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Climate Change Impact on Quiver Trees in Arid Namibia and South Africa

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1. Introduction

The climate fluctuates and changes naturally, and adding the common problems of land transformation and deforestation, its impact can be very harsh on the natural environment, and cause a decline in the biodiversity of plants and animals. *Aloe dichotoma*, common name Quiver tree, is an important part of the arid regions, such as Namaqualand and Bushmanland in South Africa, and in arid parts of southern Namibia. This succulent tree species occurs in rocky areas, and it can grow quite rapidly under the right conditions. Succulents are able to survive long periods of drought conditions, due to the fact succulent plants has special water-storing tissue which makes part of the plant fleshy, and the Quiver tree has succulent leaf and stem (Van Wyk and Smith, 1996).

The Quiver tree has a 200 year life span, and can grow up to 9 meters tall, and it occurs in summer and winter rainfall regions, and can live under a variety of climatic conditions (Fig. 1). The Quiver tree is important to the ecosystem due to the fact that it is as a source of moisture for a wide variety of mammals, birds, and insects. Foden's detailed study of the demographic data of the Quiver trees show that negligible recruitment has occurred in certain populations for 50 years, and the effects of non-climatic variables, such as herbivory, competition, seed availability, fungal pathogens, plant collection... are very small (Foden, 2002).

Today, the Quiver trees are threatened by agricultural expansion, overgrazing, and mining, as well as droughts and other climate changes (Foden, 2002). Climate changes is one of the major factors affecting the existence of Quiver trees, while the Quiver tree will unlikely to be affected by small climatic fluctuations, but will be affected larger or long term climatic changes. The Quiver tree can potentially provide a good indication of long term climate changes in the arid regions (Foden, 2002).

Previous onsite observations show that Quiver trees are very sensitive to temperature changes, and does not do well under extreme hot and dry conditions. Observations has also shown that the Quiver trees might be responding to higher temperatures by shifting its distribution range towards higher and higher altitudes, showing a preference for slightly cooler regions (Midgley et al., 2009).

Fig. 1. Quiver trees in Kaukusib Koppie, Namibia, 2008

To have a complete picture of the Quiver tree's response to recent climatic changes, samples of Quiver trees were collected from their distributional range in arid Namibia and South Africa, and this is a continuing project funded by the South African National Biodiversity Institute. However, data uncertainty accompanied the sample collections as well.

In 2001 and 2002, Wendy Foden and various assistants collected Quiver trees sample data across the whole range, sampling 53 sites in detail. In 2008 Graeme Ellis re-sampled a subset of the population, sampling 41 sites. In 2009, Res Altwegg and Cory Merow did a thorough analysis and comparison of between the 2 sets of data, for 35 sites, excluding certain sites due to lack of data for comparisons.

In this chapter, we are going one step further, that is, to try to complete all the missing data values, which will allow us to do a more complete comparison. The incomplete data issue is complicated on many fronts:

1. While the 2001-2002 data are the most complete, however, there are several sites with missing variables from the 53 sample sites.
2. The 2008 data is a subset of the original 2001-2002 data, covering 41 sites, and the 2008 data variables are not the same as the 2001-2002 data variables.
3. The 2009 analysed data comparison between 2001-2002 and 2008 data is for 35 sites, with 18 sites uncalculated due to missing data.
4. With all 3 datasets, missing data is a major part of the problem, which renders the 3 datasets incomplete and only partially comparable.
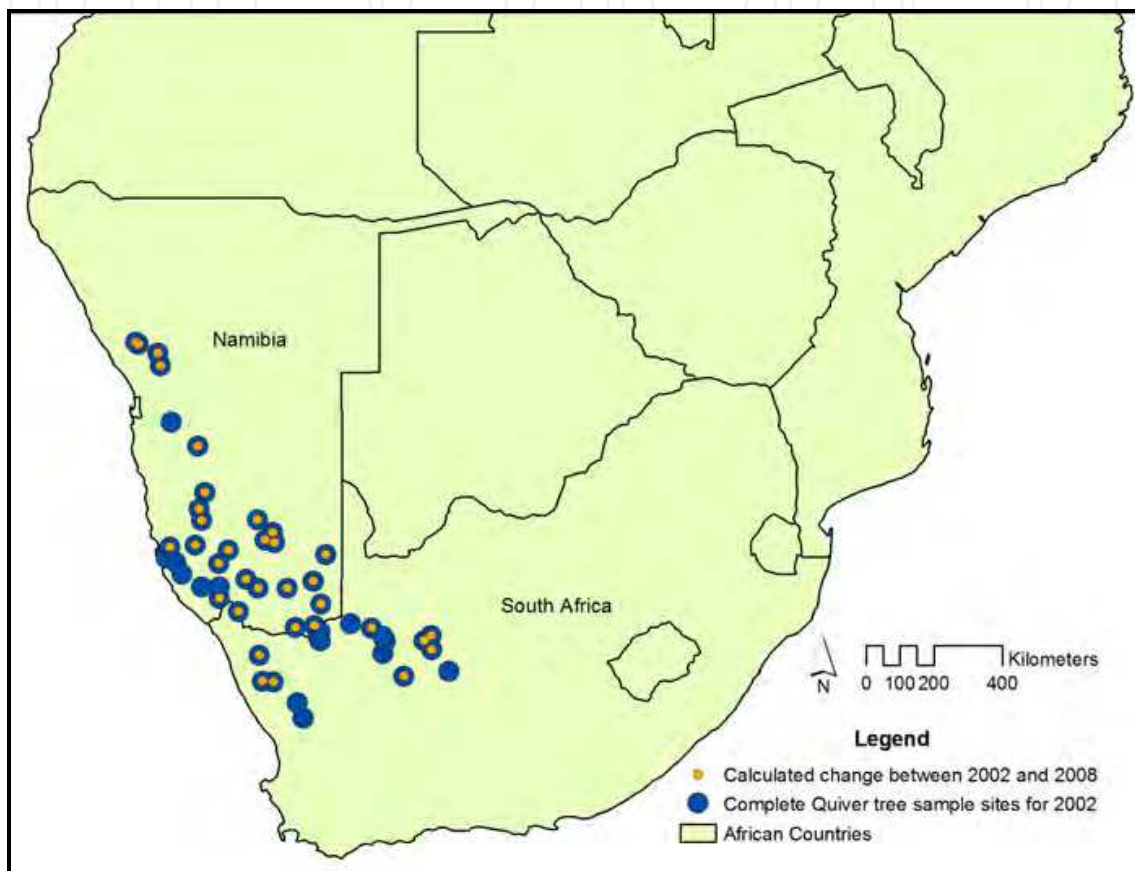

Fig. 2. Available Quiver tree sample site data in Arid Namibia and South Africa

Of course, another sample collection study would be ideal, but to due lack of funding and trained professionals, this is not possible at this stage. In any case, a full usage should be made of the 2002 and 2008 data. In Fig. 2, the Quiver trees sample sites are shown, the Quiver tree's distribution extending over the arid regions in Namibia and South Africa. As one can see from the figure, the 2008 study is a subset of the original 2002 samples.

2. Impreciseness in quiver tree's sample data

To investigate the climate change impacts on the Quiver's spatial distribution from 2002 to 2008, we must have the Quiver's population evolution information. We as biodiversity scientists need to reveal the climate change impacts on plant species based on the data collected. Only solid data-oriented analysis can provide near-true information to the public and governmental decision-making body. In this case, the Quiver tree's dataset is not

complete enough to perform a solid data-oriented analysis because of the impreciseness features of the dataset.

Impreciseness is a fundamental and intrinsic feature in a solid data oriented spatial modelling exercises due to the observational data shortage and incompleteness. Facing the impreciseness reality the spatial statisticians often rely on expert's knowledge to compensate the inadequacy and in accuracy in collected observational data. Nevertheless, such a dependence on experts' knowledge engineering will still open a backdoor to pseudo-scientific believe or claim.

Impreciseness is referred to a term with an intrinsic property governed by an uncertain measure or an uncertainty distribution for each of the actual or hypothetical members of an uncertainty population (i.e., collection of expert's knowledge). An uncertainty process is a repeating process whose outcomes follow no describable deterministic pattern, but follow an uncertainty distribution, such that the uncertain measure of the occurrence of each outcome can be only approximated or calculated.

Definition 2.1: Impreciseness is an intrinsic property of a variable or an expert's knowledge being specified by an uncertainty measure.

In geo-statistics analyst communities it is seldom to mention uncertainty measure. It is true, spatial researchers are used to the term "uncertainty", which represents randomness in their eyes. Actually, this perception is wrong. Researchers have long realized the there are many forms of uncertainty, randomness is merely a member of uncertainty family. How can we differentiate different forms of uncertainty? The answer is fairly straght forward: the appropriate measure specifies a particular form of uncertainty. For example, probability measure specifies random uncertainty.

The uncertainty modelling without a measure specification will not have an rigorous mathematical foundations and consequently the modelling exercise is baseless and blindness. In other words, measure specification is the prerequisite to spatial data collection and analysis. For example, without Kolmogrov's (1950) three axioms of probability measure, randomness is not defined and thus statistical data analysis and inference has no foundation at all.

Notice that imprecise probability theory is a potential remedy to address the observational data inaccuracy and inadequacy because most the geo-statistics analysts are familiar with probability theory. However the imprecise probability based spatial modelling might be not feasible. Just as Utikin and Gurov (2000) has commented, "the probabilistic uncertainty model makes sense if the following three premises are satisfied: (i) an event is defined precisely; (ii) a large amount of statistical samples is available; (iii) probabilistic repetitiveness is embedded in the collected samples. This implies that the probabilistic assumption may be unreasonable in a wide scope of cases."

It is therefore inevitably to seek another form of uncertainty theory to meet the impreciseness challenges. In the theoretical basket, interval uncertainty theory (Moore, 1966), fuzzy theory (Zadeh, 1965, 1978), grey theory (Deng, 1984), rough set theory (1982), upper and lower provisions or expectations (Walley, 1991), or Liu's uncertainty theory (2007, 2010) may be chosen. Nevertheless, Liu's (2007, 2010) uncertainty theory is the only one built on an axiomatic uncertain measure foundation and fully justified with mathematical rigor. Therefore it is logical to engage Liu's (2007, 2010) uncertainty theory for guiding us to understand the intrinsic character of imprecise uncertainty and facilitate an accurate mathematical definition of impreciseness in order to establish the foundations for uncertainty spatial modelling under imprecise uncertainty environments.

3. Uncertain measure foundation

The Uncertainty Theory was founded by Liu in 2007 and refined in 2010 (Liu, 2007, 2010). Nowadays uncertainty theory has become a branch of mathematics.

A key concept in uncertainty theory is the uncertain measure: Let Ξ be a nonempty set (space), and $\mathfrak{A}(\Xi)$ the σ-algebra on Ξ. Each element, let us say, $A \subset \Xi$, $A \in \mathfrak{A}(\Xi)$ is called an uncertain event. A number denoted as $\lambda\{A\}$, $0 \leq \lambda\{A\} \leq 1$, is assigned to event $A \in \mathfrak{A}(\Xi)$, which indicates the uncertain measuring grade with which event $A \in \mathfrak{A}(\Xi)$ occurs. The normal set function $\lambda\{A\}$ satisfies following axioms given by Liu (2011):

Axiom 1: (Normality) $\lambda\{\Xi\} = 1$.

Axiom 2: (Self-Duality) $\lambda\{\cdot\}$ is self-dual, i.e., for any $A \in \mathfrak{A}(\Xi)$, $\lambda\{A\} + \lambda\{A^c\} = 1$.

Axiom 3: (σ- Subadditivity) $\lambda\left\{\bigcup_{i=1}^{\infty} A_i\right\} \leq \sum_{i=1}^{\infty} \lambda\{A_i\}$ for any countable event sequence $\{A_i\}$.

Definition 3.1: (Liu, 2007, 2010) A set function $\lambda : \mathfrak{A}(\Xi) \to [0,1]$ satisfies *Axioms 1-4* is called an uncertain measure. The triple $(\Xi, \mathfrak{A}(\Xi), \lambda)$ is called an uncertainty space.

Definition 3.2: (Liu, 2007, 2010) An uncertain variable is a measurable function ξ from an uncertainty space $(\Xi, \mathfrak{A}(\Xi), \lambda)$ to the set of real numbers.

Definition 3.3: (Liu, 2010) Let ξ be a uncertainty quantity of impreciseness on an uncertainty measure space $(\Xi, \mathfrak{A}(\Xi), \lambda)$. The uncertainty distribution of ξ is

$$\Psi_\xi(x) = \lambda\{\tau \in \Xi \mid \xi(\tau) \leq x\} \tag{1}$$

Theorem 3.4: (Liu, 2007, 2010) Let $\Psi_{\xi_1}, \Psi_{\xi_2}, \cdots, \Psi_{\xi_n}$ be uncertainty distributions for the uncertainty variables $\xi_1, \xi_2, \cdots, \xi_n$ on $(\Xi, \mathfrak{A}(\Xi), \lambda)$ respectively. Let $\Psi_{(\xi_1, \xi_2, \cdots, \xi_n)}$ be the joint distribution of uncertainty vector $(\xi_1, \xi_2, \cdots, \xi_n)$. If $\xi_1, \xi_2, \cdots, \xi_n$ are independent, then

$$\Psi_{(\xi_1, \xi_2, \cdots, \xi_n)}(x_1, x_2, \cdots, x_n) = \min_{1 \leq i \leq n} \Psi_{\xi_i}(x_i) \tag{2}$$

for any real numbers $x_1, x_2, \cdots, x_n \in \mathbb{R}$.

Definition 3.5: (Liu, 2007, 2010) Let ξ be a uncertainty variable on an uncertainty measure space $(\Xi, \mathfrak{A}(\Xi), \lambda)$. The expectation ξ is defined by

$$E[\xi] = \int_0^{+\infty} \lambda\{\xi \geq r\} dr - \int_{-\infty}^0 \lambda\{\xi \leq r\} dr \tag{3}$$

provided that one of the two integrals exists at least.

Definition 3.6: (Liu, 2007, 2010) Let ξ be a uncertainty variable on an uncertainty measure space $(\Xi, \mathfrak{A}(\Xi), \lambda)$.with uncertainty distribution function and Ψ_ξ a finite expectation μ. Then the variance of ξ, denoted by $V[\xi]$, is defined by

$$V[\xi] = 2 \int_0^{+\infty} (r - \mu)(1 - \Psi_\xi(r) + \Psi_\xi(2\mu - r)) dr. \tag{4}$$

Liu's uncertainty theory (Liu, 2007, 2010) does not define multivariate uncertainty distribution, (Guo, 2010; Guo et al., 2007), except for the independent uncertainty variables.

Hence it is necessary to facilitate a framework for showing the preparation to define the uncertain covariance.

Let $\Psi_{\xi_1}, \Psi_{\xi_2}, \cdots, \Psi_{\xi_n}$ be uncertainty distributions for the uncertainty variables $\xi_1, \xi_2, \cdots, \xi_n$ on $\left(\Xi, \mathfrak{A}(\Xi), \lambda\right)$ respectively. Let $\Psi_{(\xi_1, \xi_2, \cdots, \xi_n)}$ be the joint distribution of uncertainty vector $(\xi_1, \xi_2, \cdots, \xi_n)$. Assuming that ξ_i and ξ_j two arbitrary pair of uncertainty variables within the uncertainty vector $(\xi_1, \xi_2, \cdots, \xi_n)$ which have finite expectations μ_1 and μ_2 respectively. Denote $\Psi_{(\xi_i, \xi_j)}$ bivariate uncertainty distribution function.

Definition 3.7: Let $\eta_{ij} = (\xi_i - \mu_i)(\xi_j - \mu_j)$ be product of centered uncertainty variables ξ_i and ξ_j. The uncertainty distribution of η_{ij} is defined by

$$\Psi_{\eta_{ij}}(y) = \sup_{z_1 z_2 = y} \Psi_{(\xi_i, \xi_j)}(z_i, z_j), \ \forall(z_i, z_j) \in \mathbb{R}^2 \tag{5}$$

Definition 3.8: Let $\eta_{ij} = (\xi_i - \mu_i)(\xi_j - \mu_j)$ be product of centered uncertainty variables ξ_i and ξ_j. The expectation of centered product η_{ij} is called the covariance between uncertainty variables ξ_i and ξ_j, that is by

$$\gamma_{ij} \triangleq \mathrm{E}\left[\eta_{ij}\right] = \int\limits_0^{+\infty} \left(1 - \Psi_{\eta_{ij}}(r)\right) dr - \int\limits_{-\infty}^0 \Psi_{\eta_{ij}}(r) dr \tag{6}$$

Theorem 3.9: Let $\xi_1, \xi_2, \cdots, \xi_n$ be independent uncertainty variables on $(\Xi, \mathfrak{A}, \lambda)$. Then

$$\Psi_{\eta_{ij}}(y) = \sup_{z_1 z_2 = y} \left(\Psi_{\xi_1}(z_1) \wedge \Psi_{\xi_2}(z_2)\right), \ \forall(z_i, z_j) \in \mathbb{R}^2 \tag{7}$$

Remark 3.10: Different from independent random variables X_1 and X_2, whose $\mathrm{E}\left[\left(X_1 - \mathrm{E}[X_1]\right)\left(X_2 - \mathrm{E}[X_2]\right)\right] = 0$. In uncertainty theory, independent $\xi_1, \xi_2, \cdots, \xi_n$ do not imply $\eta_{ij} = 0$.

Remark 3.11: The formation of uncertain variance-covariance does touch the detailed functional form of multivariate uncertainty joint distribution. For practical applications, the form of multivariate uncertainty joint distribution is not necessarily available, but the paired uncertainty bivariate distribution must be given.

Similar to the concept of stochastic process in probability theory, an uncertain process $\{\xi_t, t \geq 0\}$ is a family of uncertainty variables indexed by t and taking values in the state space $\mathbb{S} \subseteq \mathbb{R}$.

Definition 3.12: (Liu, 2007, 2010) Let $\{C_t, t \geq 0\}$ be an uncertain process.

(1) $C_0 = 0$ and all the trajectories of realizations are Lipschitz-continuous;

(2) $\{C_t, t \geq 0\}$ has stationary and independent increments;

(3) every increment $C_{t+s} - C_s$ is a normal uncertainty variable with expected value 0 and variance t^2, i.e., the uncertainty distribution of $C_{t+s} - C_s$ is

$$\Psi_{C_{t+s} - C_s}(z) = \left(1 + \exp\left(-\frac{\pi z}{\sqrt{3}t}\right)\right)^{-1} \tag{8}$$

then $\{C_t, t \geq 0\}$ is called an uncertain canonical process.

Theorem 3.13: Assuming that $\{C_t, t \geq 0\}$ is an uncertain canonical process. Therefore, in the autocovariance and autocorrelation of uncertain canonical process $\{C_t, t \geq 0\}$ are

$$\sigma_{s,t} = s^2 + \mathrm{E}\left[C_s\left(C_t - C_s\right)\right] = s^2 + \delta_{s,t-s} \tag{9}$$

and

$$\rho_{s,t} = \frac{s}{t} + \frac{\delta_{s,t-s}}{st}, \ (s < t) \tag{10}$$

where

$$\begin{aligned}
\delta_{s,t-s} &= E[C_s(C_t - C_s)] \\
&= \int_0^\infty \left(1 - \sup_{xy=r}\left(\Psi_{C_s}(x) \wedge \Psi_{C_{t-s}}(y)\right)\right) dr \\
&\quad - \int_{-\infty}^0 \sup_{xy=r}\left(\Psi_{C_s}(x) \wedge \Psi_{C_{t-s}}(y)\right) dr
\end{aligned} \tag{11}$$

4. Habitat measure

Note that the Quiver tree's 2002 data subset contains percentage of dead trees, percentage of juvenile trees, the total density of trees, and the average age of dead trees. Also, Quiver tree's 2008 data subset contains population growth rate, survival reproductives, survival non-reproductives, and proportion juvenile. Considering the aim of this research: climate change impacts on the Quiver tree's population, we select total density of tree (in 2002 data subset) and population growth rate (in 2008 data subset) as the our analysis data. We will build our model based on the total tree population size

$$V_i^{(k)} = A^{(k)} \kappa_i^{(k)} \tag{12}$$

where the $V_i^{(k)}$ is the total population size at year i over area size $A^{(k)}$, and total density $\kappa_i^{(k)}$.

Notice that among 53 sites, 43 sites have total density observational values. Ten sites have missing values. That is, without total density observation {10,12,14,15,17,19,33,36,37,128} site number set.

For inexperienced go-statistics analysts, kriging method might be a choice for filling the ten missing vaules. Nevertheless, after examining the 2002 total density of tree's 43 observations, we found that geometric distance does not play a role in dertermining the value of the total density of trees. we can find out that the total density observations are not similar even for the very nearby sites geometrically within the same ecological sub-region. For example, Site , see Table 1.

From Table 1, it is obvious that for the Quiver tree's growth status, $\{Z(s), s \in \mathbb{R}^2\}$, the spatial location $s \in \mathbb{R}^2$ only partially links to the tree habitation. While the geometric distance between two locations s and $s+h$ is no longer fully reflecting the habitat closeness. The Quiver tree's growth status observations reveal a fact that the total density status is extremely sensitive to the ecological conditions of individual site area (or the area habitat).

The graphical location and the isotropic distance will not offer much information, rather the Quiver tree's growth observation $Z(s)$ gives the best indication of the tree area habitat.

Group/ site no.		Coordinates		Total density of trees	Geometric distance	Difference in total density	Density / distance
		longitude	latitude				
1	40	21.64455	-30.00486	36.41	1.1977228	65.42	54.62
	42	22.83446	-29.86828	101.83			
2	101	18.20583	-30.15250	70.00	0.285919122	6.67	23.33
	102	17.92017	-30.14033	63.33	0.688683879	16.67	24.20
	103	17.83583	-29.45683	46.67	0.787944636	23.33	29.61
3	3	19.25749	-27.49479	33.33	0.003999625	52.38	13096.47
	4	19.26062	-27.49230	54.17			

Table 1. 3 groups of sites and their total densities

The measure of habitat closeness can be defined by the habitat distance, which is a virtual distance indicating the aggregate ecological environment of an area. In such a circumstance, if we still impose conventional isotropic distance assumption to construct a kriging predictor, the prediction would be no sense at all.

It is logical to argue that in order to utilize the n observations $\{Z(s), s \in \mathfrak{N}_{s_0} \subset \mathbb{R}^2\}$ contained in the neighbourhood of s_0: $\mathfrak{N}_{s_0} = \{s_0, s_1, s_2, \cdots, s_n\}$, at s_0 without an Quiver tree's observation, to predict $Z(s_0)$, utilize the habitat distance information is far more efficient that the conventional isotropic distance.

As to how to define the habitat distance measure, it depends upon the habitat spatial distribution pattern as well as the form of uncertainty governing the spatial process $\{Z(s), s \in \mathbb{R}^2\}$.

In this study, we are going to calculate habitat distance in following three approaches:

(1) Grouping method. This approach classifies total density observations $\{Z(s), s \in \mathbb{R}^2\}$ into groups by the sizes of $Z(s)$. Then, for each group, the variance is calculated. choose the variance of group observation as habitat measure. We may face the situation at which some $Z(s)$ values may be far away from those grouped observations. Then we may group them according to geometrical distance criterion, then calculate the variances for those isolated total density observations. Table 2 lists a few observational groups and group habitat distances.

It is logical to ignore those 3 groups because of extreme group variances, which should not accepted as habitat measures.

(2) Inverse-distance methods. Notice that there are ten sites without total density observations and thus their habitat measures cannot be determined. However, later we will see the empirical habitat measure is necessary for uncertain kriging.

In this paper, we propose two schemes for addressing the habitat measure at missing total density value site. The first one is the conventional inverse distance estimation. The second one is utilizing the empirical habitat distance for uncertain inverse distance estimation.

The conventional inverse distance estimation. Table 5 summarizes the results (at $\lambda = 1.0$ because near optimal $\lambda = 0.1$ gives illogical empirical results).

Group/ Site no.		Coordinates		Total density of trees	Habitat measure
		longitude	latitude		
1	42	22.83446	-29.86828	101.83	1.1112310
	11	18.18643	-26.21253	100.00	
	113	22.18500	-29.06700	100.00	
2	20	16.23986	-25.59329	90.48	2.0052690
	13	15.15805	-21.48867	91.70	
	124	19.43333	-28.83333	93.30	
3	4	19.26062	-27.49230	33.33	3.4715580
	2	19.28217	-28.66671	33.33	
	40	21.64455	-30.00486	36.41	
	123	19.40000	-28.98333	36.70	
4	104	17.28650	-28.30430	40.00	11.1111222
	108	19.45333	-28.10333	43.33	
	103	17.83583	-29.45683	46.67	
5	107	18.56950	-27.68433	113.33	11.5226107
	29	15.47427	-26.58937	106.67	
	30	16.76122	-27.03209	111.11	
6	41	22.37461	-29.29727	86.05	11.5534900
	121	19.43333	-29.06667	80.00	
	122	19.43333	-29.06667	80.00	
	3	19.25749	-27.49479	85.71	
7	112	22.37000	-28.93500	130.00	14.9633000
	126	21.10000	-29.40000	123.30	
	26	16.31455	-27.64893	130.00	
8	23	15.62385	-26.99582	22.22	17.0993200
	9	17.01403	-26.66638	28.07	
9	102	17.92017	-30.14033	63.33	19.9113500
	1	18.78301	-28.71597	63.33	
	101	18.20583	-30.15250	70.00	
	125	20.23333	-28.61667	70.00	
	120	18.83333	-30.70000	73.30	
10	110	18.98883	-31.10050	50.00	21.5049200
	5	19.59336	-26.79313	54.17	
	24	15.78774	-27.31541	59.26	
11	106	17.98333	-26.40217	166.67	53.3333900
	18	16.21400	-23.95119	153.33	
	105	18.23967	-26.47550	153.33	
	22	15.36674	-26.88367	166.67	
	28	16.14727	-26.54360	166.67	

Table 2. Groups of total densities and habitat measures (group variances)

It is obvious that there are five sites left listed in Table 3.

Group/ site no.		Coordinates		Total density of trees	Group variance
		longitude	latitude		
12	127	21.16667	-29.08333	6.70	
13	34	16.77862	-27.64536	282.61	1843.7403440
	111	18.98567	-31.10583	343.33	
14	109	20.79000	-28.74017	200.00	12482.0000000
	21	16.31081	-25.88543	252.17	

Table 3. 3 Groups of total densities left with group variances

Site no.	Coordinates		Predicted total density of trees	Predicted habitat measure
	longitude	latitude		
15	14.57582	-21.20986	103.2131	1.1112310
14	14.63088	-21.26169	102.9913	1.1112310
12	15.21586	-21.81786	102.3649	1.1112310
17	15.51133	-23.30893	110.5426	11.5226107
19	16.39317	-25.14609	115.2105	11.5226107
33	16.77479	-27.94278	121.9919	14.9633000
36	17.47540	-27.45209	106.7434	11.5226107
10	17.78013	-25.87191	110.3903	11.5226107
37	17.80606	-27.67034	101.0099	1.1112310
128	21.10000	-28.95000	82.67477	11.5534900

Table 4. 10 Sites of Inverse Distance predicted total densities

From Table 4, we can see that since the estimated total density estimators are calculated in terms of graphical distances. Those estimators are empirical prior information. As to habitat measure, they are taking the values by comparing the estimated total density to the group total density values in Table 4. Definitely, the empirical habitat measures are not all accurate.

(3) Uncertain canonical process regression methods. Because the Quiver tree's total density is very sensitive to local area ecological environments, it is logical to consider if some uncertain relationship between the observed total density and ecological environmental variables, say, annual temperature, and annual rainfall. Table 4 lists the data, from which a linear relationship between group average total density y_{d_i} and group average annual temperature T_{d_i} and group average annual rainfall R_{d_i} at the empirical distance d_i, $i = 1, 2, \cdots, 11$, is intended to establish.

The uncertain regression model takes a form:

$$y_{d_i} = \alpha_0 + \alpha_1 T_{d_i} + \alpha_2 R_{d_i} + \sigma C_{d_i},$$
$$i = 1, 2, \cdots, 11$$

(13)

where errors C_{d_i}, $i = 1, 2, \cdots, 11$ are from the uncertain canonical process $\{C_d, d \in [0, +\infty)\}$. As to $\{C_d, d \in [0, +\infty)\}$. The fitted regression is

$$\hat{y}_{d_i} = \underset{(66.6838)}{500.4016} + \underset{(6.1464)}{30.1100} T_{d_i} - \underset{(2.0621)}{8.8953} R_{d_i},$$

$$i = 1, 2, \cdots, 11$$

(14)

Site no.	Coordinates		Predicted total	Predicted habitat
	longitude	latitude	density of trees	measure
15	14.57582	-21.20986	110.3210	11.5226
14	14.63088	-21.26169	26.5995	17.0993
12	15.21586	-21.81786	55.0573	21.5049
17	15.51133	-23.30893	83.5152	11.5535
19	16.39317	-25.14609	8.72890	2.0582
33	16.77479	-27.94278	147.0394	53.3334
36	17.47540	-27.45209	72.2531	19.9114
10	17.78013	-25.87191	20.9684	17.0993
37	17.80606	-27.67034	29.9036	17.0993
128	21.10000	-28.95000	101.3857	1.1112

Table 5. 10 Sites of Regression Predicted total densities left with habitat measures

However, it is necessary to mention that the uncertain regression model is carried on the group average total density against group average annual temperature and group annual rainfall and thus the predictability is limited although the model goodness-of fit ($R^2 \approx 0.7$) is far better than that of classical regression model ($R^2 \approx 0.21$), whose coefficients for annual temperature and annual rainfall are both insignificant statistically. We are not going to use these regression predicted total density of trees as the basic results for evaluations of climate change impacts.

Finally, we must emphasize that for any given spatial process $\{Z(s), s \in \mathbb{R}^2\}$, which has no order, this fact would prevent geostatistical analysts from utilizing 1-dimensional statistical approaches for predictions, for example, the uncertain regression engaged. But after defining appropriate habitat distance for spatial process, then the habitat distance set can be indexed an uncertain canonical process as the desired partner process, and hence the intrinsic covariance structure of the partner process will be available and thus simplify greatly the semi-variogram computations, while in probabilistic kriging the theoretical semi-variogram must be replaced by sample or experimental semi-variogram. The uncertain semi-varogram is semi-data oriented, in contrast, the probabilistic sample or experimental semi-variogram is fully data-oriented.

5. Uncertain kriging predictor

We first point out that kriging predictor is not intrinsic to the probabilistic spatial statistics. As long as variance, covariance, and semi-variogram concepts can be established on some uncertain theory, no matter it is Zadeh's fuzzy theory, rough set theory, grey theory, random set theory, or interval theory, or Liu's uncertainty theory, new kriging predictor can

be solidly established with similar mathematical formulae as that of probabilistic ordinary kriging (Cressie, 1991). However, the geometric location s should be replaced by habitat distance $d(s)$, which is the square root of habitat measure.

An uncertain semi-variogram is defined by

$$2\gamma\left(d_{s_i} - d_{s_j}\right) = V\left(Z\left(d_{s_i}\right) - Z\left(d_{s_j}\right)\right) \tag{15}$$

where d_{s_i} and d_{s_j} are two habitat distances at location s_i and location s_j respectively. The uncertain kriging predictor is defined by

$$Z\left(d_{s_0}\right) = \sum_{i=1}^{n} \lambda_i Z\left(d_{s_i}\right) \tag{16}$$

where $\lambda_1, \lambda_2, \cdots, \lambda_n$ are determined by minimizing the following objective function.

$$\mathrm{E}\left[\left(Z\left(d_{s_0}\right) - \sum_{i=1}^{n} \lambda_i Z\left(d_{s_i}\right)\right)^2\right] - 2\psi\left(\sum_{i=1}^{n} \lambda_i - 1\right) \tag{17}$$

where ψ is the Lagrange's multiplier. Then the uncertain kriging equation system is given by

$$\underline{\lambda}_U = \Gamma_U^{-1}\underline{\gamma}_U \tag{18}$$

where

$$\begin{aligned}
&\underline{\lambda}_U = \left(\lambda_1, \lambda_2, \cdots, \lambda_n, \psi\right)', \\
&\underline{\gamma}_U = \left(\gamma\left(d_{s_1} - d_{s_0}\right), \gamma\left(d_{s_2} - d_{s_0}\right), \cdots, \gamma\left(d_{s_n} - d_{s_0}\right), 1\right)' \\
&\Gamma_U = \left(o_{ij}\right)_{(n+1)\times(n+1)} \\
&o_{ij} = \begin{cases} \sigma^2 & i = j = 1, 2, \cdots, n \\ \gamma\left(d_{s_i} - d_{s_j}\right) & i \neq j = 1, 2, \cdots, n \\ 1 & i = n+1, j = 1, 2, \cdots, n \\ 0 & i = j = n+1 \end{cases}
\end{aligned} \tag{19}$$

Theorem 5.1: Let

$$\underline{\lambda} = \left(\lambda_1, \lambda_2, \cdots, \lambda_n\right)' \tag{20}$$

then,

$$\underline{\lambda}' = \left(\underline{\gamma} + \underline{1}\frac{\left(1 - \underline{1}'\Gamma^{-1}\underline{\gamma}\right)}{\underline{1}'\Gamma^{-1}\underline{1}}\right)\Gamma^{-1} \tag{21}$$

where

$$\psi = -\frac{\left(1 - \underline{1}'\Gamma^{-1}\underline{\gamma}\right)}{\underline{1}'\Gamma^{-1}\underline{1}} \tag{22}$$

Theorem 5.2: Let $d_{s_i,s_j} \triangleq d_{s_j} - d_{s_i}$, $d_{s_i} \le d_{s_j}$. Then the semi-variogram of habitat distance d_{s_i,s_j} is

$$\gamma\left(d_{s_i,s_j}\right) = \frac{1}{2}\left(d_{s_j} - d_{s_i}\right) - \delta_{d_{s_i},d_{s_j}-d_{s_i}} \tag{23}$$

Proof: It is noticed that for $\forall d_{s_i} \le d_{s_j}$

$$
\begin{aligned}
&\gamma\left(d_{s_i,s_j}\right) \\
&= \frac{1}{2}\mathrm{E}\left[\left(Z\left(d_{s_i}\right) - Z\left(d_{s_j}\right)\right)^2\right] \\
&= \frac{1}{2}\mathrm{E}\left[\left(\left(Z\left(d_{s_i}\right) - m\right) - \left(Z\left(d_{s_j}\right) - m\right)\right)^2\right] \\
&= \frac{1}{2}\mathrm{E}\left[\left(Z\left(d_{s_i}\right) - m\right)^2\right] + \frac{1}{2}\mathrm{E}\left[\left(Z\left(d_{s_j}\right) - m\right)^2\right] \\
&\quad - \mathrm{E}\left[\left(Z\left(d_{s_i}\right) - m\right)\left(Z\left(d_{s_j}\right) - m\right)\right] \\
&= \frac{1}{2}\left(\sigma^2\left(Z(s_i)\right) + \sigma^2\left(Z(s_j)\right)\right) - \mathrm{E}\left[\varepsilon\left(d_{s_i}\right)\varepsilon\left(d_{s_j}\right)\right] \\
&= \frac{1}{2}\left(d_{s_i} + d_{s_j}\right) - \sigma_{d_{s_i},d_{s_j}} \\
&= \frac{1}{2}\left(d_{s_i} + d_{s_j}\right) - \left(d_{s_i} + \delta_{d_{s_i},d_{s_j}-d_{s_i}}\right) \\
&= \frac{1}{2}\left(d_{s_j} - d_{s_i}\right) - \delta_{d_{s_i},d_{s_j}-d_{s_i}}
\end{aligned}
\tag{24}
$$

However, at location s_0, there is no observation $Z(s_0)$ and thus the habitat distance d_{s_0} is undefined. It is necessary to "define" the habitat distance d_{s_0} in order to carry on the uncertain kriging predictions.

Definition 5.3: If geometric location s_k is close to s_0, at which $Z(s_k)$ is observed, then the habitat distance of $Z(s_k)$ is defined as the habitat distance d_{s_0} at location s_0.

There is possibility that some $\lambda_{i_{np}} < 0$. Sort $\{\lambda_1, \lambda_2, \cdots, \lambda_n\}$ such that $\lambda_{(1)} \le \lambda_{(2)} \le \cdots \le \lambda_{(n)}$,

assuming $i_p : \lambda_{(i_p-1)} < 0, \lambda_{(i_p)} > 0$ e that there are n_{np} terms which but $\sum_{i=1}^{n_{s_0}} \lambda_{(i)} = 1$, but

$\sum_{i=1}^{n_{s_0}} \left|\lambda_{(i)}\right| > 1$. Let us define the adjusted coefficient $\lambda_i^{adjusted}$ as

$$
\lambda_{(i)}^{adjusted} = \begin{cases} \dfrac{1}{\left(i_{s_p}\right)-1}\left(1-\dfrac{\displaystyle\sum_{i=(i_p)}^{(n_{s_0})}\lambda_i}{\displaystyle\sum_{i=(1)}^{(n_{s_0})}|\lambda_i|}\right) & \text{if } (i)<(i_p) \\[4mm] \dfrac{\lambda_{(i)}}{\displaystyle\sum_{(i)=1}^{(i_{n_{s_0}})}|\lambda_i|} & \text{if } (i)\geq(i_p) \end{cases} \tag{25}
$$

It is obvious that constraint

$$
\sum_{(i)=1}^{(n_{s_0})}\lambda_{(i)}^{adjusted}=1.0 \tag{26}
$$

is truly kept and also all $\lambda_i^{adjusted}\in(0,1)$.

We will calculate those uncertain kriging predictors for the ten sites {10,12,14,15,17,19,33,36, 37,128} without total density observations in following 4 steps.

Step 1: Determine the 10 neighbourhoods

$$
\left\{\mathcal{N}_{s_0^{(k)}}\right\}_{k=1}^{10} \tag{27}
$$

where $s_0^{(k)}\in\{10,12,14,15,17,19,33,36,37,128\}$. Each $\mathcal{N}_{s_0^{(k)}}$ contains six sites with observed total density values.

Step 2: For each individual neighbourhood $\mathcal{N}_{s_0^{(k)}}$, for example, $\mathcal{N}_{s_0^{(k)}}=\left\{s_1^{(k)},s_2^{(k)},\cdots,s_6^{(k)}\right\}$, determine the corresponding habitat distance from Table 3, 4, and 6, respectively, denoted by

$$
\mathcal{D}^{(k)}=\left\{d_{s_1^{(k)}},d_{s_2^{(k)}},\cdots,ds_6^{(k)},d_{s_0^{(k)}}\right\} \tag{28}
$$

Step 3: Calculate those uncertain semi-variograms

$$
\gamma\left(d_{s_i^{(k)},s_j^{(k)}}\right),\ \forall d_{s_i^{(k)}}<d_{s_j^{(k)}}\ \text{ and }
$$

$$
\gamma\left(d_{s_0^{(k)},s_i^{(k)}}\right),\ \forall d_{s_0^{(k)}}<d_{s_i^{(k)}}\ (\text{or } \gamma\left(d_{s_i^{(k)},s_0^{(k)}}\right),\ \forall d_{s_i^{(k)}}<d_{s_0^{(k)}}) \tag{29}
$$

in terms of

$$
\gamma\left(d_{s_i^{(k)},s_j^{(k)}}\right)=\frac{1}{2}\left(d_{s_j^{(k)}}-d_{s_i^{(k)}}\right)-\delta_{d_{s_i^{(k)}},d_{s_j^{(k)}}-d_{s_i^{(k)}}} \tag{30}
$$

with

$$\delta_{d_{s_i^{(k)}}, d_{s_j^{(k)}} - d_{s_i^{(k)}}}$$
$$= \int_0^\infty \left(1 - \sup_{xy=r} \left(\Psi_{C_{d_{s_i^{(k)}}}}(x) \wedge \Psi_{C_{d_{s_j^{(k)}} - d_{s_i^{(k)}}}}(y) \right) \right) dr \qquad (31)$$
$$- \int_{-\infty}^0 \sup_{xy=r} \left(\Psi_{C_{d_{s_i^{(k)}}}}(x) \wedge \Psi_{C_{d_{s_j^{(k)}} - d_{s_i^{(k)}}}}(y) \right) dr,$$

Step 4: Calculate $\left\{ \lambda_1^{(k)}, \cdots, \lambda_6^{(k)} \right\}$ according to equation (25).

Step 5: Calculate the kriging predictor

$$Z\left(s_0^{(k)} \right) = \sum_{i=1}^{n^{(k)}} \lambda_i^{(k)} Z\left(s_i^{(k)} \right), \qquad (32)$$

The upper bound $1 \leq n^{(k)} \leq 6$, in case of $n^{(k)} < 6$, which implies some locations have the same habitat distance value, we simply put the average of total density values with the same habitat distance to participate the uncertain kriging predictor computations.

Step 6: Repeat **Step 2** to **Step 5**, until all 10 uncertain kriging predictors are calculated. Then stop.

Table 7 summarizes uncertain kriging predictor values, and lists the no total density observation sties (similar to Table 6).

site no.	Coordinates		Uncertain kriging predicted total density of trees
	longitude	latitude	
15	14.57582	-21.20986	132.446
14	14.63088	-21.26169	155.987
12	15.21586	-21.81786	177.641
17	15.51133	-23.30893	132.567
19	16.39317	-25.14609	99.266
33	16.77479	-27.94278	62.493
36	17.47540	-27.45209	117.045
10	17.78013	-25.87191	121.982
37	17.80606	-27.67034	72.249
128	21.10000	-28.95000	44.087

Table 6. Uncertain Kriging Predictions for 10 sites

Next, we will use uncertain kriging methods to predict the missing values for the population growth rate. There are 18 sites without values: Site number {120,111,110,125,22,23,24,26,123,124,121,122,17,34,126,128,127,42}

| site no. | Coordinates | | Habitat measure | Uncertain kriging Predicted population growth rate |
	longitude	latitude		
120	18.83333	-30.7	19.91135	1.02490171
111	18.98567	-31.1058	1843.74	1.027150902
110	18.98883	-31.1005	21.50492	1.025065854
125	20.23333	-28.6167	19.91135	1.01815189
22	15.36674	-26.8837	53.33339	0.995053254
23	15.62385	-26.9958	17.09932	1.030192199
24	15.78774	-27.3154	21.50492	1.036620495
26	16.31455	-27.6489	14.9633	1.006659104
123	19.4	-28.9833	3.471558	1.001714497
121	19.43333	-28.8333	2.005269	1.004648936
124	19.43333	-29.0667	11.55349	1.014237773
122	19.43333	-29.0667	11.55349	1.014237773
17	15.51133	-23.3089	11.5535	0.999365585
34	16.77862	-27.6454	1843.74	1.000142274
126	21.1	-29.4	14.9633	1.02687582
128	21.1	-28.95	1.1112	1.014980439
127	21.16667	-29.0833	2.0582	1.005842705
42	22.83446	-29.8683	1.111231	1.003521691

Table 7. Uncertain Kriging Predictions for 18 sites

6. Climate change impacts

Now we are ready to calculate the missing values of 2008 total density of trees, which are 25 sites. We utilize the compound growth rate formula:

$$\kappa_{2008}^{(k)} = \kappa_{2002}^{(k)} \left(1 + r^{(k)}\right)^6 \qquad (33)$$

Denote the Site k population growth rate during i years' period as $\rho_{(i)}^{(k)}$, then, we can use the compound growth formula,

$$\rho_{(i)}^{(k)} = \left(1 + r^{(k)}\right)^i \qquad (34)$$

Then

$$r^{(k)} = \exp\left(\frac{1}{i} \ln\left(\rho_{(i)}^{(k)}\right)\right) - 1 \qquad (35)$$

Therefore, if the total density $\kappa_{2002}^{(k)}$ is available, no matter it is observed or predicted in terms of uncertain kriging approach, $\kappa_{2008}^{(k)}$ will be determined.

After the calculations, we have complete data of $\kappa_{2008}^{(k)}$ and $\kappa_{2008}^{(k)}$ for site k, then The change in site k will be

$$\delta^{(k)} = \kappa^{(k)}_{2008} - \kappa^{(k)}_{2002} \qquad (36)$$

The final uncertain predicted results together with the original sampled results of 2002 and 2008 are shown in the Fig. 3. The reason that they look exactly the same with absolutely no difference at all, is because the increase and decrease in total densities are so small, that they cannot be viewed just by looking at the intervals.
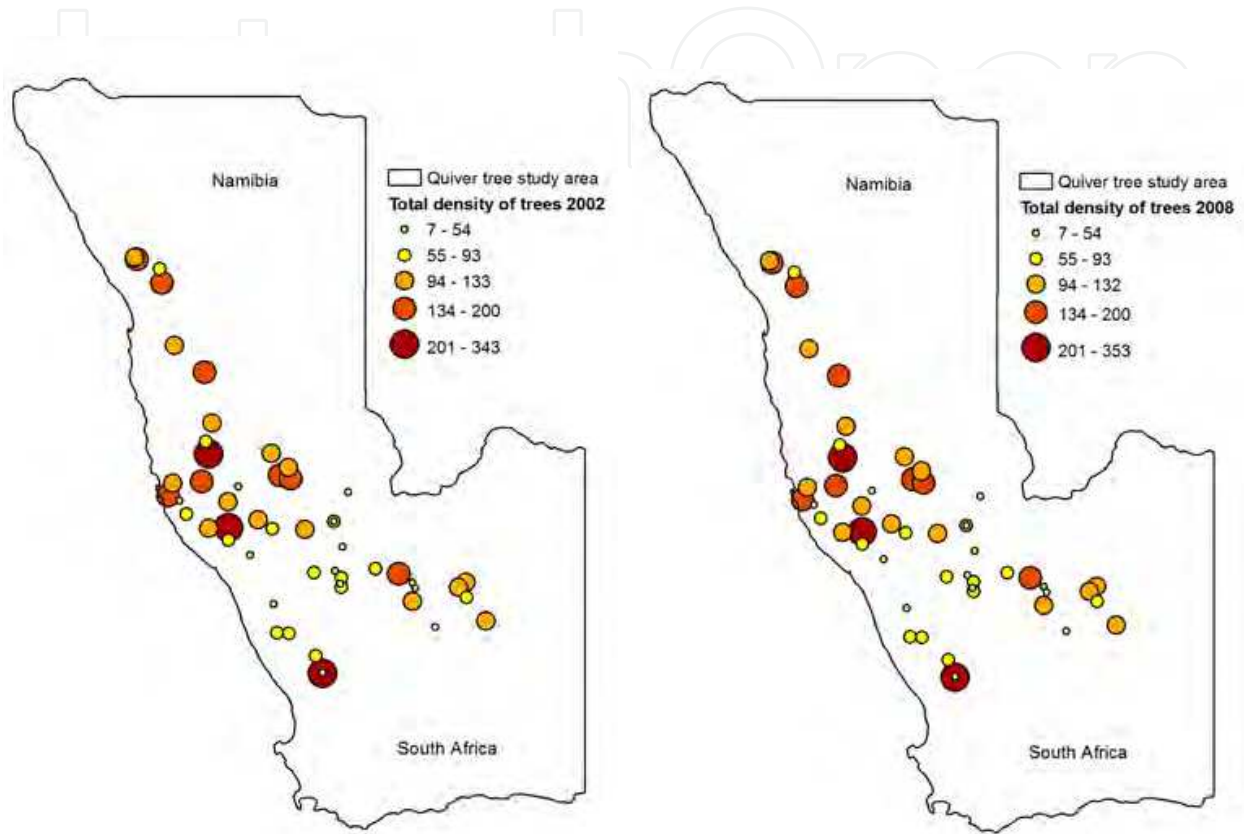

Fig. 3. Sampled and Predicted total density of Quiver trees in Namibia and South Africa, 2002 and 2008

In Fig. 4 the Ordinary kriging prediction maps of sampled and predicted total density of Quiver trees in 2002 and 2008 are shown. Since the population increase and decrease are very small, which is why they are only reflected using kriging maps. However, the kriging maps are slightly distorted in value, due to re-calculations of sample and predicted values, and the average mean values are used.

Table 8 and Fig. 5 show the change in the total density of Quiver trees over a 6 year period, between 2002 and 2008.

	Negative change ($\delta^{(k)} < 0$)	Positive change ($\delta^{(k)} > 0$)	unchanged ($\delta^{(k)} = 0$)
No. Of sites	7	18	28
Percentages	13.21%	33.96%	52.83%

Table 8. Climate change impact on total density of Quiver trees over 6 year period
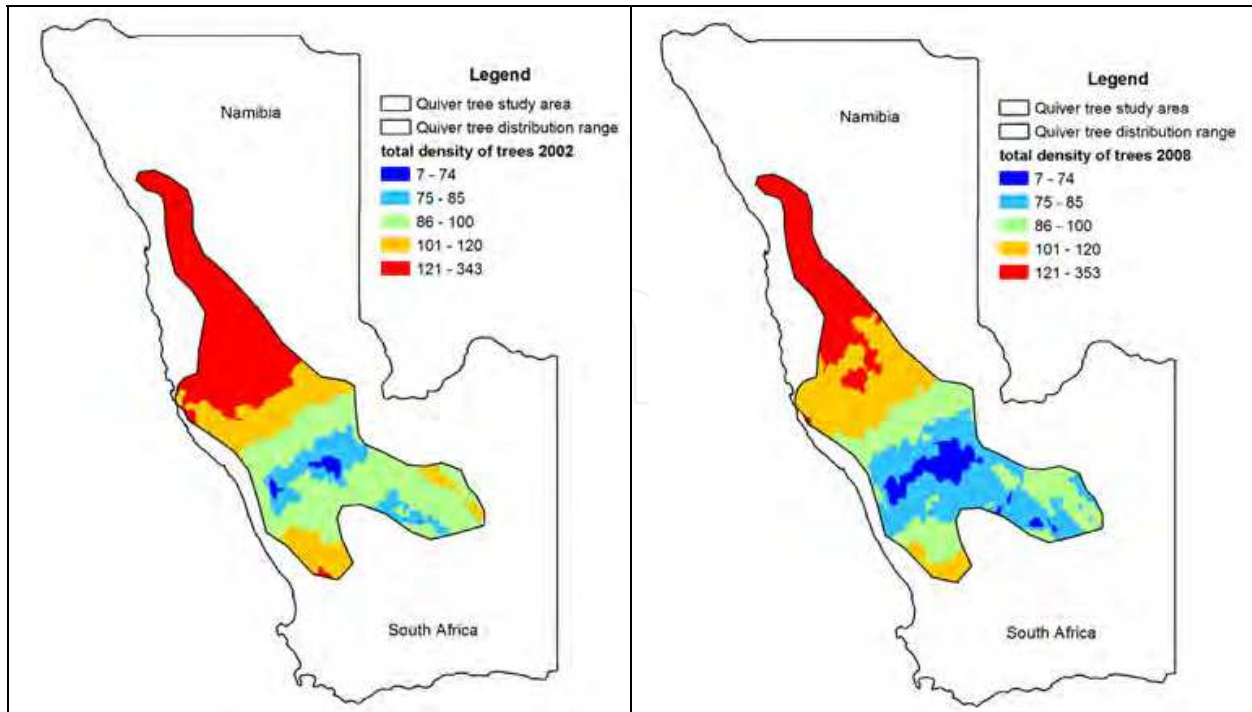
Fig. 4. Ordinary Kriging prediction maps of the total density of Quiver trees, 2002 and 2008
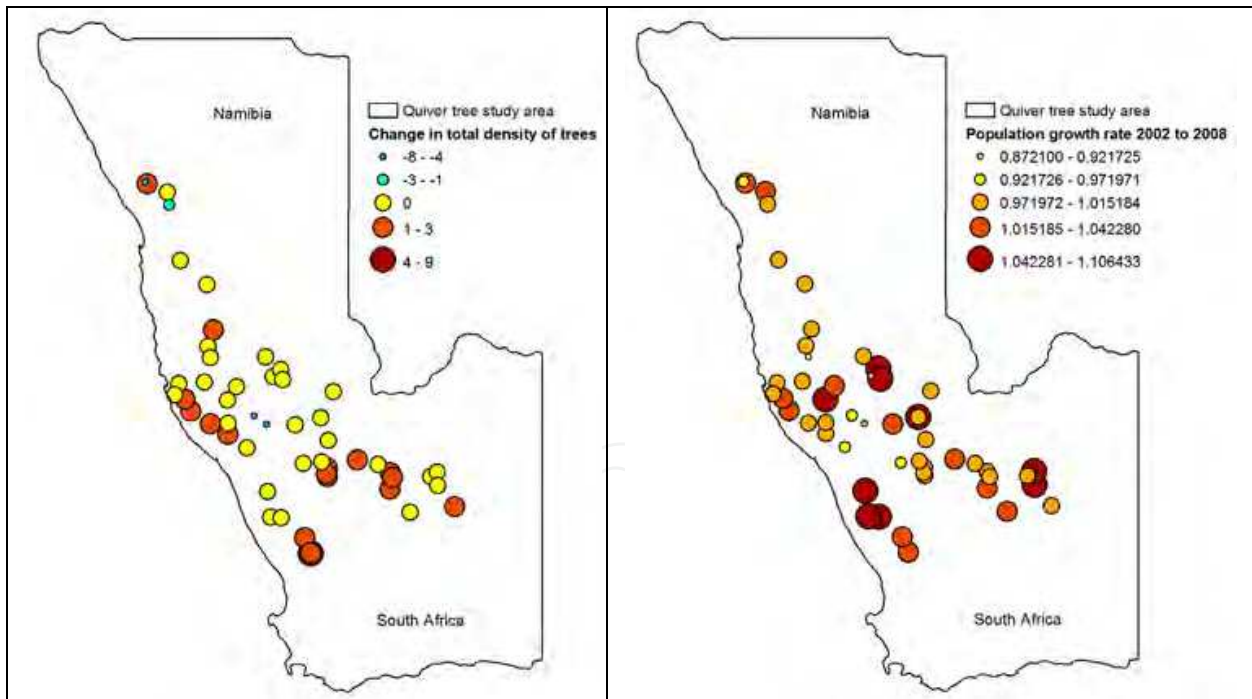
Fig. 5. Predicted change in total density of trees, and calculated population growth of Quiver trees, between 2002 and 2008

As one can see from the Fig. 5 change map, the change in total density of trees is very small. Most sample sites show no changes at all, with 18 sites show an increase of 1 to 9 trees, and 7 sites showing a decrease of 1 to 8 trees. These are small but definite changes in Quiver tree's total density over the 6 year period, between 2002 and 2008.

7. Conclusion

In this paper, we utilize the partially collected Quiver tree's sample data, 2002 and 2008 datasets, particularly, the total density of trees to evaluate the climate change impact on the Quiver tree's population. Because the data collection sites are only 53 and the Quiver tree's population size is extremely sensitive to it habitat environment, the conventional methodologies are not applicable. Based on our observations, we propose the habitat measure to catch up the closeness of the Quiver tree's population, which is later defining the habit distance of the tree's population. The habitat distance set is then regarded as the partner process index set. Therefore, we are able to engage Liu's Uncertainty theory for developing a new uncertain kriging approach to facilitate the prediction task: utilizing "complete" (53 values) data to perform the change evaluation. Once the missing values are filled, the evaluation of climate change can be performed. We are aware that our new prediction results have not had a validation process because of the time-constraint. In the future, it is necessary to engage the model accuracy and validation checking. Overall, there is a small but definite change in Quiver trees over the 6 year period, between 2002 and 2008, possibly due to climate changes over time.

Of course, monitoring the Quiver trees and using it as a climate change indicator, is a continuing process and effort for the South African National Biodiversity Institute. The results from this paper help to complete the missing data or un-sampled data, and would be useful for future comparisons, when another sample collection is made. The uncertain prediction methods and calculation process may be useful with other kinds of plant species data that displays similar problems, such as missing sample values. The predicted values together with the real sample values could be very useful in examining climate change impact over time and for studying the comparisons of plant species from different periods.

8. Acknowledgements

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Climate Change - Geophysical Foundations and Ecological Effects

Edited by Dr Juan Blanco

This book offers an interdisciplinary view of the biophysical issues related to climate change. Climate change is a phenomenon by which the long-term averages of weather events (i.e. temperature, precipitation, wind speed, etc.) that define the climate of a region are not constant but change over time. There have been a series of past periods of climatic change, registered in historical or paleoecological records. In the first section of this book, a series of state-of-the-art research projects explore the biophysical causes for climate change and the techniques currently being used and developed for its detection in several regions of the world. The second section of the book explores the effects that have been reported already on the flora and fauna in different ecosystems around the globe. Among them, the ecosystems and landscapes in arctic and alpine regions are expected to be among the most affected by the change in climate, as they will suffer the more intense changes. The final section of this book explores in detail those issues.

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