Forest Management Adaptation to Gradual Climate Change and Extreme Events

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Abstract: We extend existing stand-level decision models of forest managers in the presence of two aspects of climate change: Gradual climate change and extreme event risk. The forest managers adapt to the climate change by choosing optimal planting density and rotation age to maximize their net benefit. The possibility of species switch is also considered. Based on simulation results, we find that the net benefit and decision making are sensitive to the extreme event risk, implying the importance of adaptation to extreme events. With gradual climate change, longleaf pine may have some comparative advantage when it gets warmer and wetter. This implies that species switch can be an important adaptive action under some climate scenario.

1 Introduction

Adaptation to climate change is receiving increasing attention in academic research, and its importance is being recognized in national and international policy debates on climate change. Adaptation is a potential response to the advent or prospect of anthropogenic climate change and thus can modify the impacts of climate change. There is an extensive literature focused on agricultural adaptive response to gradual climate change (Easterling et al., 1993; Kaiser, et al., 1993; Mendelsohn et al., 1994; Segerson et al., 1999; McCarl et al., 2001). In forestry sector, there is some literature that examines forest ecosystem impacts of gradual climate change (e.g. Prasad and Iverson, 1999-ongoing). Some study the economic impact of gradual climate change (e.g. Abt and Murry, 2001; Callaway, et al., 1994; Sohngen and Mendelsohn, 1996). These studies suggest that adaptation measures can and should be applied to managing natural resources, especially to those human-managed forests, in order to moderate harmful impacts of climate change. Some adaptive measures are identified, such as change of harvest decision, improving tree species (fire resistant and drought resistant), change of land uses, change of planting dates, choice of planting sites and so on. Besides the gradual climate change impact, there is also literature on forest managers' adaptation to risks from wildfires or other discrete events that are correlated with gradual climate change (Haight, 1995; Amacher et al., 2005). But it lacks literature that study forest management adaptation to gradual climate change and extreme events.

This paper provides an integrated analysis of forest management response to a likely known trend in changing climate in addition to a lesser known risk of discrete events, examining how forest managers

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might respond to the gradual climate change and extreme events by taking adaptive actions, such as change of rotation age, planting density and species. We use a Decision Simulation(DS) Approach where we first estimate the empirical model of growing stock volume with gradual climate change. Then the value function with risk of extreme events is established. Finally the value function is optimized with respect to the decision variables and simulations are conducted to examine the sensitivity of the adaptive actions to gradual climate change and risk of extreme events. The DS approach is applied to the pine plantations (loblolly pine, longleaf pine and slash pine) in the southern eastern U.S.

2 Decision Simulation Approach

2.1 Estimate the Empirical Volume Function with Gradual Climate Change

2.1.1 Data

Forest yield data came from the Forest Inventory and Analysis (FIA) database. FIA data are collected periodically on permanent plots across the south. FIA database has a uniform data structure for forestry inventories. It contains extensive data on forest area attributes such as stand age, stand size, diameter, height, species and so on. There are nine data tables in the FIA Database. For this paper, I use three of them: the Condition Table, the Tree Table and the Plot Table. For more information about FIA database, please go to:
http://www.ncrs2.fs.fed.us/4801/FIADB/fiadb_documentation/SNAPSHOT_DB_V2pt1_JULY_2006.pdf
The forest data is processed using SAS. Plot level data is obtained for growing stock volume per acre, density, stand age, physical region, slope and site class for the three species (loblolly pine, slash pine and longleaf pine) in the 12 southern eastern states of United States.

National climate data is downloaded from PRISM website (http://www.ocs.oregonstate.edu/prism/index.phtml). PRISM uses point data, a digital elevation model(DEM), and other spatial data sets to generate estimates of annual, monthly and event-based climatic elements that are gridded and GIS compatible. The climate data is first imported into ArcGIS and then to SAS to obtain county level average maximum temperature, average minimum temperature and average precipitation in the last 20 years in those 12 states. Next, county level climate data is attached to the plot-level forestry data. Tables 1-3 present the descriptive statistics by species.

Prices used in this paper are based on real-life data from Dr. Abt. They are prices for the three size classes of trees: Pine pulp wood(PPW), small sawtimber(CNS) and pine sawtimber(PST).

Table 1: Descriptive statistics for loblolly pine

Variables	Description(units)	Mean	Std Dev	Minimum	Maximum
V	Growing stock volume per acre(cubic feet)	1333.5	1110.89	0.58	10228.6
X	Stand age(years)	18	7.771	1	44
d	density(100 trees per acre)	3.92	3.396	0.06	40.12
$MaxT$	average maximum temperature(Celsius)	23.86	1.366	18.94	27.38
$MinT$	average minimum temperature(Celsius)	11.07	1.488	6.03	16.07
ppt	precipitation(mm)	1.32	0.132	1.08	1.83
S	slope	5.6	7.196	0	155
L	site class	3.8	0.992	1	6

Table 2: Descriptive statistics for slash pine

Variables	Description(units)	Mean	Std Dev	Minimum	Maximum
V	Growing stock volume per acre(cubic feet)	1209.9	994.58	1.86	10035.1
X	Stand age(years)	19	9.076	3	48
d	density(100 trees per acre)	3.85	2.929	0.06	29.79
$MaxT$	average maximum temperature(Celsius)	25.85	0.647	22.33	27.38
$MinT$	average minimum temperature(Celsius)	13.05	0.949	10.10	16.35
ppt	precipitation(mm)	1.355	0.137	1.136	1.713
S	slope	1.3	2.385	0	25
L	site class	4.3	0.808	2	6

2.1.2 Model Selection and Estimation Results

Growing stock volume per acre is regressed on stand age, density, slope, physical region, site class and the three climate variables for the three species. Different functional forms (log-linear, log-log, non-linear) are considered and compared. Based on the AIC and BIC, the log-linear form seems to be more appropriate than the log-log and non-linear forms. Results presented here are based on the log-linear form. As to variable selection, following criteria are used.

- Statistical significance(p-value)
- R-square, AIC and BIC
- Inclusion of significant temperature and precipitation variables

Table 3: Descriptive statistics for longleaf pine

Variables	Description(units)	Mean	Std Dev	Minimum	Maximum
V	Growing stock volume per acre(cubic feet)	872.06	841.00	7.78	3659.4
X	Stand age(years)	30.9	19.381	7	75
d	density(100 trees per acre)	1.75	1.513	0.06	6.87
$MaxT$	average maximum temperature(Celsius)	25.06	1.137	22.82	27.45
$MinT$	average minimum temperature(Celsius)	12.55	1.541	10.18	16.13
ppt	precipitation(mm)	1.391	0.192	1.138	1.713
S	slope	3.6	4.251	0	20
L	site class	4.9	0.819	3	6

The following models are chosen based on the above criteria.

- For loblolly pine: $(R^2 = 0.533, N = 3349)$
  $$\widehat{\log V}_i = -\underset{(-11.42)}{12.31^b} + \underset{(39.69)}{0.338^b} X_i - \underset{(-27.90)}{0.0055^b} X_i^2 + \underset{(11.27)}{0.113^b} d_i - \underset{(-9.92)}{0.0047^b} d_i^2 - \underset{(-3.36)}{0.008^b} S_i - \underset{(-12.48)}{0.205^b} L_i - \underset{(-1.49)}{0.044^c} max_i + \underset{(2.73)}{0.266^b} min_i + \underset{(2.21)}{1.719^b} ppt_i - \underset{(-2.47)}{0.169^b} min_i \cdot ppt_i$$
- For slash pine: $(R^2 = 0.560, N = 901)$
  $$\widehat{\log V_i} = -\underset{(-2.12)}{60.77^b} + \underset{(24.12)}{0.366^b} X_i - \underset{(-18.87)}{0.006^b} X_i^2 + \underset{(4.75)}{0.123^b} d_i - \underset{(-4.03)}{0.006^b} d_i^2 - \underset{(-6.05)}{0.27^b} L_i + \underset{(1.58)}{0.075^c} min_i + \underset{(1.84)}{4.11^c} max_i - \underset{(-3.53)}{0.98^b} ppt_i - \underset{(-1.92)}{0.084^b} max_i^2$$
- For longleaf pine: $(R^2 = 0.674, N = 59)$
  $$\widehat{\log V_i} = -\underset{(-1.99)}{90.84^b} + \underset{(5.61)}{0.153^b} X_i - \underset{(-3.92)}{0.001^b} X_i^2 + \underset{(2.57)}{0.699^b} d_i - \underset{(-3.28)}{0.144^b} d_i^2 + \underset{(1.52)}{3.13^c} max_i - \underset{(-1.94)}{3.32^b} min_i + \underset{(2.32)}{95.97^b} ppt_i + \underset{(1.97)}{0.124^b} min_i^2 - \underset{(-1.93)}{11.12^b} ppt_i^2 - \underset{(-1.6)}{2.534^c} max_i \cdot ppt$$

  Where i represents the ith plot

  N is the number of observation

  [a]Figures in parentheses are "t" ratios

  [b]significant at 5% level, [c]significant at the 10% level

Stand age, its square term, density, its square term and precipitation are significant across all models. Physical region is generally not significant and thus is excluded from any model. It is probably because that the data lacks regional variation within species and that climate variables explain some regional variation. Slope and site class are significant for loblolly pine but not for longleaf pine. For slash pine, site class is significant but slope is not.

2.1.3 Empirical Response to Climate

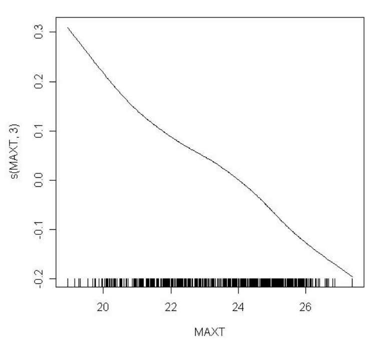
To verify the above log-linear models and to obtain a smooth relationship with climate variables, partially linear models are applied. Partially linear models have both parametric and non-parametric components, which can be written as:

$$\log V_i = Z_i^T \beta + s(T_i) + \varepsilon_i$$

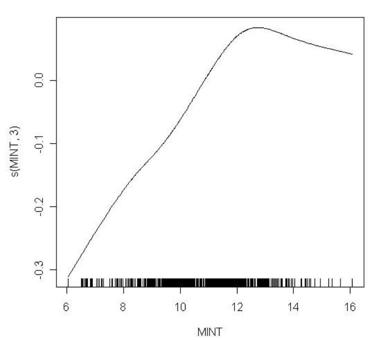
Where Z_i is a vector of explanatory variables except the climate variables,
β is a vector of parameters,
T_i is a vector of climate variables,
$s(\cdot)$ represents smooth function.

The partially linear models are fitted for each species using GAM function in R. The results are plotted in Figure 1-3, which indicate the empirical volume response to climate. The relationship between the mean function of $\log V$ and climate variables displayed below is consistent with our estimates from the log-linear models.

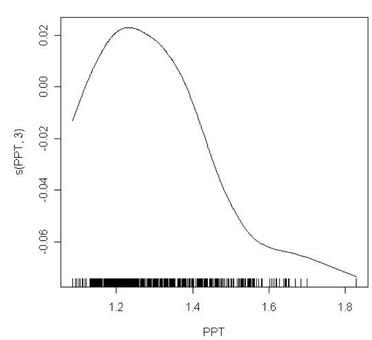
The plots show that the growing stock volume has non-linear relationship with the three climate variables except the response of loblolly pine to the maximum temperature. The relationship is not same across the species. Especially, the response of longleaf pine to minimum temperature is different from the other two species, which could imply the potential advantage of longleaf pine to gradual climate change. If we only look at the increase from the mean levels of the climate variables (note that the mean levels are different across species), it seems that a little increase of maximum temperature may lower the volume. Similarly, a little increase of precipitation from its mean level may also reduce the volume. But a little increase of minimum temperature may augment the volume.



(a) Maxinum temperature

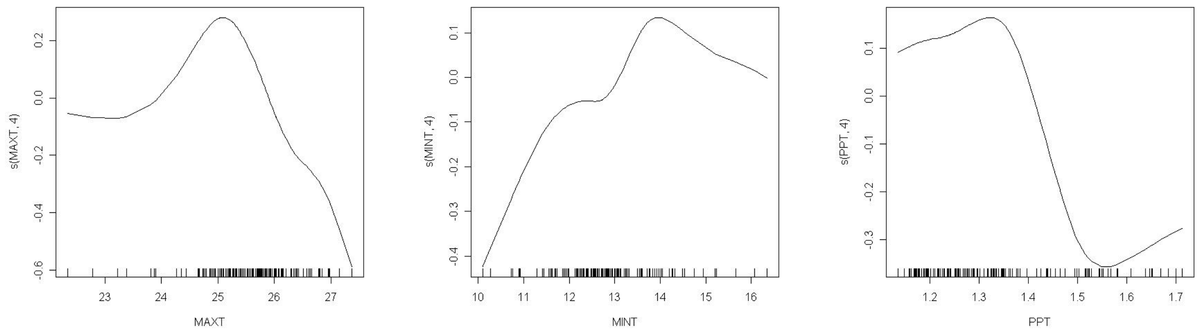


(b) Mininum temperature



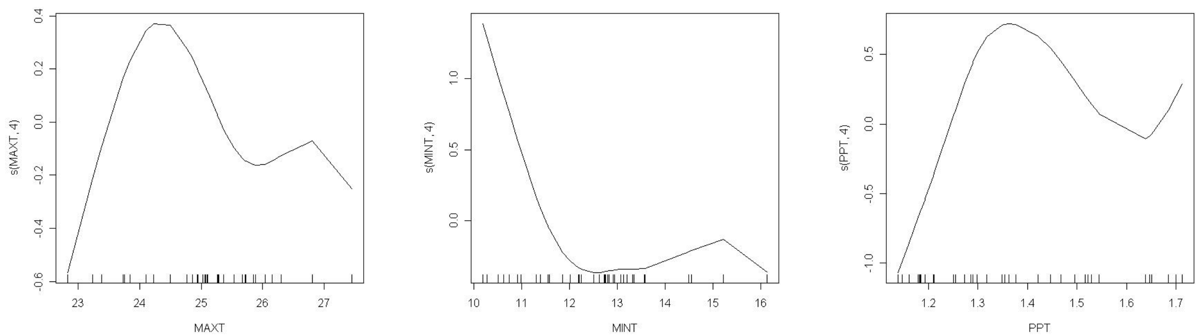
(c) Precipitation

Figure 1: Loblolly pine response to climate



(a) Maxinum temperature (b) Mininum temperature (c) Precipitation

Figure 2: Slash pine response to climate



(a) Maxinum temperature (b) Mininum temperature (c) Precipitation

Figure 3: Longleaf pine response to climate

2.2 Value Function with Risk

In this paper, we are modeling two aspects of climate change. The first described above examines how gradual climate change (mean temperature and precipitation) may affect optimal management and species choice. The second aspect is how discrete events which may be associated with the gradual climate change, such as hurricanes and wildfire, affect optimal choices.

Following Amacher(2005), the timing of discrete events (including harvest) on a forest stand is a random variable that has the following mixed distribution.

$f(X) = \lambda(X) \cdot e^{-m(X)} \quad if\ 0 \leq X < T$

$f(X = T) = e^{-m(T)} \quad if X = T$

Where X is the timing of discrete events (including harvest),
T is the rotation age,
$\lambda(X)$ is the risk of extreme events per period,
$m(X) = \int_0^x \lambda(t)dt$ is the aggregate level of extreme event risk.

If the extreme events happen before the harvest, the net rent at time X is given by:

$Y_1 = -50 - c_2 \cdot d \quad if\ X < T$

Where c_2 is the cost of planting on damaged land,
d is the planting density.

If the extreme events happen after the harvest, the net rent at time X is given by

$Y_3 = p(T, d) \cdot V(T, d) - c_1 \cdot d \quad if\ X > T$

Where $p(T, d)$ is price per unit,
$V(T, d)$ is the growing stock volume per acre,
c_1 is the cost of planting on undamaged lands.

$p(T, d)$ is obtained by first fitting price as a function of diameter and then fitting diameter as a function of stand age and density. The regression results are shown in table 4.

Table 4: Functional forms and base values of parameters used in simulation

Type	Function and parameter values
Volume per acre	V(X,d)
Average extreme events arrival rate	Constant arrival rate: $\lambda = \frac{t_0}{t_b - t_a} (t_a = 0, t_b = 50)$
	Rising arrival rate: $\lambda = 2t_0 \frac{(X - t_0)}{(t_b - t_a)(t_c - t_a)} (t_a = 0, t_b = t_c = 50)$
	Falling arrival rate: $\lambda = 2t_0 \frac{(t_b - X)}{(t_b - t_a)(t_b - t_c)} (t_a = t_c = 0, t_b = 50)$
Planting costs	undamaged land: $C_1 = 50 + 0.08d$ for loblolly and slash Undamaged land: $C_1 = 50 + 0.15d$ for longleaf
	damaged land:$C_2 = 50 + 0.05d$ for loblolly and slash damaged land:$C_2 = 50 + 0.1d$ for longleaf
diameter	$dia = 5.29 + 0.16X - 0.21d$ –loblolly pine
	$dia = 6.47 + 0.11X - 0.75d$ –longleaf pine
	$dia = 5.41 + 0.13X - 0.22d$ –slash pine
price	$P = 7.1 + 0.00008dia^5$ for low prices
	$P = 8.18 + 0.00023dia^5$ for high prices

Following the analysis of Reed(1984), the forest manager's value function(net benefit) can be written as:

$$NB = \frac{E(e^{-rX}Y)}{(1 - E(e^{-rX}))} = \frac{\int_0^T \lambda(X) \cdot e^{-m(X)} \cdot e^{-rX} Y_1 dX + e^{-m(T)} \cdot e^{-rT} \cdot Y_3}{r \cdot \int_0^T e^{-m(X) - rX} dX}$$

The first and second order conditions with respect to the climate variables can be derived analytically since climate variables only appear in the Y_3 function. For loblolly pine, the first order condition (FOC) is negative w.r.t. $MaxT$, i.e. the net benefit decreases as average maximum temperature increases. As to $MinT$, the sign of FOC depends on the precipitation level. When precipitation is less than $1574mm$, net benefit increases as average minimum temperature increases. If precipitation is greater than $1574mm$, net benefit decreases as average minimum temperature increases. Similarly, the sign of the first order condition w.r.t. *ppt* depends on minimum temperature. If $MinT$ is less than $10.17°C$, net benefit increases with *ppt*. If $MinT$ is greater than $10.17°C$, net benefit decreases with *ppt*.

For slash pine, increase of *ppt* dampens the net benefit while increase of $MinT$ increases the net benefit. The impact of $MaxT$ is two-sided. When $MaxT$ is below $24.46°C$, net benefit goes up as $MaxT$ increases. But if $MaxT$ is above $24.46°C$, net benefit goes down with it.

For longleaf pine, when $MinT$ is less than $13.39°C$, NB is decreasing with $MinT$. But when $MinT$ is greater than $13.39°C$, NB increases as $MinT$ goes up. As to $MaxT$, the sign of FOC depends on the precipitation level. If *ppt* is lower than $1235mm$, NB increases as $MaxT$ goes up. But if *ppt* is greater than $1235mm$, NB decreases as $MaxT$ goes up. The sign of FOC $w.r.t.$*ppt* is not decided because it depends on both *ppt* and $MaxT$. But if we fix $MaxT$ at its mean level ($25.06°C$), NB increases with *ppt* until *ppt* reaches $1460mm$. After that point, NB decreases with *ppt*.

The first order condition w.r.t. the decision variables (T, d) are complicated and deriving comparative static results analytically is generally infeasible. Simulation is used therefore.

2.3 Simulation

Assume that forest managers would choose T and d (rotation age and density) to maximize the value function, i.e.

$$MAX_{T,d} \frac{\int_0^T \lambda(X) \cdot e^{-m(X)} \cdot e^{-rX} Y_1 dX + e^{-m(T)} \cdot e^{-rT} \cdot Y_3}{r \cdot \int_0^T e^{-m(X)-rX} dX}$$

R is used to conduct the simulation. Five percent interest rate is assumed throughout the analysis. To examine the risk sensitivity, constant risk and rising risk are applied. To inspect the price sensitivity, two sets of prices are used. The low prices are $7/ton, $12/ton, and $20/ton for PPW, CNS and PST respectively. The high prices are $8/ton, $22/ton and $45/ton. Functional forms and parameter values used in the simulation are listed in table 4.

3 Results and Sensitivity Analysis

Table 5-7 show the simulation results. Each table presents the corresponding risk and price scenarios, where the climate variables are first fixed at their mean levels and then some perturbations are conducted to examine the climate impact on forest manager's behavior.

- Increase $MaxT$ by $1.2°C$ (2F) only
- Increase $MinT$ by $1.5°C$ (2.6F) only
- Increase *ppt* by 75mm only
- "Rising all"—-Increase $MaxT$ to $26°C$, $MinT$ to $16°C$ and *ppt* to $1450mm$

In table 5, constant average arrival rate of the extreme events ($t_0 = 1$) and low prices are assumed. At the mean climate level, the forest manager of loblolly pine would plant 740 trees/acre and harvest 26 years later, which produces a net benefit of $359.81/acre. When the perturbed climate is applied, it seems that the optimal net benefit is more sensitive to temperature than to precipitation. When the maximum temperature increases by 2F, the forest manager would adapt by planting less trees (730 trees/acre) and lengthen the rotation (26.1 years). But the optimal net benefit would still decrease. This seems to be against the intuition that forest managers should decrease the rotation age when it is less profitable. But it can make sense because the increase of maximum temperature may reduce the plants' net primary productivity or growth function. Lower growth would lengthen the time required to obtain high valued products. When minimum temperature increases by 2.6F, the forest manager could gain from this change with the planting density increasing by 10 trees/acre and the rotation age decreases by 0.06 years. The increased precipitation seems to incur a little loss to the forest manager of loblolly pine and the adaptation is weak in this case. But note that these increases are applied to average levels of precipitation. The last perturbation is to increase all of the climate variables, $MinT$, $MaxT$, and *ppt*. The net benefit of loblolly pine drops a little bit ($4.36/acre) with minor adaptation.

The results for slash pine shares some similarity with that of loblolly pine. Increase of maximum temperature reduces the net benefit and the forest manager adapts by planting less slash pines and harvesting later. When minimum temperature increases, the forest manager gains and they adapt by planting more trees and harvest earlier. More precipitation seems to be harmful and forest manager would plant less trees and increase the rotation age. In case of "all rising", the forest manager would gain in net benefit by planting more trees per acre and shorten the rotation, which is different from the results of loblolly pine. In addition, the net benefit is more sensitive to gradual climate change for slash pine with larger change in the adaptive actions.

The results for longleaf pine differ from those of loblolly and slash pine in several ways. The rotation age is much longer and the planting density is much lower than the other two species. When the maximum temperature increases by 2F, the loss in the net benefit is the largest among the three species but the adaptation is weak (i.e. plant one less tree per acre and harvest 0.09 year earlier). When the minimum temperature increases by 2.6F, there is almost no adaptation and the forest manager would lose $11/acre. Also different from loblolly and slash pine, in case of increased rainfall, the adaptive actions are to reduce both density and rotation and thus the forest manager would gain in net benefit rather than lose. In situation of "all rising", it indicates a gain in net benefit with shorter rotation and lower density.

Table 5: Results for the three species with constant risk and low prices

Species	$MaxT$	$MinT$	ppt	NB^*	d^*	T^*
Loblolly	23.86(75F)	11.07(52F)	1.320	359.81	7.40	26.04
	+1.2(2F)			-21.80	-0.09	0.05
		+1.48(2.6F)		27.78	0.10	-0.06
			+75mm	-4.72	-0.02	0.01
	26	16	1.45	-4.36	-0.02	0.01
Slash	25.85(78.5)	13.05(55.5)	1.355	236.60	6.72	25.60
	+1.2(2F)			-97.94	-0.81	0.43
		+1.48(2.6F)		35.17	0.17	-0.10
			+75mm	-21.17	-0.13	0.07
	26	16	1.45	28.64	0.14	-0.08
Longleaf	25.06(77)	12.55(54.6)	1.391	292.71	1.71	55.80
	+1.2(2F)			-120.75	-0.01	-0.09
		+1.48(2.6F)		-11.27	0	0.01
			+75mm	18.13	-0.03	-0.19
	26	16	1.45	113.41	-0.02	-0.16

In Table 6, the extreme event risk is increasing with stand age, i.e. $\lambda = 2t_0 \frac{(X-t_0)}{(t_b-t_a)(t_c-t_a)}$ with $t_0 = 2.2$

We can compare Table 5 and 6 to examine the risk impact on adaptation and net benefit. With rising risk, the net benefit drops across all three species and all climate perturbations. The forest manager would adapt to this situation by shortening the rotation age and increasing the planting density. For loblolly pine at the mean climate, the net benefit is reduced by about $40/acre, density increases by about 55 trees per acre and rotation age goes down by more than 2 years. For slash pine, the net benefit reduces by about $24/acre, density increases by about 25 trees per acre and rotation age decreases by about 2 years. For longleaf pine, the net benefit drops dramatically by more than $150/acre and the rotation also decreases dramatically (more than 20 years).

In Table 7, rising risk and high prices are used. Comparing Table 7 with Table 6, we can study the impact of price. As expected, when prices go up, the forest manager would gain in net benefit ($229/acre

Table 6: Results for the three species with rising risk and low prices

Species	$MaxT$	$MinT$	ppt	NB^*	d^*	T^*
Loblolly	23.86(75F)	11.07(52F)	1.320	320.24	7.97	23.62
	+1.2(2F)			-19.67	-0.09	0.05
		+1.48(2.6F)		25.07	0.11	-0.06
			+75mm	-4.26	-0.02	0.01
	26	16	1.45	-3.93	-0.02	0.01
Slash	25.85(78.5)	13.05(55.5)	1.355	212.55	6.99	23.62
	+1.2(2F)			-88.70	-0.82	0.42
		+1.48(2.6F)		31.88	0.17	-0.10
			+75mm	-19.18	0.31	0.07
	26	16	1.45	25.96	0.14	-0.08
Longleaf	25.06(77)	12.55(54.6)	1.391	109.73	1.75	32.99
	+1.2(2F)			-53.74	-0.10	0.89
		+1.48(2.6F)		-5.00	-0.01	0.06
			+75mm	7.82	0.01	-0.09
	26	16	1.45	50.19	0.04	-0.45

for loblolly, \$129/acre for slash, and \$123/acre for longleaf) across all species. And therefore the forest manager will harvest later (1.4 years more for slash pine, 2.3 years more for loblolly pine and 4 years more for longleaf pine). But surprisingly the planting density for loblolly pine and slash pine drop dramatically. This may result from the negative relationship between price and density. The new set of prices put much weight on bigger trees. The forest manager may have to reduce the planting density to obtain big trees.

4 Summary and Discussion

Two aspects of climate change are considered in this paper: The gradual climate change and the occurrence of climate-related extrem events. The former is built into our DS model through the empirical volume function and the second aspect is modeled via the value function with risk. We use both parametric and non-parametric models to estimate the volume function for each species and the results seem consistent across the two types of models. By conducting simulations, we find that the net benefit and forest managers' decisions are quite sensitive to the risk (the second aspect), which implies that forest management adaptation to extreme events maybe important. With the gradual climate change our results show that longleaf pine may have some comparative advantage when it gets warmer and wetter. This implies that species switch could be an important adaptive action under some climate scenario.

Yield risk and price risk are not taken into account in this paper. We are currently working on this by establishing stochastic price and volume models. Confidence intervals for the simulated optimum can be

Table 7: Results for the three species with rising risk and high prices

Species	$MaxT$	$MinT$	ppt	NB^*	d^*	T^*
Loblolly	23.86(75F)	11.07(52F)	1.320	549.55	4.03	25.93
	+1.2(2F)			-30.52	-0.05	0.02
		+1.48(2.6F)		38.68	0.05	-0.02
			+75mm	-6.67	-0.01	0
	26	16	1.45	-6.16	-0.01	0
Slash	25.85(78.5)	13.05(55.5)	1.355	341.89	4.35	25.00
	+1.2(2F)			-127.30	-0.57	0.25
		+1.48(2.6F)		45.39	0.12	-0.06
			+75mm	-27.42	-0.09	0.04
	26	16	1.45	36.96	0.10	-0.05
Longleaf	25.06(77)	12.55(54.6)	1.391	232.58	1.43	37.02
	+1.2(2F)			-98.88	-0.04	0.27
		+1.48(2.6F)		0.82	0	0.02
			+75mm	14.33	0	-0.02
	26	16	1.45	91.90	0.02	-0.12

obtained. Thus the option of species switch can be examined further.

In the future, we would consider risk preferences of the forest managers and study its impact on adaptation. Another extension would be incorporation of the relationship between the two aspects into the DS model. Some previous literature suggested that the gradual climate change affects ENSO and NAO and thus influence the frequency of natural disasters (Calzadilla, 2005). My study will use these relationships to model their impact on adaptation. In addition, appropriate climate scenarios need to be chosen for simulation purpose. Thus adaptive responses can be simulated within species as well as across species. Although the volume functions have been estimated across the South, they can be “localized” by using climate from specific regions in the South. With local growth, price and climate data, we will be able to map spatial variation in adaptability for different climate scenario.

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