For each application, I chose a specific percent pumping reduction (*ppr*), or percent cutback in groundwater abstraction (e.g., 50%), as well as a specific focal elevation in a wetland basin (e.g., 50 cm above basin bottom). Focal elevation and *ppr* were then held constant for all iterations of that application. In each iteration, I projected a single *dWL* value using random parameter values for the *ppr-dWL* statistical model. The generated value for *dWL* was then used to project a single *hp* from a model linking *dWL* to *hp*, again with random error added to *hp*, and so on for projecting a single C_s from the *hp-C_s* relationship (Fig. 2). Each iteration of the routine uses a new random draw for parameter values or residual error in the three relationships, although all draws of a specific parameter (e.g., slope

of the hp - C_s relationship) are from the same probability distribution for that parameter. When iterated 50,000 times, this routine generates a distribution of C_s values that are reasonable (given uncertainty in statistical models) for any ppr and elevation. By resampling parameter and residual error values from their own probability distributions, in order to obtain a distribution of some projected variable (e.g., C_s) that is itself probabilistic, I employ a Monte Carlo method of incorporating uncertainty into statistical relationships. Holtgrieve et al. (2010) and Houska et al. (2014) illustrate similar Monte Carlo approaches that resample from parameter distributions to estimate uncertainty in model output, although many types of Monte Carlo application exist.

2.3. *Lessened abstraction (ppr) and change in water level (dWL)*

To statistically model the relationship between ppr and dWL , I acquired data on these two variables from an experiment conducted by Tampa Bay Water (TBW, 2009). This water utility company lessened groundwater abstraction in eleven wellfields at the beginning of water year 2003 (01 Oct 2002), and defined ppr for each wellfield as the percent decrease in mean daily water abstraction between a 6-y window (1997-2002) of higher abstraction and the subsequent 6-y window (2003-2008) of lower abstraction (year numbers refer to water years). For context, ppr ranged among the eleven wellfields from 8% (abstraction reduced from 43.4 to 39.9 ML d⁻¹) to 60% (abstraction reduced from 54.7 to 22.1 ML d⁻¹). The absolute change in abstraction (change in ML d⁻¹) and the percent change in abstraction (ppr) were correlated ($r = 0.82$, $n = 11$ wellfields). Abstraction throughout the full consolidated wellfield network was reduced by 35%, from 571 ML d⁻¹ during 1997-2002, to 373 ML d⁻¹ during 2003-2008. An additional reference area was identified where no abstraction occurs and thus $ppr = 0$.

The *dWL* for each area (each wellfield and reference area) was defined as mean precipitation-corrected water table elevation during the period of lower abstraction (2003-2008) minus water table elevation during the earlier period of higher abstraction (1997-2002). Mean water table elevation for each area and time period was calculated from water level observations made at least monthly at replicate ($n = 10-63$) water-table monitoring stations (TBW, 2009). The 2003-2008 period of low abstraction was rainier than during 1997-2002, so even the reference area (where precipitation was 7.6 cm/yr greater during 2003-2008 than during 1997-2002) exhibited a 12 cm rise in water level. Accordingly, I adjusted water table elevation in the reference area by -12 cm, so that *dWL* attributable solely to lessened abstraction would be zero in the reference area, as *ppr* = 0 in the reference area. Likewise, I down-adjusted water table elevation in the eleven wellfields proportional to their increased precipitation following 2002 (i.e., by -1.6 cm per 1 cm excess annual precipitation). This approach assumes that water level rise per unit increase in precipitation is the same in the reference and all wellfield areas, which may not be true owing to possible differences among areas in hydraulic conductivity of soil and underlying strata.

To describe the relationship between these two variables, I compared linear (*dWL* rises at a uniform rate with *ppr*) and asymptotic (*dWL* rises at a decelerating rate with *ppr*) models. Asymptotic models were poor because extreme parameter correlations prevented model convergence, and the data points themselves exhibited no visual evidence of *dWL* leveling off at high *ppr*. I thus adopted the linear regression model

$$dWL = v_0 + (v_1 \times ppr) \quad (\text{eq. 1}).$$

This model fit the data with $R^2 = 0.35$ ($n = 12$ wellfield and reference areas). Parameter estimates were $v_0 = 18.8$ (S.E. = 13.5) and $v_I = 1.05$ (S.E. = 0.40), with a parameter correlation of -0.85, yielding a joint parameter space shown in figure 2A. After choosing a *ppr* for a given application of the error propagation routine, the first step of a single iteration was to project a *dWL* by using eq. 1, with values for v_0 and v_I randomly drawn from their joint parameter space. Each of the 50,000 iterations drew, at random, a different pair of v_0 and v_I values from this parameter space, yielding 50,000 different projected *dWL* values for a given *ppr*.

2.4. Change in water level (dWL) and wetland hydroperiod (hp)

To statistically model the relationship between *dWL* and *hp*, I used a frequency analysis of water level elevation in each of 56 depressional-basin wetlands throughout west-central Florida (Nilsson et al., 2013). This analysis determined hydroperiod, or the percent of time that any given elevation within a wetland basin is inundated. Across the 56 wetland basins, the average hydroperiod ($\hat{h}$) at any given elevation above basin deep point (z , cm) was best described by the polynomial function

$$\hat{h} = 59.3 - ([5.23 \times 10^{-6}] \times z^3) - ([3.10 \times 10^{-3}] \times z^2) - (0.590 \times z) \quad (\text{eq. 2}).$$

Around this average $\hat{h}$ (solid curve in figure 2B), there is variation among the 56 wetlands in hydroperiod at any given elevation. Consequently, at any given elevation, hydroperiod has a standard error of 7.48 (estimated from Nilsson et al., 2013).

In a single iteration of the error propagation routine, a value for $\hat{h}$ at the focal elevation was determined from eq. 2, where $z = \text{focal elevation} - dWL$ (with that iteration's *dWL* value

coming from eq. 1). Then to this $\hat{h}$ value, I subsequently added random hydroperiod error (ε_h) drawn from a normal distribution with mean zero and standard deviation 7.48, so that $hp = \hat{h} + \varepsilon_h$. Each iteration drew, at random, a different ε_h . Boundary conditions of 0% and 100% were imposed on hp . (Note, whereas z is elevation above basin deep point, the depth profile is inverted for display purposes in figures 2B and 3.)

2.5. Wetland hydroperiod (hp) and soil carbon (C_s)

To statistically model the relationship between hp and C_s , I acquired data on these two variables from 32 wetland bathymetric contours that spanned a gradient in hydroperiod (Lewis and Feit 2015). These 32 contours were apportioned as two contours (one shallow, one deep) in each of 16 cypress swamp basins. The elevations of all 32 contours were surveyed. Along each contour line, a soil core was collected to 30.5 cm depth from five equally spaced points around the wetland. The five cores for each contour were combined and homogenized into a composite sample. A subsample from each composite was then dried, milled, and analyzed for carbon as a percent of soil mass via elemental analysis (ECS 4010, Costech, Inc., Valencia, CA, USA). The hydroperiod of each contour line was calculated as the percentage of time that it was inundated during the 5-year period preceding soil sampling. A contour was deemed inundated if its elevation was less than the water table elevation measured at a staff gage in the same wetland. Among the 32 contours, hydroperiod during the 5 years preceding soil sampling varied over the range 0-67% of time inundated. This variation in hydroperiod is explained by depth (the shallower contour in a basin had a shorter hydroperiod) and wetland identity (at a standard depth, wetlands more exposed to nearby groundwater abstraction had shorter hydroperiods). In any case, the 32 contours provide an informatively broad hydroperiod gradient to identify any

hydroperiod effects on soil C. After comparing candidate models, this relationship was best fit with the linear regression

$$C_s = b_0 + (b_1 \times hp) \quad (\text{eq. 3}).$$

This model fit the data with $R^2 = 0.49$. Parameter estimates were $b_0 = 1.90$ (S.E. = 0.29) and $b_1 = 0.0724$ (S.E. = 0.0134), with a parameter correlation of -0.62, yielding a joint parameter space shown in figure 2C. For a single iteration of the error propagation routine, I used the hp determined in the preceding step to project a C_s by using eq. 3, with values for b_0 and b_1 randomly drawn from their joint parameter space. This linear model (eq. 3) derives from a one-time synoptic survey of hp and C_s . It is possible that if C_s were tracked longitudinally (through time) at a single location as hydroperiod first declined (during intensification of groundwater abstraction) and then recovered (during abstraction cutbacks), data would reveal a different relationship. This form of uncertainty (model uncertainty) is addressed in the Discussion.

2.6. Application and corroboration

I ran applications of this routine at a range of ppr values (0-100%) factorially crossed with a range of focal elevations (0-100 cm above basin deep point). In each application (i.e., at a specified ppr and focal elevation), the routine was iterated 5×10^4 times, as the obtained distributions for dWL , hp , and C_s were stationary after 10^4 iterations. Objective 1 was to determine whether soil C probability distributions can be distinguished between scenarios with lessened groundwater abstraction vs. with intense abstraction. To satisfy this objective, I calculated overlap and the Bhattacharyya distance (a divergence measure) among C_s probability

distributions at $ppr = 0, 30, 70$, and 100 , which I refer to as full, moderate, low, and completely-eliminated abstraction, respectively. Overlap and distance among C_s probability distributions were evaluated at 10, 50, and 90 cm above basin deep point. To satisfy objective 2, I conducted a sensitivity analysis that identified the most strategic place in the pathway of relationships to reduce uncertainty in order to tighten frequency distributions of C_s . In particular, I decreased the standard errors in v_0 , v_1 , ε_h , b_0 , and b_1 by 50% and reran the above applications (factorial combinations of ppr and focal elevation). Then, I identified how changes in these errors affected the breadth of the C_s frequency distribution.

Soil C data are not available from times of both high and low groundwater abstraction (a fact motivating this Monte Carlo exercise). However, the hypothesis that lessened abstraction produces greater soil C would garner corroborative support if data confirm the antecedent, namely, that lessened abstraction produces longer hydroperiods in the very same wetlands where hydroperiod correlates with soil C (those wetlands where Lewis and Feit [2015] identified the $hp-C_s$ relationship in eq. 3). I thus obtained water level data observed from staff gages mounted within these 16 carbon-study wetlands, and computed annual hydroperiod (% time soil is inundated over a 1-y period) for each of the 12 water years considered in this study (1997-2008). Annual hydroperiod was determined in each wetland for each 10-cm increment of bathymetric depth over the 10-50 cm depth range. Annual hydroperiod was first detrended for effects of precipitation by taking residuals from a regression of annual hydroperiod as a function of annual precipitation ($R^2 = 0.16$). Then at each basin depth, I tested the prediction that detrended annual hydroperiod would be negatively correlated with annual groundwater abstraction volume ($n = 12$ years), with hydroperiod at a given depth in each year averaged across wetlands. Raw water

level data from staff gages were provided by Tampa Bay Water and by the Southwest Florida Water Management District, as detailed in Lewis and Feit (2015).

3. Results

3.1. Soil C probability distributions and groundwater abstraction

Projected mean soil C differed among scenarios of groundwater abstraction. At full abstraction ($ppr = 0$), the deep portions of wetland basins exhibited mean soil C concentrations of nearly 7% (carbon as a percent of soil mass), with soil C diminishing to about 2% at higher elevations (shallower depths) in a wetland basin (Fig. 3). At more substantial cutbacks in abstraction (high ppr), large C pools were projected across the full depth profile, with C concentrations grading from >8% in wetland bottoms to nearly 7% at upper basin edges.

Probability distributions for soil C were relatively distinct when comparing full ($ppr = 0$) and moderate ($ppr = 30$) groundwater abstraction at shallow depths. Soil C probability distributions overlapped more extensively (diverged less) when comparing scenarios of low vs. eliminated abstraction (in higher ppr ranges), and when comparisons were made at deep bathymetric positions in wetland basins. At the shallow position of 10 cm depth, for instance, the probability distribution for soil C at full abstraction ($ppr = 0$) overlapped only 26% of the soil C distribution at moderate abstraction ($ppr = 30$), and these two distributions showed relatively large divergence (0.56) (Table 2). At the deeper 50-cm and 90-cm contours, the probability distributions for soil C at $ppr = 0$ and at $ppr = 30$ exhibited greater overlaps of 49% and 71%, respectively, and showed lower divergence scores of 0.23 and 0.07, respectively (Table 2, Fig. 4). The probability distribution for soil C at moderate abstraction ($ppr = 30$) overlapped the

distribution at low abstraction ($ppr = 70$) by 63% at 50 cm basin depth. Between low and eliminated abstraction (from $ppr = 70$ to $ppr = 100$), probability distributions for soil C diverged little from one another, thus overlapping extensively.

Distributions for soil C probabilities thus overlapped extensively when comparing between scenarios with relatively severe cutbacks in abstraction, and when comparing between any abstraction scenarios at deeper basin positions. In such situations, hydroperiod approached its upper limit of 100%, and therefore the mode of the soil C distribution stopped moving upward as ppr increased. Additionally, probability distributions for soil C got broader at high ppr (standard deviation in C_s increased; Fig. 4), exacerbating overlap. Conversely, positive skewness decreased as ppr increased, so C_s frequency distributions grew less low-biased as their modes shifted upward, thereby decreasing overlap at increasing abstraction cutbacks.

3.2. Reducing error to tighten soil C probability distributions

Five terms are varied in this routine: v_0 , v_I , ε_h , b_0 , and b_I . Reducing variation in the slope (b_I) of the hp - C_s relationship by 50% (narrowing the distribution from which b_I could be drawn) greatly improved certainty in soil C. That is, the probability distribution of C_s values projected by the error propagation routine was much tighter when b_I was drawn from a normal distribution with a standard deviation of 0.0067 (half s.e. b_I) than from a distribution with a standard deviation of 0.0134 (full s.e. b_I) (Fig. 5). This narrowing in the distribution of C_s , as a result of halving standard deviation in b_I , was evident across the entire spectrum of groundwater abstraction from full ($ppr = 0$) to completely eliminated ($ppr = 100$) and across all basin depths (0-100 cm). Reducing variation in b_0 (drawing b_0 values from a normal distribution with a standard deviation of half s.e. b_0) also narrowed the distribution in C_s , although less tightly than

when variation in b_I was halved. The C_s distribution was tightened only slightly or not at all when variation was reduced in v_I , v_0 , and ε_h .

3.3. Lessened abstraction and hydroperiod recovery

At bathymetric depths of 20-50 cm in the 16 swamps investigated in the soil C study (Lewis and Feit, 2015), hydroperiods exhibited significant negative correlations with groundwater abstraction. That is, annual hydroperiods in these particular wetlands were generally longer in years when groundwater abstraction was less (Fig. 6). On average, hydroperiod at 20 cm depth was 20% during the 2003-2008 period and 11% during the preceding 1997-2002 period of intense abstraction, for a Δhp of $20 - 11 = 9\%$. Recall that hydroperiod data in figure 6 are actually residuals from a hydroperiod-precipitation regression. After correcting hydroperiod for precipitation effects, the difference in hydroperiod between the 2003-2008 period and the 1997-2002 period is $\Delta hp_{corr} = 8\%$. At bathymetric depths of 30, 40, and 50 cm, Δhp_{corr} is 11, 12, and 17%, respectively. The subset of wellfields where these 16 swamps were located experienced an average cutback in groundwater abstraction of $ppr = 30$, which is projected by the error propagation routine to yield a Δhp of 20-25%. Thus, the error propagation routine projects that cutbacks in abstraction will yield greater rebounds in hydroperiod than were actually observed in the 16 carbon-study wetlands. Nevertheless, water level data from the carbon-study wetlands confirm that hydroperiods are longer when abstraction is scaled back, except at the highest elevations (10 cm bathymetric depth), where hydroperiods are naturally short in these intermittently flooded ecosystems.

4. Discussion

The success of ecological restoration is best evaluated with holistic indicators that integrate many aspects of an ecosystem (Pander and Geist, 2013). This recognition has motivated the development of biotic indices that summarize the integrity and resilience of wetland communities (Jaunatre et al., 2013; Reiss, 2006). Wetland SOC is a holistic indicator because in addition to regulating many ecosystem services as described above, SOC reflects the balance between major ecosystem metabolic processes (primary production, decomposition) and the plant and microbial assemblages responsible for them (Hobbie 2015). The many valued services provided by wetland SOC have been degraded by decades, if not centuries, of wetland dewatering (Erwin, 2009). Wetland dewatering opens a window for massive soil C efflux via accelerated aerobic decomposition and C leaching, motivating restoration efforts that often begin with attempts to reestablish wetland hydrology (Zedler and Kercher, 2005). A principal restoration question is whether reestablished wetland hydrology inhibits C efflux pathways and allows soil C to reaccumulate. I now consider whether soil C probability distributions can be distinguished among scenarios of groundwater abstraction, identify where to reduce error in order to tighten these distributions, and evaluate whether wetland hydrology actually was rehabilitated when abstraction was lessened. Additionally, I discuss limits to inference in the event that stakeholders might wish to interpret soil C probability distributions projected here.

4.1. Soil carbon distributions at different groundwater abstraction levels

Given signs on the parameters in equations 1-3, an increase in soil C is a deterministic projection of less abstraction (of increasing ppr). Accordingly, the pertinent question is whether this soil C increase is detectable given error in the relationships linking lessened abstraction with soil C. At a basin depth of 50 cm, soil C distributions at $ppr = 0$ and at $ppr = 30$ overlapped by

49%, with a divergence score of 0.23 (Table 2, Fig. 4). Whether this degree of separation indicates a meaningful increase in wetland soil C is in the eye of the beholder. Conventional statistics that indicate whether different *ppr* scenarios have equal mean soil C (the null tested by a *P* value) would not be particularly useful when we are interested in changes in distributions (Ellison, 1996). The soil C probability distributions themselves depict a range of soil C values that might be expected with a given cutback in groundwater abstraction. Presenting outcomes this way allows stakeholders with diverse perspectives to draw their own conclusions about whether any projected increases in wetland soil C are convincing, and whether any increase is by a meaningful amount. This information can then inform wetland managers or other stakeholders in evaluating whether increases in soil C meet restoration goals, and whether the costs of less water abstraction are merited by the magnitude and certainty of ecological gains.

While the importance of projected increases in soil C is open to interpretation, one outcome is objectively apparent. Namely, increases in soil C became less detectable (soil C increases were smaller and probability distributions less distinct) at progressively greater cutbacks in groundwater abstraction. These results suggest that soil C stocks are not notably improved if low-volume abstraction is further scaled back to zero abstraction, indicating that low-volume groundwater abstraction may not measurably impact wetland soil C.

4.2. Improving detection of soil C gains

Even small increases in soil C might be detectable if soil C probability distributions could be tightened. Within the context of relationships presented here, the best way to tighten soil C probability distributions is to reduce parameter uncertainty in the relationship between hydroperiod and soil C. Certainty in soil C does not improve by improving certainty in

relationships between hydroperiod and wetland basin elevation, nor between water level elevation and groundwater abstraction.

There are at least three ways to improve certainty in the $hp-C_s$ relationship. First, soil C could be estimated with more accuracy. Soil C can exhibit high spatial variation within a wetland. Error arising from observation and process uncertainties that push observed soil C away from its hydroperiod signal could be minimized with extensive within-wetland sampling (Cohen et al., 2008). The Lewis and Feit (2015) study (the information source for the $hp-C_s$ relationship, eq. 3) acknowledge within-wetland soil variability by compositing five soil cores per sample, and by minimizing variation among cores by taking them from the same depth contour. Nevertheless, more within-wetland sampling could yield a soil C datum that better reflects a wetland's hydrology. Second, sampling a greater number of wetland ecosystems (greater sample size at the level of statistical replication) would reduce standard errors in the parameters (b_0 and b_1) of the soil C-hydroperiod relationship. Third, soil C could be longitudinally sampled through time in wetlands undergoing attempted hydrology reestablishment, as well as in reference ecosystems with unimpaired long hydroperiods that may serve as restoration targets. This approach would track changes in soil C in response to changes in hydroperiod, and overcome the model uncertainty that is one weakness of my approach here.

4.3. Scope of uncertainty and limits to inference

Output from the error propagation routine supports the inference that wetland soil C storage increases when groundwater abstraction is cut back from high to moderate volumes. For instance, soil C distributions were most distinct when comparing $ppr = 0$ and $ppr = 30$, notably similar to the magnitude (35%) of actual cutback in 2002 in west-central Florida. Cautious

application of these results mandates considering the nature of error propagated in the error propagation routine.

Relationships in this routine are clouded by three forms of uncertainty (Hilborn and Mangel, 1997). Observation uncertainty arises from biases and errors in sampling technique when empirical data are collected. Process uncertainty arises from stochasticity inherent in the system under investigation. Observation and process uncertainty introduce variability in the magnitude of a response variable (dWL , hp , or C_s) at any level of its predictor (ppr , dWL , or hp , respectively). For instance, dWL may exhibit great variability at any level of abstraction cutback (ppr) because a wetland's hydrologic regime is regulated by other factors (such as local climate, soil properties, and basin bathymetry) that introduce process uncertainty (large parameter variances) into the dWL - ppr relationship (Park et al., 2014). Observation and process uncertainty are incorporated in each relationship in my error propagation routine by resampling parameter values from known parameter variances or residual error from a known distribution of residuals.

Model uncertainty is the lack of understanding about mechanisms and processes intrinsic to the system being modeled (Chatfield, 1995). The mean and variance in water level change (dWL) following lessened abstraction (ppr) is directly estimated from experimental abstraction cutbacks, so the dynamic response of water level elevation to lessened abstraction is known, regardless of the "true" mechanistic model relating these two variables. Model uncertainty is thus subsumed by the statistical model (eq. 1) relating ppr to dWL . The relationship linking water table elevation with hydroperiod (eq. 2) is largely a conversion. Rising water tables necessitate more protracted inundation, so model uncertainty does not apply.

However, this study does not account for model uncertainty in the relationship between soil C and hydroperiod. The error propagation routine uses a relationship (eq. 3) that was fit by

synoptically quantifying carbon in short-hydroperiod and long-hydroperiod soils. In fact, this comparative synoptic approach is used in some other self-described "restoration" studies that lack data prior to hydrology manipulation. Soil C in any single location might not increase, as hydroperiod recovers, along the trendline of eq. 3 (Fig. 2C). Soil C may increase along a lower, slower trajectory that either is hysteretic or recovers to a lower equilibrium C concentration (Moreno-Mateos et al., 2012). I make this suggestion because hydrologically degrading a wetland undoubtedly initiates processes and feedbacks that inhibit the functional recovery of that wetland even when hydrology is reestablished (Curtis et al., 2014; Heffernan et al., 2008; Hobbs, 2007). For instance, in short-hydroperiod, C-depleted soil, the initial reestablishment of long hydroperiods may cause soil C to temporarily decline even further, because soil rewetting relieves water limitation and activates nutrients for the microorganisms that decompose soil organic matter (Battle and Golladay, 2001; Corstanje and Reddy, 2004; Fenner and Freeman, 2011). Additionally, recovery of soil C may lag the reestablishment of long hydroperiods because degraded soils lack the "starter" organic matter needed for soil water retention and capillarity, which in turn maintain the soil anoxia that permits C accumulation (DeBusk and Reddy, 2003). Soil C at any given hydroperiod is thus likely lower during water table rebound than during draw down, so eq. 3 may over-project soil C.

5. Conclusions

I assembled a step-by-step sequence of causal relationships, coupled with error propagation, to project probabilistic outcomes of wetland soil C in response to cutbacks in groundwater abstraction. Human appropriation of fresh water is accelerating, which affects

ecosystem services in water-supply areas. Allocating water back to these services would benefit society, because, for instance, wetland soil C storage mitigates atmospheric radiative forcing (Mitsch et al., 2013). Projected soil C was most distinguishable between full and moderate (30% less) abstraction. With more severe abstraction cutbacks, gains in projected soil C became more marginal and uncertain, suggesting that wetland soil C pools are not notably impacted by low-volume abstraction. Yet, even small gains in soil C might be detectable if soil C probability distributions were tightened, which would best be accomplished by reducing uncertainty in the relationship between hydroperiod and soil C pool size. In addition to improving parameter certainty in this relationship, the very shape of dynamic soil C response to recovering hydroperiod needs better resolution. This model uncertainty, coupled with overestimation of hydroperiod rebound following abstraction cutbacks, mandates caution when using results here to infer that wetland soil C pools grew in response to west-central Florida's groundwater conservation experiment. The main benefits of the step-by-step error propagation routine are that it is a platform for assimilating information to project probabilistic responses of ecosystem function to attempted wetland restoration, and it stimulates scrutiny to identify the domains most in need of increased certainty.

546

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 771

Figure captions

Figure 1. Study landscape in peninsular west-central Florida, USA. Bold numbers on population density map (right panel) indicate locations of groundwater abstraction wellfields. Aerial photograph (upper left) shows a representative view, from a portion of wellfield 5, of the wetland complex native to this region. Darker elements are cypress swamp wetlands and lighter matrix is pine flatwoods upland. Photo: USDA-FSA Aerial Photography Field Office. Population census block data: U.S. Census Bureau.

Figure 2. Error propagation routine. (A) Relationship between percent reduction in groundwater pumping (ppr) and change in water table elevation (dWL). (B) Relationship between depth into wetland basin downward from top (0 cm) of basin and wetland hydroperiod (hp). Distribution shows probability of hp at a given depth. (C) Relationship between hp and soil C pool size (C_s). In (A) and (C), ranges of distributions for slope and intercept parameters are indicated, and insets show joint space for these parameters. (D) Example distribution of C_s from 5×10^4 iterations of the routine. The C_s distribution is shown both as a box-and-whisker plot and as a histogram.

Figure 3. Mean soil C concentration projected from error propagation routine across a profile of wetland basin bathymetric depth and across a gradient of cutback in groundwater abstraction.

Figure 4. (Bottom) Probability distributions (shown as box and whisker plots) of soil C (C_s) at various cutbacks in groundwater abstraction, from no cutback ($ppr = 0$, or full abstraction) to complete cutback ($ppr = 100$). Box midlines are medians, boxes span the interquartile range

(IQR), and whiskers (which terminate in short horizontal tick marks) extend $1.5 \times \text{IQR}$ above and below the 75th and 25th percentiles, respectively. Outliers beyond the whiskers are shown as individual points, though appear to create a line where many points partially overlap. (Top) Breadth (s.d.) of the C_s distribution widens, and the median of the distribution shifts higher in the C_s range (decreasing positive skew), as abstraction is increasingly cut back. Scenarios shown here are at basin depth of 50 cm.

Figure 5. Soil C probability distribution narrows notably when uncertainty (s.e.) is reduced in the slope of the relationship between soil C and hydroperiod. Reducing s.e. of other factors in the error propagation routine did not similarly tighten the C_s distribution. This example is for a basin depth of 50 cm. Boxes, whiskers, and outliers are as described in figure 4.

Figure 6. At wetland bathymetric depths of 20-50 cm, wetland inundation time was longer in years with less groundwater abstraction. A datum point depicts an annual hydroperiod averaged among 16 wetlands plotted against mean daily abstraction during that year. Annual hydroperiods are detrended for effects of precipitation. Triangles indicate water years 1997-2002 and circles indicate water years 2003-2008. Linear regression statistics are shown.

812
813 Table 1. Soil characteristics in cypress swamp basins in west-central Florida. Data computed
814 from $n = 32$ soil samples, 30.5 cm deep, that intentionally span a hydroperiod gradient (Lewis
815 and Feit 2015). Percent data are percentages of total soil mass (organic matter, C, and N) or of
816 the mineral soil fraction (sand, silt, and clay). C:N is a molar ratio.
817

Metric	% organic				bulk density			
	matter	% C	% N	C:N	% sand	% silt	% clay	(g soil / cm ³)
Minimum	1.66	0.73	0.031	19.71	84.0	1.4	0.0	0.54
Maximum	20.60	8.89	0.497	33.35	97.5	12.6	4.1	1.54
Median	4.75	2.47	0.106	25.21	95.1	3.6	1.4	1.19
Mean	5.95	2.89	0.137	25.64	94.0	4.5	1.6	1.10
St. Dev.	4.11	1.79	0.097	3.19	3.3	2.7	1.0	0.27

818
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819
820 Table 2. Separation of distributions. Overlap and Bhattacharyya distance between soil C
821 probability distributions compared among scenarios of full ($ppr = 0$), moderate ($ppr = 30$), low
822 ($ppr = 70$), and eliminated ($ppr = 100$) groundwater abstraction, at bathymetric depths into a
823 wetland basin of 10, 50, and 90 cm.
824

Depth (cm)	Abstraction	Proportion overlap			Bhattacharyya distance		
		full	moderate	low	full	moderate	low
10	moderate	0.26			0.56		
	low	0.11	0.39		1.29	0.39	
	eliminated	0.08	0.26	0.76	1.55	0.64	0.05
50	moderate	0.49			0.23		
	low	0.29	0.63		0.56	0.13	
	eliminated	0.24	0.52	0.87	0.69	0.21	0.01
90	moderate	0.71			0.07		
	low	0.56	0.81		0.18	0.03	
	eliminated	0.52	0.77	0.95	0.21	0.05	0.00

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Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6