A SPATIO – TEMPORAL ANALYSIS OF TEA PRODUCTIVITY AND QUALITY IN NORTH EAST INDIA

Rishiraj Dutta

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Dedicated to my father (Dr. Bimal Kumar Dutta)
and my mother (Late Dr. (Mrs.) Aroti Dutta)

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Summary

In India, the tea industry plays a leading role as a foreign exchange earner and a source of livelihood to over a million people. Therefore maintaining the productivity and quality of tea is a national concern. Well-managed tea plantations can remain in production for up to 100 years. However, it has been observed that the peak production period occurs between 20 – 40 years. Commercial tea production in India started in the 19th century with the arrival of the British. Presently, there are more than 1400 tea estates in North India and about 200 in South India. Average tea production in India during 2004 – 2007 was 980 million kg obtained from an area of 523,000 ha against a national consumption level of 802 million kg. During recent years, it has been observed that tea production in India tends to decline. This is attributed to factors such as ageing plantations, high cost of production, and below-adequate quality control at the processing levels. To gain a better understanding of some of the factors affecting tea agro-ecosystems in India and to suggest improvements, four studies were carried out in this thesis using data from tea estates in Northeast India.

First, tea production data for ten years from seven plantations were analyzed at two spatial scales: the entire estate and the sections within estates. Tea yield was taken as the dependent variable, being driven by differences in age as a proxy for genotype (G), soil pH, soil organic carbon and rainfall as environmental factors (E) and fertilizer application and pruning cycles as management factors (M). A thorough statistical analysis shows that plant age had a negative and N fertilizer application a positive effect on tea yield. Pruning analysis was inconclusive due to the recovery time needed for freshly pruned plants. Tea yield was positively correlated with rainfall and had a weak but significant correlation with soil organic carbon as long as the latter had levels $< 2\%$. Spatial dependence could be observed at the section level while including N fertilizer as an independent variable.

Second, the monitoring of tea replantation was studied using multi-temporal satellite data. Monitoring identifies four phases of replantation and rejuvenation, starting at the time of uprooting and finishing when new plants are planted. Haar, Daubechies and Symlets wavelets were used at different stages of replantation to extract information at different

scales and compared at different levels of decomposition. Informative patterns for each stage of replantation were selected at individual sections within the estate, on the basis of spatial correlation. The study shows that levels 3 and 4 gave superior information as compared to the other levels. The selected patterns were weakly correlated with slope, flow accumulation and CTI while management activities and small variation in elevation proved less efficient in explaining the extracted patterns. The asymmetric Daubechies-4 wavelet gave the best results for extraction of fine features, whereas the symmetric Symlets-8 wavelet best represented extraction of smooth features. Although a strong quantitative linear relationship between the extracted patterns and topographic parameters could not be established, it showed that wavelets are useful to extract patterns and interpret spatial variations observed at different stages of tea replantation.

Third, improvement in the characterization of tea quality was looked into. It depends on the different chemical constituent present on the leaves and also on the cultivars used, plucking standards, pruning types and the fermentation. Using normalized difference vegetation index (NDVI), near infrared (NIR) spectroscopy and statistical models, relationships were established between green leaf and black tea quality parameters. Statistical analysis shows that liquor brightness is affected by the levels of caffeine content, theaflavins and catechins. Relationships exist between quality parameters and remote sensing in particular. NDVI has a positive relation with caffeine, Theogallin, Epicatechin (EC), and Epicatechingallate (ECG) while NIR is negatively related to caffeine, theogallin, and catechins. The study concludes that NDVI and NIR spectroscopy have a large potential to be used for monitoring tea quality in the future and that further attempts should be made by analyzing different clones and deriving their relationships from remote sensing data and linking it to tea production and quality. Under the condition of maximum biomass, concentration of foliar biochemical parameters can be monitored using NDVI.

Finally, a three-year field trial was executed at Tocklai Tea Research Association, Jorhat, to somehow ‘validate’ the findings from the first part of the research, which was entirely based on secondary data from the estates in the region. Most of the G, E and M factors used in that study were applied again in the trial. On top of that, a model known as CUPPA Tea, developed in Tanzania, was calibrated using the data obtained from the field trial. Plant age and N, P and K fertilizer applications show very clear effects on tea yield, and more pronounced than in the secondary data study. In a multiple regression analysis, the two factors combined also gave highly significant results. Monthly rainfall also had a significant positive effect on monthly yields. The latter was improved when rainfall in month x was related to the tea yield of month $x + 1$. The CUPPA Tea model was parameterized to better represent G, E and M conditions in Northeast India. The analysis allowed observed and predicted yields of seedling, clonal and mixed tea to match reasonably well, showing that it is worth further developing CUPPA Tea for the Indian situation. The model was most sensitive to photoperiod and changes in optimum temperature for shoot growth and extension. Further calibrations and validations require a sharp genotype focus and future simulations should be done based on individual cultivars.

The study focused on tea plantations in Northeast India. By integrating G × E × M factors, wavelets for monitoring replantation patterns, remote sensing for quality assessment and yield simulation through CUPPA Tea model, the study tried to identify different factors affecting tea yield and its causes for decline. The study shows that statistical methods and remote sensing can be used as efficient tools for quantifying and monitoring tea replantation and to study tea quality. Such methods and tools provide the means for the future monitoring of tea plantations. Remote sensing further has the potential to contribute to reviving the tea sector. Remote sensing tools such as wavelets could delineate site specific management zones to get a better understanding about the soil and vegetation status within the section thereby giving indication about the sections to be replanted on time to maintain yield. In order to do so, strategic decisions about uprooting and replanting tea plantations should be given careful considerations at the estate, section and plant levels. The use of space technology requires that plantation managers should be given adequate knowledge to handle such technologies efficiently. This way, they might improve the productivity from their land and to optimize plantation input costs. Such issues would go a long way to arrive at a complete revival of the tea sector in Northeast India.

Samenvatting

De thee industrie speelt een belangrijke rol als bron van inkomen voor meer dan een miljoen mensen. Ook zijn de exportinkomsten op nationaal niveau van belang. Het is daarom evenzo van nationaal belang om de productiviteit en de kwaliteit van thee te handhaven. Thee plantages die goed worden onderhouden kunnen in productie blijven voor een periode van 100 jaar. Er is echter waargenomen dat er een piek in de productie optreedt wanneer de plant tussen de 20 en 40 jaar oud is. Commerciële theeproductie is in India begonnen met de komst van de Engelsen in de 19e eeuw. Op dit moment zijn er meer dan 1400 thee plantages in Noord India en ongeveer 200 in Zuid India. De gemiddelde thee productie in India in de periode tussen 2004 en 2007 was 980 miljoen kg, terwijl de omvang van de plantages 523000 ha bedroeg en de nationale consumptie van thee 802 miljoen kilo was. In de afgelopen jaren tekent zich een afname van de productie van thee af. Deze wordt toegeschreven aan factoren zoals het uitputten van de plantages, de hoge productiekosten en een suboptimale kwaliteitscontrole tijdens de verschillende productiefasen. Dit proefschrift beschrijft vier studies die zijn uitgevoerd om een beter inzicht te krijgen in sommige factoren die doorwerken in de thee agro-systemen in India. Hierbij zijn gegevens gebruikt van theeplantages uit Noord India.

De eerste studie gebruikt productiegegevens van thee op twee schaalniveaus, die gedurende 10 jaar op zeven plantages zijn verzameld, op het plantageniveau en op het sectieniveau. De theeopbrengst is gebruikt als de afhankelijke variabele. De verklarende variabelen zijn de leeftijd van de theeplant als een proxy voor het genotype (G), de pH van de bodem, het organisch stofgehalte van de bodem en de neerslag als omgevingsvariabelen (E) en de toediening van kunstmest en het patroon van snoeicycli als management factoren (M). Statistische analyse laat zien dat theeproductie negatief gekoppeld is aan leeftijd en positief aan de toediening van stikstof. Een analyse van de snoeicycli gaf geen eenduidig antwoord vooral omdat het onduidelijk is hoe lang een plant nodig heeft om te herstellen van het snoeien. Er was een positieve correlatie tussen theeoogst en neerslag en een zwakke, maar significante correlatie met het organisch stofgehalte van de bodem, zolang deze lager was dan 2%. Tenslotte was er sprake van een duidelijke ruimtelijke samenhang op het niveau van de secties bij het opnemen van stikstof als een verklarende variabele.

De tweede studie richtte zich op het monitoren van theeplantages, waarbij gebruik gemaakt is van multi-temporele satellietgegevens. Bij het monitoren worden vier fasen onderscheiden gedurende het herplantings- en verjongingsproces van een theeplantage vanaf het moment dat de oude planten worden verwijderd tot het moment dat nieuwe planten worden geplant. Haar, Daubechies en Symlet wavelets zijn gebruikt in deze vier fasen om informatie te verzamelen op verschillende schalen. Deze zijn vergeleken op 6 decompositieniveaus. Informatieve patronen tijdens iedere fase van dit proces zijn geselecteerd voor individuele secties binnen een plantage op basis van ruimtelijke correlatie. De studie laat zien dat de decompositieniveaus 3 en 4 betere informatie geven dan de andere niveaus. De waargenomen patronen waren zwak gecorreleerd met helling, waterstagnatie en CTI, terwijl managementactiviteiten en kleine verschillen in terreinhoogte minder bijdragen aan het verklaren van de waargenomen patronen. De asymmetrische Daubechie-4 wavelet gaf het beste resultaat bij de extractie van lokale objecten, terwijl de symmetrische Symlet-8 wavelet het beste resultaat gaf bij de extractie van meer globale variatie. Een sterke lineaire relatie tussen de geëxtraheerde patronen en topografische parameters kon niet worden vastgesteld. Wel werd duidelijk dat wavelets nuttig zijn om patronen te extraheren en om de ruimtelijke variatie te verklaren die kan worden waargenomen tijdens de verschillende stadia van het herplantings- en verjongingsproces van een theeplantage.

De derde studie richt zich op het karakteriseren van theekwaliteit. Deze hangt af van verschillende chemische componenten die aanwezig zijn op de theebladeren, maar ook van de cultivars, de manier van plukken, de wijze van snoeien en de fermentatie. Relaties zijn vastgesteld tussen de kwaliteitsparameters van groene bladeren en zwarte thee door gebruik te maken van de NDVI, nabij-infrarood (NIR) spectroscopie en statistische modellen. De statistische analyse laat zien dat de helderheid van de vloeistof wordt beïnvloed door de niveaus van cafeïne, theegeurstoffen en catechines. Relaties bestaan tussen de kwaliteitsparameters en remote sensing. In het bijzonder heeft de NDVI een positieve relatie met cafeïne, theogalline, epicatechine en epicatechingallate (ECG), terwijl NIR een negatieve relatie heeft met cafeïne, theogalline, en catechines. De studie concludeert dat NDVI en NIR spectroscopie een goede mogelijkheid bieden om theekwaliteit te monitoren en dat verdere studies moeten worden uitgevoerd, met name gericht op verschillende klonen. Hierbij moet gezocht worden naar relaties tussen remote sensing gegevens en theeproductie en kwaliteit. Onder voorwaarde van maximale biomassa kan de concentratie van biochemische bladparameters worden gemonitord via de NDVI.

Tenslotte is een driejarig veldexperiment uitgevoerd bij de Tocklai Thee Onderzoekassociatie in Jorhat om de bevindingen uit het eerste gedeelte van het onderzoek te valideren. Deze bevindingen waren volledig gebaseerd op secundaire gegevens van de plantages in het gebied. De meeste eerdere G, E en M factoren zijn opnieuw gebruikt in dit experiment. Daarnaast is gebruik gemaakt van het CUPPA Tea model, dat is ontwikkeld in Tanzania. Dit model is gekalibreerd met gegevens uit het veldexperiment. Leeftijd van de theeplant en N, P en K bemesting laten duidelijke effecten zien op theeopbrengst, effecten die zelfs sterker waren dan in de eerdere studies. In een meervoudige regressieanalyse lieten de gecombineerde factoren een significante relatie zien. Maandelijkse neerslag liet een significant positief effect zien op maandelijkse oogsten. Dit effect is nog sterker als de neerslag in maand x wordt gerelateerd met de oogst in maand $x + 1$. Parameters voor het CUPPA Tea model zijn zo gekozen dat het model de G, E en M condities in Noord India goed weergeeft. De analyse liet zien dat waargenomen en voorspelde oogsten van jonge planten, klonen en gemengde theeplanten redelijk overeen kwamen. In die zin is het waardevol om voort te gaan met een verdere ontwikkeling van het CUPPA Tea model binnen de Indiase context. Het model is gevoelig voor de fotoperiode en voor veranderingen in de optimale temperatuur voor de groei van jonge scheuten en uitbreiding. Verdere calibratie en validatie vereisen een betere focus op het genotype en toekomstige modelsimulaties moeten worden uitgevoerd op individuele cultivars.

Het proefschrift concentreert zich op theeplantages in Noordoost India. Het probeert om de verschillende factoren te identificeren die de theeoogst verklaren en aanleiding kunnen geven voor de terugval in de opbrengst. Het doet dit door het integreren van G × E × M factoren, wavelets voor het monitoren van patronen tijdens het herplantingsproces, remote sensing beelden voor het schatten van kwaliteit en oogst simulaties met het CUPPA Tea model. Het proefschrift laat zien dat statistische methoden en remote sensing beelden gebruikt kunnen worden als efficiënte middelen voor het kwantificeren en het monitoren van theeherplanting en om theekwaliteit te bestuderen. Zulke methoden kunnen in de toekomst verder gebruikt worden. Remote sensing biedt verder de mogelijkheid om bij te dragen aan het vernieuwen van de theesector in India. Wavelets toegepast op satellietbeelden zouden dienstbaar kunnen zijn binnen de context van precisielandbouw bij het bepalen van managementzones om zodoende een beter inzicht te krijgen in de status van bodem en vegetatie binnen een sectie. In die zin kunnen ze een indicatie geven welke secties geschikt zijn voor herplanting om het productieniveau te garanderen. Om dit uit te voeren, moeten strategische beslissingen over het weghalen van theeplanten en het herplanten van theeplantages zorgvuldig worden overwogen op het niveau van de plantage, de sectie en de individuele theeplant. Het gebruik van ruimtetechnologie vereist dat de managers op de plantage voldoende kennis van zaken hebben om deze technologie efficiënt te kunnen gebruiken. Op die manier kan de productiviteit van het land verbeteren en kunnen investeringen worden geoptimaliseerd. Dergelijke zaken kunnen op termijn bijdragen aan het herstel van de theesector in Noordoost India.

1

General Introduction

1.1 Global tea production

Tea (*Camellia sinensis*) is a leading cash crop in world agriculture and is grown in more than 32 countries in an area of 2.8 million ha. The main tea producing countries are China, India, Sri Lanka, Kenya, Indonesia, Turkey, Iran, Georgia, Japan, Vietnam, Bangladesh, Argentina, Malawi, Uganda, Zimbabwe and Tanzania. Among them, China and India are the leading tea producers producing 1310 and 979 million kg in 2009 whereas the world tea production was 3860 million kg in that year (Figure 1.1) and the world export was 1571 million kg (Figure 1.2), (Tea Statistics, Tea Board of India, 2009). Prices of tea at different world auctions varied during 2009 with the Indian tea auction at \$ 2.17 kg^{-1}, Sri Lankan tea auction at \$ 3.15 kg^{-1} and African tea auction at \$ 2.29 kg^{-1} (Table 1.1). During 2008, the global demand of tea was 3596 million kg (Table 1.2). Since the world population is expected to increase to approximately 9 billion in 2050, the tea market is expected to grow as well.

1.2 Tea in India

Tea is indigenous to India and is an important beverage. Average tea production in India has increased from 850 million kg during the years 2000 – 2003 to 980 million kg between 2004 and 2007, covering an area of 523,000 ha (Tea Statistics Annual Report, 2007). Domestic consumption of tea in India was 802 million kg with a per capita consumption of 701 g $head^{-1}$ in 2008 (Tea Statistics, Tea Board of India, 2008). The region wise average yield of tea in India in 2008 was 1597 kg ha^{-1} for North India and 2062 kg ha^{-1} for South India. Tea industry in India also employs a large labour force. Tea Board of India statistics shows that an estimated number of 1.3 million labourers were employed by the tea industry in 2007.

There are numerous tea estates in Northeast India which are owned by either the private companies or by government entities. Tea estates in India generally range in size from 100 – 500 ha (Figure 1.4). After tea leaves are collected from the individual plants, tea is manufactured in the factories that involve a series of processes such as withering, rolling, fermentation, drying, and sorting. The manufactured tea is then graded and tasted for quality before being sent out for distribution and export.

Origin, distribution and consumption

Tea cultivation was introduced in India by Robert Bruce in 1823 during the British colonial time in the 19th century. This was followed by the establishment of the first tea plantation in 1839 with seeds brought from China. Tea is an evergreen shrub from the genus *Camellia* that includes some 82 species (Banerjee, 1992). Of all the *Camellia* spp., tea is the most important variety, both commercially and taxonomically, and it is entirely cultivated to produce a stimulant brew. The two main varieties are *Camellia sinensis* var. *assamica* with relatively large leaves, and *Camellia sinensis* var. *sinensis* with small semi-erect leaves (Figure 1.3). The standard quality of made tea from wild *assamica* bushes was established in 1839. Thereafter, tea plantations spread quickly in North and South India. North India currently contributes to 3/4th of the total tea production. North India has approximately 1400 large tea estates against 200 in South India. Assam as the largest tea producing state in India has more than 1200 estates with a total production of 488 million kg (Tea Statistics, Tea Board of India, 2008).

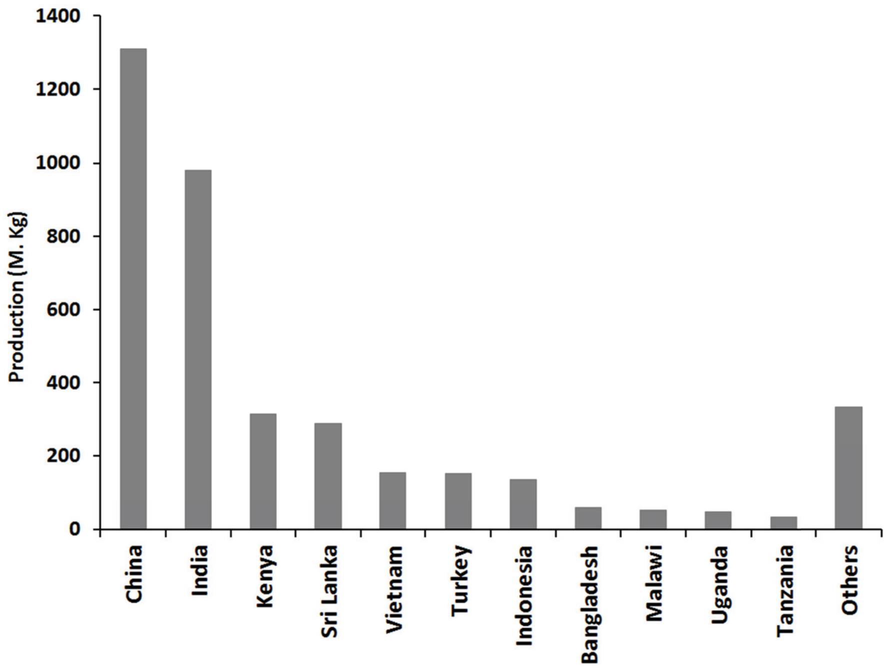

Figure 1.1: World tea production (million kg) in 2009 (Source: Tea Board of India)

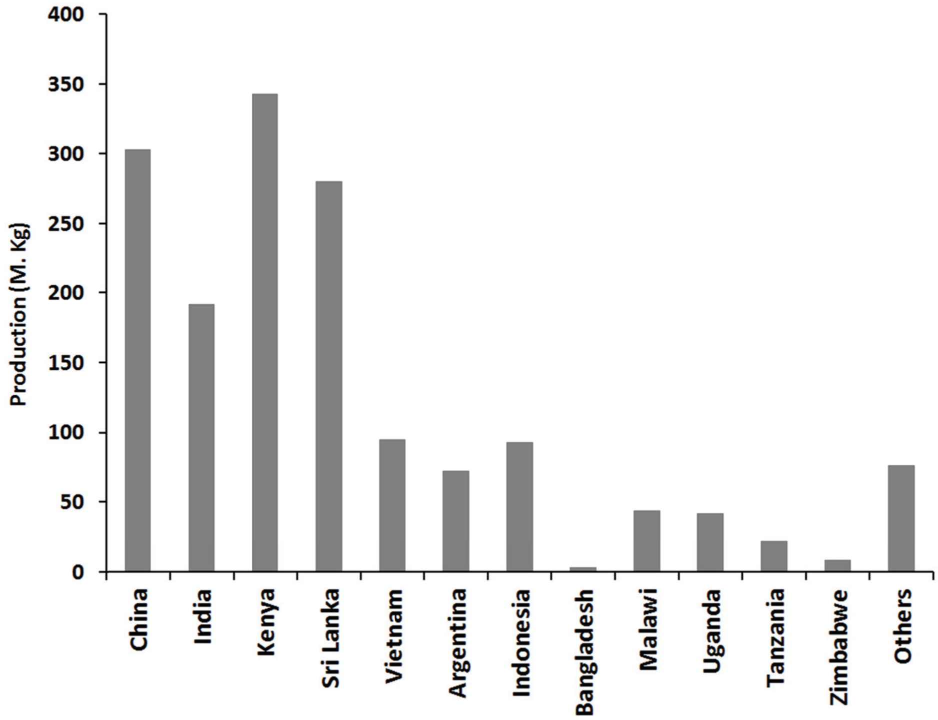

Figure 1.2: World tea export (million kg) in 2009 (Source: Tea Board of India)

World Auctions			
Year	*Indian Tea Auction*	*Sri Lankan Tea Auction*	*African Tea Auction*
2000	1.37	1.75	2.02
2003	1.20	1.54	1.54
2004	1.42	1.78	1.55
2005	1.32	1.84	1.47
2006	1.46	1.90	1.93
2007	1.62	2.51	1.66
2008	2.00	2.83	2.18
2009	2.17	3.15	2.29

Table 1.1: World tea auction (USD kg^{-1}) between 2000 and 2009 (Source: Tea Board of India).

Regions	Production (M. kg)
Europe	500
America	163
West Asia	410
Asia other than West	2219
North Africa	191
Africa other then North	92
Oceania	21

Table 1.2: Regionwise global demand of tea (million kg) in 2008 (Source: Tea Board of India).

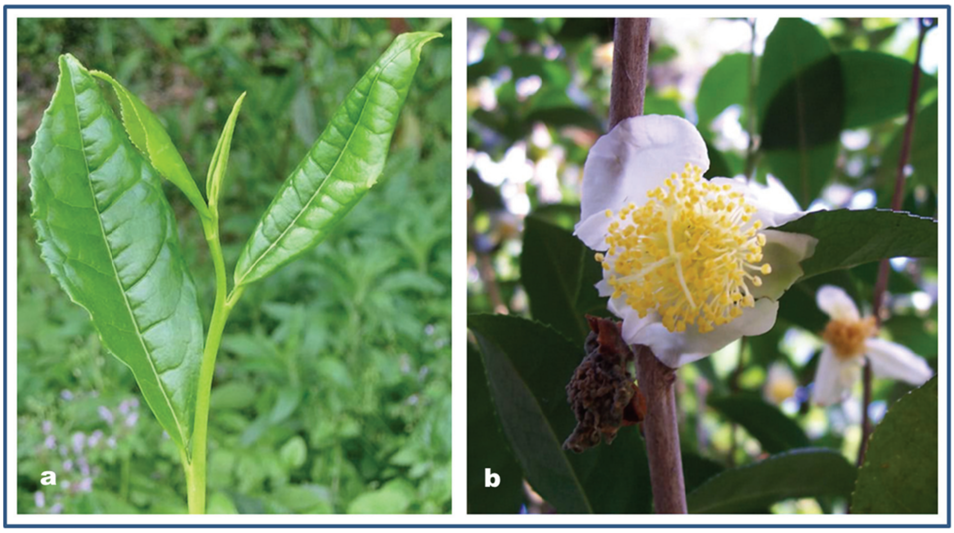

Figure 1.3: Two species of *Camellia sinensis* (a) *Camellia sinensis* var. sinensis and (b) *Camellia sinensis* var. assamica (wild variety)

1.3 Declining yields

The tea industry is one of the oldest organized industries in India with a large network of tea producers, retailers, distributors, auctioneers, exporters and packers, employing one of the largest workforces in the country. The tea plantations supplement the economic life through employment generation and social welfare at the grassroots level. During recent years, the tea industry in Northeast India started to face many problems. Information collected from the Tea Research Association as well as from estate management shows a decline in yield that is most likely due to old age of plantations, inability to compete with other tea producing countries due to high cost of production, organization of small holder farmers, and poor quality control at the processing level (Dutta, 2006). The quality of tea has also deteriorated as planters are emphasizing quantity above quality (Ghosh and Roy, 2004). Economic life of the tea bush is 40 – 50 years. Older plantations show a decreased yield. Old age of individual plants affects the production of tea at the plantations, whereas the slower pace of replantation with the rate of replanting being less than 0.5 % as against the desired level of 2 % and the consistent fall in auction prices adversely affects production at the plantations. The consequent decline in productivity has led many gardens to close down. Tea as a perennial crop is affected by several factors, be it genotype (G), environment (E) and management (M). Uncontrolled environmental conditions and different management practices may have an adverse effect on tea yield which may be the potential causes of such decline. Tea as a mono-cultured crop has to stand in the field for many years, resulting in degradation of soil environment, be it physical, biological or chemical in nature. The mono-culture of tea causes improper soil functioning such as compactness, and loss of fertility (Barua, 1969). Kamau (2008) stated that young tea plantations have been associated with higher productivity in most tea growing areas. Research carried out on the productivity and resource use in ageing tea plantations in Kenya also showed that significant differences in the mean tea yield occurs mainly due to differences in management practices, use of tea genotypes, and age of the plantations.

1.4 Characteristics of tea

Tea grows under a wide range of climatic conditions from equatorial to humid and temperate climates. It requires a moderately hot and humid climate with well drained fertile acid soils on highlands. Climate influences yield, crop distribution and quality. Rainfall distribution should be adequate for maintaining sustained high yield of tea throughout the season. The average annual rainfall in Northeast India ranges from 2000 – 4000 mm. Temperature affects tea yield by influencing the rate of photosynthesis and controlling growth and dormancy. An ambient temperature between 13°C and 28 – 32°C is conducive for tea growth. Flushing commences from March with the rise in temperature. A humid climate and high relative humidity (RH) favours tea growth.

Tea grows on a wide variety of soils of any texture ranging from sandy loam to clays including silts and loams. It requires deep and well-drained soil (Dey, 1969) with a preferred soil pH of 4.5 to 5.5 and more than 2% organic matter (www.tocklai.net).

Different cultural practices depend on altitude and topography of the tea area. Tea is grown from almost sea level in India and Indonesia towards altitudes above 2200 m in Kenya (Kamau, 2008). In India, the ideal recommended bush population is 12,345 plants per hectare with spacings of 105 – 110 cm between rows and 60 – 75 cm between plants. The planting is done either as single or double hedge, but mostly single hedge planting is followed. Manuring and fertilizer applications are important to ensure adequate replenishment of nutrients in the soil removed by harvest.

1.5 Quality aspects

Apart from quantity also, the quality of tea is important from an economic perspective, as good quality means higher prices. International standards are vital to facilitate international tea trade, and to ensure that consumers' expectations in the higher quality segments of the market are met. Tea quality is determined based on its grading, colour of the leaf, make and style, sorting, nose, feel, liquor, colour and quality (www.tocklai.net). Factors like colour, appearance, flavour and mouth feel jointly make up the quality of tea. These factors are influenced by the levels of chemical constituents produced during manufacture (Wood and Roberts, 1964). Caffeine plays a vital role in tea quality characteristics such as briskness and other taste properties (Dev Choudhury et al., 1991; Hilton and Ellis, 1972; Roberts, 1962; Sanderson, 1972) and it is an important parameter for the evaluation of tea quality (Khokhar and Magnusdottir, 2002; Owuor et al., 1986; Yao et al., 2006). Caffeine is a white, bitter crystalline alkaloid and is a component that stimulates the nervous system. A cup of tea contains about 40 mg of caffeine. Most teas from North Indian regions have high (3.4 – 3.9%) soluble caffeine contents which may cause the high briskness of these teas (Borse et al., 2002).

Quality aspects are tasted by an experienced taster in order to ascertain the quality prior to sale or possibly blending tea. A tea taster uses a cup of tea and noisily slurps the liquid into his or her mouth. This ensures that both the tea and sufficient oxygen is passed over all the taste receptors on the tongue to give an even taste profile of the tea. The flavor characteristics and leaf color, size and shape are then graded by the tea taster to quantify the overall quality. Tea liquors should never be dull to the eye and the degree of brightness often corresponds closely to quality. Once the quality has been tasted or graded, each tea company places a value based on market trends, availability and demand.

1.6 Remote sensing and tea

Remote sensing has been widely used for forecasting the yield for different types of crops, finding diseases, estimating biomass and moisture stress in plants (Aase and Siddoway 1981, Clevers 1989). Almost a negligible amount of remote sensing work has been done at the tea plantation level. An understanding of the spectral characteristics of tea at this level is important for monitoring the growth of plants and estimating tea yield (Rajapakse et al., 2002). Remote sensing offers an efficient and reliable means of collecting the required information, in order to map tea type and acreage (Dutta, 2006) whereas high resolution satellite imageries (LISS III/ LISSIV) could provide the structural information on vegetation health. Information from remotely sensed data can be stored into Geographic Information System (GIS) which when combined with ancillary data could provide various insights into the chemical and phonological aspects of the crop. Early inspection for crop health is critical in ensuring good tea productivity. High resolution satellite data such as LISS IV, ASTER, and Quickbird could help to detect stress associated with moisture deficiencies, insects, fungal and weeds infestation and differences in soil and nutrient deficiencies. Also crops affected by conditions that are too dry or wet, early enough to provide an opportunity for the planters to mitigate (Dutta, 2006). Attempts to monitor diseased tea areas in India using remote sensing showed that plantations could be monitored and that diseased areas could be delineated despite the presence of shade trees (Dutta et al., 2008). The presence of shade trees between the tea canopies resulting in excessive interclass mixing obstructs an effective use of remote sensing data.

In agricultural scenarios, management activities are guided by changes in crop and soil conditions that are most likely to vary within the field. Therefore, quantifying patterns of crops and soil conditions during the growing seasons increasingly helps in proper management and decision making. Mathematical tools such as wavelets have been applied in the past on images for e.g. a multiscale pattern analysis on specific crop features (Epinat et al., 2001). Li and He (2008) successfully discriminated tea varieties by comparing different wavelet transform models. One idea that is considered in this study is to monitor spatial patterns of vegetation and bare soil occurring during the different stages of tea replantation using high resolution satellite data, leading for example to a better understanding of the causes of such patterns. This study will further explore the possibility of using remote sensing and spectroscopic data to monitor green leaf and black tea quality parameters using high resolution ASTER data and NIR spectroscopy.

1.7 Data quality

Data quality is a pillar in GIS implementation and application as reliable data are indispensable to allow the user obtaining meaningful results. In agricultural studies, crop modeling can be addressed using statistical means. Tea, as a perennial crop, is difficult to model. Uncertainty is due to the limited amount of data. A careful analysis therefore requires a statistically oriented approach, where limited data availability may overcome the absence of models and a full set of observations.

This thesis considers different scales. Within India, the highest relevant scale level is the region. Within each region, we consider estates, and within each estate, there are sections with sizes between 10 and 15 ha. Sections contain tea plants of different varieties, of different age, and are managed on an individual basis. Each tea plant has its leaves, which give clues to the quality of tea in the final product.

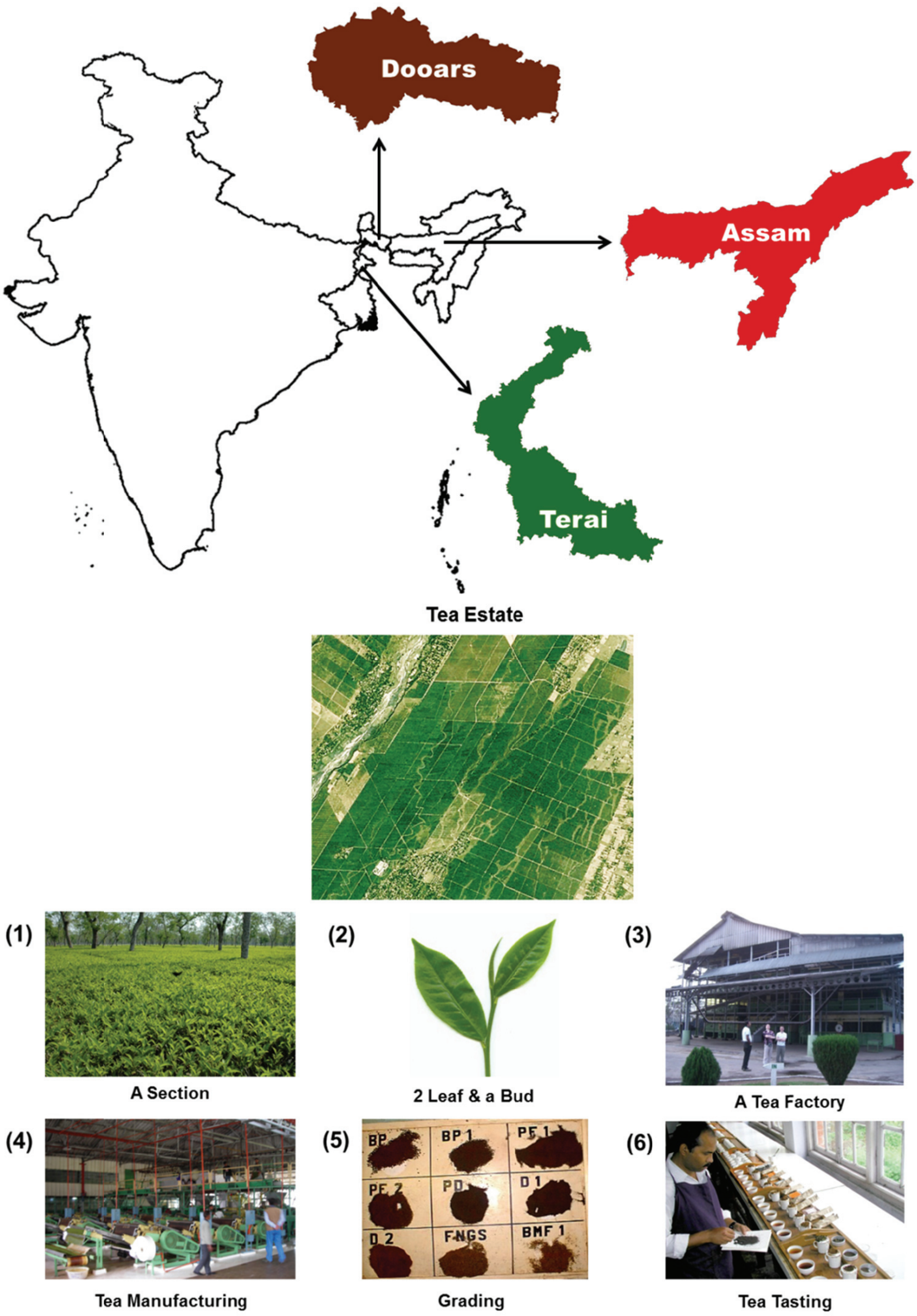

Figure 1.4: Tea producing areas of Northeast India and an overview of a tea estate in India (From estate to tea tasting)

1.8 Spatial and non-spatial approaches for quantifying factors affecting tea yield

Data driven studies may benefit from statistical approaches, linear regression as well as more advanced spatial statistical methods to identify relations between yield and factors affecting it. Different models can then be compared to analyze the variations at the estate level in different regions. Tea yield can be considered as a continuous dependent variable that linearly depends on explanatory variables.

An essential choice is the scale of observation in space and time. A choice for a combination of data has to be motivated by the questions to be addressed, by the scale of the process as well as by the availability of the data. Spatial dependence of the data could be included to investigate existing spatial variability at the section level. Although it may exist as well between estates, there would be little use to incorporate this, due to major differences in conditions affecting tea productivity. The major sources of spatial variation in the tea yield at the section level are the genotype, environment and management aspects. It can be hypothesized that inclusion of spatial dependencies for these variables may lead to changes in parameter size effects and their significance as well. At an even finer scale level, i.e. at the within-section level when analyzing individual plants, spatial dependence may have a much larger effect (Stein et al., 2000).

1.9 The need to revive the tea sector in Northern India

The Indian tea industry has been passing through a long period of lower tea prices that were continuously falling caused by increasing costs of production, sluggish growth rate in domestic demand and increased age of tea bushes adversely affecting the viability of the estates. This has resulted in poor yields arising out of the poor condition of the estates, poor management and the management's reluctance to carry out replantation-rejuvenation at regular intervals which is very important in terms of quantity, quality and price realization (Ministry of Commerce, Government of India). Therefore, in order to revive the tea sector, conscious efforts need to be made to improve the overall productivity, to reduce production cost, to improve quality and to adopt better management strategies. Proper knowledge about the various inputs applied to soil to increase the fertility and availability of organic carbon/potash/sulphur is important so that effective soil management techniques could be put into action. Use of space technology may also come in handy for monitoring the plantations from time to time. As tea is an important beverage, from both management and commercial point of view, exploring the role of remote sensing and GIS and other key parameters in the GIS environment would help managers to identify the affected areas within their estates and take remedial measures. Integrating remotely sensed data with secondary data can provide a deep insight into the cultural practice being implied to the tea ecosystem.

1.10 Objectives

This study uses data at the two spatial scales: estate and section level. The data were collected from seven tea estates of Northeast India ranging in the period from 5 – 10 years. Daily weather data were collected from the weather stations of the individual estates. All the tea estates maintain a detailed record of yearly and monthly data, either digital or analogue, including yield (both green leaf and made tea), plant age, irrigation and management data and also replanting programmes both at the estate and at the section level. Based on the available data, this thesis tries to contribute in four ways:

1. To analyze tea yields as a function of genotype, environment and management (G×E×M) and to investigate the effect of plant age, environmental, and management factors on tea yields in Northeast India.
2. To monitor tea plantations at different spatial scales using remote sensing and extracting spatial patterns of vegetation and bare soils during tea replantation and understanding the causes of such patterns from multi-temporal data.
3. To assess tea quality based on quality data, near infrared (NIR) spectroscopy and remotely sensed (NDVI) data for recognition of tea leaf chemistry differences and exploring these methods to develop an approach for quality monitoring.
4. To measure and model tea productivity and to simulate yield by seasonal data using the CUPPA Tea model.

1.11 Thesis Outline

Chapter 2 covers analysis related to genotype (G), mimicked by plant age, and environmental (E) and management (M) factors that influence tea yields. Effect of age (G), rainfall, soil organic carbon and pH (E), and NPK fertilizer application and pruning regime (M) on tea yields in seven tea plantations in Northeast India, over a 5 to 10 year period between 1998 and 2007 were investigated. Two spatial scales were involved: the entire estates (for rainfall), and the sections within the estates (for the other variables). Statistical modelling and spatial analysis were done at the two scales for the different estates to detect the degree of relationship between G×E×M and tea yield.

Chapter 3 explores the application of remote sensing in monitoring the different stages of replantation using spatial data at different spatial scales. Wavelets such as Haar, Daubechies and the Symlets were extensively used to extract patterns and were compared at different levels of decomposition. The extracted patterns were identified and analyzed using topographic and hydrological parameters.

Chapter 4 explores different methods for determining and monitoring tea quality using GIS data and remotely sensed NDVI and Near Infrared (NIR) spectroscopy. NDVI was extracted from ASTER data. The study focused on monitoring green and black tea quality parameters using remote sensing, spectroscopy and statistical models and to investigate the relations existing between them.

Chapter 5 quantifies the effects of different yield-determining factors on tea yield. A field trial was executed in 2007, 2008 and 2009 at Tocklai Tea research station. Data were also used to calibrate the CUPPA Tea model developed by the University of Cranfield for Tanzanian conditions.

Chapter 6 provides the conclusions, reflections and further recommendations.

2

Effects of plant age, environmental and management factors on tea yield

This chapter covers analysis related to genotype (G) mimicked by plant age, and environmental (E) and management (M) factors that influence tea yields. Effect of age (G), rainfall, soil organic carbon and pH (E), and NPK fertilizer application and pruning regime (M) on tea yields in seven tea plantations in Northeast India, over a 5 to 10 year period between 1998 and 2007 were investigated. Two spatial scales were involved: the entire estates (for rainfall), and the sections within the estates (for the other variables). Statistical modelling and spatial analysis were done at the two scales for the different estates to detect the degree of relationship between G×E×M and tea yield.

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Abstract

In this study, we quantify the effect of plant age and environmental (rainfall, pH, soil organic carbon) and management (NPK fertilizers, pruning) factors that influence tea yields. The motivation for the study is that, recently, tea yield has stagnated in North Eastern India. We applied a statistical analysis on the agronomical factors influencing yield at the estate level as well as the within estate section level, using the datasets collected at seven tea estates between 1998 and 2007. The rationale was to identify the genotype, environmental and management variables that have a significant influence on tea yield at the two spatial scales. Mean tea yields range between 1500 and 2500 kg ha^{-1}. Tea yield is correlated with rainfall ($R^2 = 0.665$ at one estate, $R^2 = 0.249$ on an average) and it has a weak but significant correlation with organic carbon ($R^2 = 0.1$ on average) on estates where organic carbon contents < 2%. Plant age had a negative ($R^2 = 0.28$ on average) and N fertilizer application a positive effect ($R^2 = 0.30$ on average) on tea yield. Combined analysis of the effect of age and fertilizer application gave higher regression coefficients than separate analysis (R^2 values ranging between 0.146 – 0.637). A pruning analysis was inconclusive due to the recovery time needed for freshly pruned plants. At the section level, we could include spatial dependence using spatial autoregression at one estate with sufficient data. Spatial dependence was shown most clearly in a reduced linear mixed model that only includes N fertilizer as an independent variable. We conclude that at the estate level, major differences in tea yield occurred due to variation in management practices and uncontrolled environmental factors. Tea yield at the section level is mostly affected by age and N application.

2.1 Introduction

Tea (*Camellia sinensis*) is a leading cash crop in world agriculture. Figure 2.1 shows that production has increased from 850 million kg during the year 2000 – 2003 to 980 million kg 2004 – 2007. The main tea producing countries are China, India, and to a lesser degree Sri Lanka, Kenya, and Indonesia. Since the world population is expected to increase to approximately 9 billion in 2050, the tea market is expected to grow as well (Tea Statistics Annual Report, 2007a). In India, stagnation in tea production and decline of tea quality are seen as major problems by the tea industry (Dutta, 2006). This is attributed to several factors, such as old age of tea bushes, declining soil health, and increased incidence of pests and diseases.

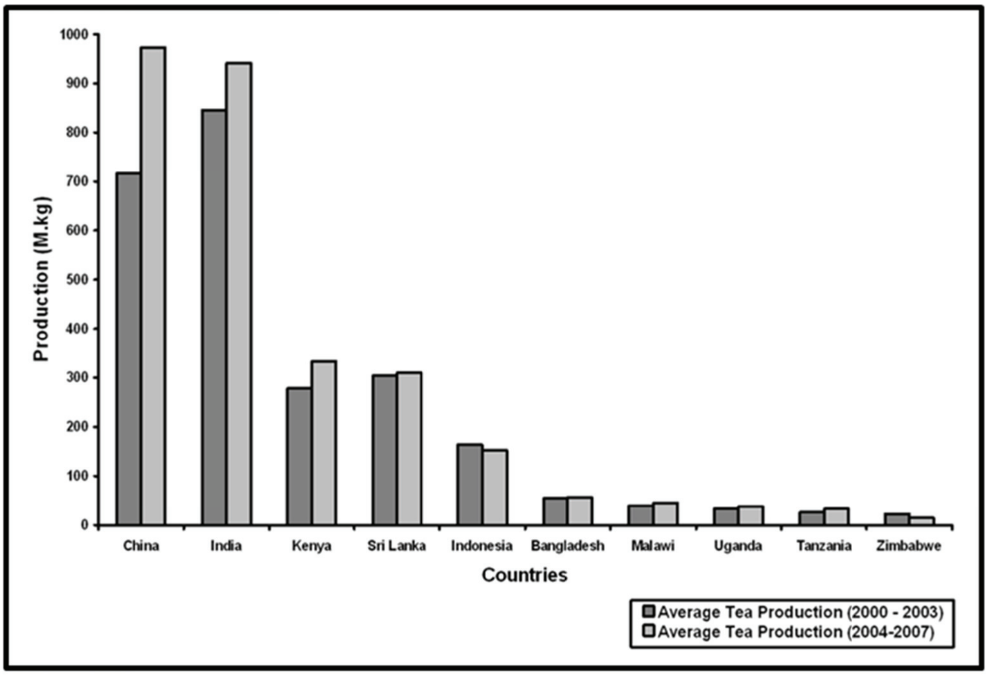


Figure 2.1: Average tea production (× 10^6 kg) of major tea producing countries between 2000 and 2007 (Source: Tea Statistics Annual Report: Production of Tea in India 2007b)

Tea production can be studied by unraveling the effects of different production drivers, grouped under (i) Genotype (G), (ii) Environment (E), and (iii) Management (M). Variables and interactions between them can be optimized given production, trade, and consumption strategies by farmers, industry, and society. Kropff and Struik (2003) identified two major approaches to study G × E × M interactions, i.e., the use of traditional statistical approaches for analyzing large datasets of multi-locational trials, and the use of simulation approaches to study the performance of different genotypes with different physiological, morphological, and phenological traits in response to environmental and management factors.

Kamau (2008) carried out a research on the productivity and resource use in ageing tea plantations in Kenya, and observed that significant differences in the mean tea yield were mainly due to differences in management practices, use of tea genotypes, and age of the plantations. The authors involved in this research also concluded that further improvement in tea productivity should take into account the interactions between G × E × M as was found in food crops (Spiertz et al., 2007).

As concerning the environment (E), research in Kenya revealed that tea production is influenced by seasonal weather conditions in both clonal and seedling plantations (Othieno et al., 1992; Kamau et al., 2003). Tea is grown in a wide range of soils, but can particularly favor low pH soils well (Othieno, 1992). Tea research in Kenya took place on soils with pH ranging between 3.5 and 4.7, which was below pH values in natural forest soils (Kamau, 2008). Tea grown on soils generally seem to have a high organic matter and nutrient content as compared to other soils (Solomon et al., 2002; Hartemink, 2003; Tchienkoua and Zech, 2004; De Costa et al., 2005).

Pruning is seen as an important management (M) practice in tea. It renews the plant, provides stimulus for vegetative growth to divert stored energy for production of growing shoots, corrects past defects in bush architecture, maintains ideal frame height for economic plucking, improves bush hygiene, and reduces the incidence of pests and diseases (Barua, 1969). On nitrogen fertilizer use, Kamau (2008) found that its effect on tea production was positive, but related to plant age and genotype. Use of nitrogen fertilizers in tea plantations is widely practiced and results in improved productivity per unit area under good management in commercial tea plantations with the rates ranging from 100 kg N $ha^{-1}yr^{-1}$ in India and Kenya (Bonheure and Willson, 1992) to 1200 kg N $ha^{-1}yr^{-1}$ for green tea in Japan (Watanabe, 1995). It was also found that higher application of nitrogen causes higher acidification and nutrient imbalances (Owino, 1991; Bonheure and Willson, 1992), whereas increased nitrogen emissions threaten ecological sustainability of tea production (Newbould, 1989). Studies have also revealed that older tea plantations do not respond to nitrogen fertilizer, so the applications should be restricted to low levels (about 50 kg N $ha^{-1}yr^{-1}$) required to maintain quality (Owuor and Odhiambo, 1994) and to prevent damage by pests during stress periods (Sudoi et al., 1996). According to Kamau et al. (2008), planting of improved genotypes and implementing appropriate N management strategies are key factors to avoid the risk on decline of productivity and profitability associated with ageing and bush degradation. N management strategies should be based on the yielding potential of tea bushes in the target environment as defined by plant genotype and age of plantations.

The objective of the research described in this paper is to analyze a number of factors regarding tea production and yield. Therefore, we investigated the effect of age (G), rainfall, soil organic carbon and pH (E), and NPK fertilizer application and pruning regime (M) on tea yields in seven tea plantations in North East India, over a 5 to 10 year period between 1998 and 2007. All the seven tea plantations are owned by the private tea companies. Two spatial scales are involved: the entire estates (for rainfall), and the sections within the estates (for the other variables). Also, at the section level for one of the estates and for one year, a geostatistical analysis was done to detect the degree of spatial correlation among sections in an estate.

2.2 Materials and methods

2.2.1 Study Area

Tea in North Eastern India occurs in three major regions: Assam (Upper Assam and South Bank), Terai and Dooars (Figure 2.2). Major characteristics of the regions are given in Table 2.1.

Assam has a tropical monsoon type of climate accompanied by heavy showers and high humidity with hot summers and cold winters. With an annual tea production of 480 million kg and an average yield of 1534 kg ha^{-1} in 2007 it covers approximately 17% of the world's tea production (Tea Statistics Annual Report, 2007b). Estate data used from this region include two from the Upper Assam district (UA1, UA2), and one from the South Bank district (SB1).

The Terai region has gently sloping land, and the elevation ranges between 80 – 100 m above mean sea level. It has a tropical savannah climate in the south and humid subtropical climate in the north. At least 15 % of the area is devoted to tea. Terai has an annual production of 78 million kg and an average annual yield of 3202 kg ha^{-1} in 2007 (Tea Statistics Annual Report, 2007a). Most estates have undertaken replantation in this region followed by improved management practices. In this area, we analyzed data from two estates (TR1, TR2).

The Dooars region is located at the foothills of the eastern Himalayas, bordering Bhutan. It has an altitude of 1750 m in the north and 90 m in the south. Half the area is hilly, whereas the other half is made up of plains. Summers are hot and accompanied by monsoon rains while the winters are cold and foggy. Dooars has an annual production of 142 million kg of tea with an average annual yield of 1950 kg ha^{-1} in 2007, (Tea Statistics Annual Report, 2007b). In this area, we analyzed data from two estates (DR1, DR2). DR1 is located at an altitude of 90 m above mean sea level while DR2 is located at 530 m above mean sea level.

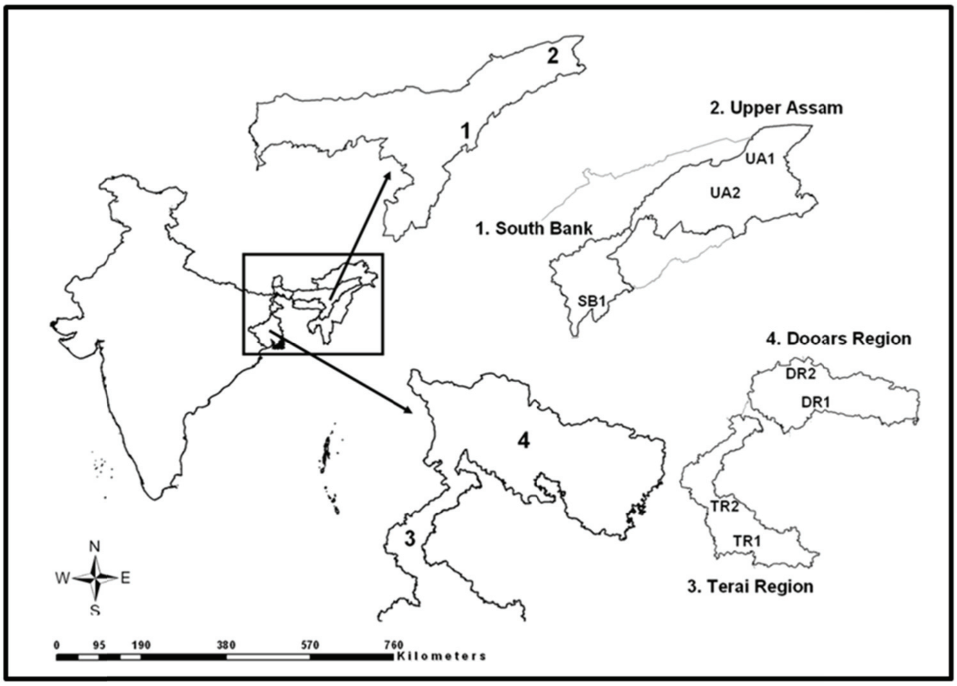


Figure 2.2: Locations the estates used in this study within the tea growing regions in NE India.

	Assam	North Bengal	
Regions	Upper Assam & South Bank	Terai	Dooars
Area (km^2)	78000	12000	8800
Tea Area (km^2)	3183	243	729
Maximum Temperature (°C)	35 – 38	38 – 45	27 – 35
Minimum Temperature (°C)	6 – 8	15	15 – 20
Annual Rainfall (mm)	2000 – 3000	3500 – 4000	3500
Soil classification	Ultisols	Ultisols	Ultisols
Soil pH	4.2 - 5.8	4.5 - 5.5	4.5 - 5.5

Table 2.1: Statistical information about the major tea growing regions in Eastern India

2.2.2 Field Data

Indian tea estates range in size between 100 and 500 ha. Each estate is divided into different sections, typically of a size between 10 and 15 ha. Sections contain tea plants of different varieties, of a different age, and are managed on an individual basis. Tea yield data were available at the level of the estate and for individual sections, in most cases for the period between 1998 and 2007. Climatic data (rainfall, temperature, and sunshine hours) were available at the estate level, where these are collected routinely. Individual estates have their own meteorological station that collects the data regularly.

In the absence of consistent genotypic data, plant age has been used as a proxy indicator at the section level for six estates (DR1 has no age data at the section level). Sectionwise soil pH and percentage organic carbon (OC) data were collected from the topsoil (0-15 cm). The pH was measured by the standard potentiometric method with a glass electrode (Jackson, 1973), whereas organic carbon has been determined by the wet digestion method (Walkley and Black, 1934; Jackson, 1973; Tandon, 1993). For estates SB1 and TR1, three and four years of soil data were available respectively, whereas DR1 (pH and organic carbon) and DR2 (pH only) had seven years of data. No soil data were available for UA1, UA2, and TR2. Data on fertilizer application were available for all estates, apart from TR2. On pruning, tea farmers recognize medium prune (MP), medium skiff (MS), deep skiff (DS), light prune (LP), light skiff (LS), level of skiff (LOS), and unpruned (UP). MP removes the knots and unproductive excess woods and facilitate consolidation by infilling the vacancies. MS regulates crop distribution, reduces the effects of drought, incidence of excessive dormant shoots formation and the height of plucking. DS regulates crop distribution and reduces the effects of drought, excessive creep, and the height of plucking table. LP helps to renew the wood, regulate crop distribution, reduces pests and diseases and maintain ideal frame height of the bushes. LOS level the plucking surface at 4 – 6 cm above the tipping mark. LS is given up to 1 cm above the previous tipping height to maintain the plucking table.

The section data for 2004 of estate TR1 (yield, age, NPK fertilizer) were also analyzed for spatial correlation.

2.2.3 Statistical Analysis

We relate the variation in yield to variables that could at least partly account for the observed variation using a least squares analysis. A relevant distinction concerns the different spatial scales for which different data are available in space. We distinguish the region *r*, from the estate *e* and the section within the estates *s*, respectively. In time, annual data were considered throughout. As concerns notation, we use the subscript e to denote estate specific yield, and we use between brackets the scale in space and time of observation. All parameters are given by Greek symbols, coefficients β for the continuous effects and coefficients γ, δ, and η for the qualitative effects.

Yield, at Estate Level. For each year, descriptive statistics (minimum, maximum, mean yield) are computed at the estate level. The mean is calculated as the sum of the annual yields ($Y_e(t)$) at an estate *e*, divided by the number of years.

Yield, at Section Level. For each year, descriptive statistics are calculated at the section level for each tea estate. The mean is calculated as the sum of the annual yields ($Y_e(s,t)$) at an estate *e*, divided by the number of years and the number of sections.

Rainfall. A linear regression analysis relates the annual yield to the rainfall data obtained from the estates:

$$Y_e(t) = \beta_0 + \beta_1 \cdot rain_r(t) + \varepsilon(t) \qquad [2.1a]$$

where, $Y_e(t)$ is the estate specific yield for year (t) = 1998,…,2007, $rain_r(t)$ is the rainfall in region r in which the estate is located and $\varepsilon(t)$ is the error, assumed to be independent. Because large amounts of rainfall occur that may have an adverse effect on tea yield we also apply a model with a squared rainfall term:

$$Y_e(t) = \beta_0 + \beta_1 \cdot rain_r(t) + \beta_2\, rain_r^2(t) + \varepsilon(t) \qquad [2.1b]$$

Finally, we include the different estates into this equation as estate specific differences may occur:

$$Y_e(t) = \beta_0 + \beta_1 \cdot rain_r(t) + \beta_2 \cdot rain_r^2(t) + \gamma_i \,.\, Estate_i + \varepsilon(t) \qquad [2.1c]$$

where $Estate_i$ is the qualitative estate effect.

pH and Organic Carbon. A regression analysis is carried out at the section level for individual estates on yield with soil pH and organic carbon as explanatory variables. A linear model was implemented to relate pH and OC with yield at the section level:

$$Y_e(s,t) = \beta_0 + \beta_1 \cdot pH(s,t) + \beta_2 \cdot OC(s,t) + \varepsilon(s,t) \qquad [2.2]$$

where $pH(s,t)$ is the pH in the section s in year t and OC(s,t) is the amount of organic carbon at section s in year t.

Pruning. An analysis of variance was carried out to investigate the effect of pruning on tea yield at the section level. This model is written as:

$$Y_e(s,t) = \beta_0 + \eta_k \cdot Prune_k(s,t) + \varepsilon(s,t) \qquad [2.3]$$

where, $Prune_k(s,t)$ is the k^{th} pruning type applied at section s and year t, with pruning types as presented in the section 'field data' and applied in the year before the yield. In addition, we compared the effect of an arbitrary pruning ($\eta = 1$) with no pruning ($\eta = 0$) both at estate and at the section level and also carried out a multiple comparison test to investigate the significance in differences between the different pruning types.

Age. A sectionwise linear regression analysis is carried out to investigate the effect of age on yield. The analysis was carried out on each estate separately with sectionwise yield as the response variable and age as the explanatory variable. This model is written as:

$$Y_e(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \varepsilon(s,t) \qquad [2.4a]$$

where *Age(s,t)* is the age of the yield in section s in year t, respectively while $\varepsilon(s,t)$ is the error assumed to be independent. In addition, we applied a model including a quadratic age term:

$$Y_e(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot Age^2(s,t) + \varepsilon(s,t) \qquad [2.4b]$$

to take the clear quadratic behavior of yield with age into account.

Fertilizers. An estate level regression analysis was also carried out on section-wise yields with N, P, and K fertilizer application as explanatory variables, applying the following model:

$$Y_e(s,t) = \beta_0 + \beta_1 \cdot N(s,t) + \beta_2 \cdot P(s,t) + \beta_3 \cdot K(s,t) + \varepsilon(s,t) \qquad [2.5]$$

where *N(s,t)*, *P(s,t)*, and *K(s,t)* are the amounts of N, P, and K applied to section s in year t, respectively. $\varepsilon(s,t)$ is independent and identically distributed (i.i.d.) random variables.

Age and Fertilizers. Combining all years, an estate specific regression analysis is carried out on section-wise yields with age, and N, P, and K fertilizer application as the explanatory variables, applying the following model at the estate level:

$$Y_e(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot N(s,t) + \beta_3 \cdot P(s,t) + \beta_4 \cdot K(s,t) + \varepsilon(s,t) \qquad [2.6]$$

where *N(s,t)*, *P(s,t)*, and *K(s,t)* are the amounts of N, P, and K applied to section *s* in year *t*, respectively. The coefficients in equation [2.6] are estimated using an ordinary least squares analysis, i.e. taking the $\varepsilon(s,t)$ to be independent and identically distributed (i.i.d.) random variables. This assumption, due to the limited number of observations on N, P, and K in each year, is relaxed in the next step.

Age and Fertilizers Using Spatial Auto Regression. A within estate model is defined in a single year t that has sufficient data at the section level to allow a spatial analysis:

$$Y_t(s) = \beta_0 + \beta_1 \cdot Age_t(s) + \beta_2 \cdot N_t(s) + \beta_3 \cdot P_t(s) + \beta_4 \cdot K_t(s) + \varepsilon_t(s) \quad [2.7a]$$

where we now assume that the observations follow a conditional spatial autoregressive (CAR) model (Ripley and Molina, 1989). Using a matrix type notation, the model is formulated as:

$$Y_t(s) = X_t(s)\,\beta + \lambda\, W_t(s) + \varepsilon_t(s) \quad [2.7b]$$

Here, the matrix $X_t(s)$ contains the observations on the explanatory variables age, N, P, and K fertilizer, λ is a parameter describing spatial dependence, and the matrix $W_t(s)$ denotes a neighborhood matrix. The quality of fit is given by the Akaike's Information Criterion (AIC), an index used as an aid to choosing between competing models. For *m* parameters, the model is defined as AIC = $-2L_m + 2 \cdot m$, where L_m is the maximized log-likelihood. Lower values of the index indicate the preferred model, that is, the one with the fewest parameters that still provides an adequate fit to the data. In our study, only the year t = 2004 has sufficient data for this analysis.

<u>Linear Mixed Model Analysis.</u> The spatial regression analysis for the yield in a single year *t* combining all estates applies a linear mixed model (Schabenberger and Pierce, 2002), to include measuring the spatial dependence. This is the same model as [2.7a] but we now estimate the coefficients β under the assumption that the residuals have a spatial correlation, modeled by the variogram. This analysis is being done in two steps: first a full model is applied, including all the terms on the right hand side. This is followed by a reduced model analysis, in which only the significant terms are maintained. Again, the year 2004 has sufficient data for this analysis at the section level which includes age data and fertilizer data (NPK).

In this study, the statistical and spatial analysis was carried out using the statistical packages such as Statistical Package for Social Sciences (SPSS) 15 for the period April 2008 – 2010 (Field, 2004) and R 2.8.0. (Venables and Smith, 2003)

2.3 Results

2.3.1 Descriptive Statistics at the Estate and Section Level

Table 2.2 shows that the mean tea yield of the different estates ranges between 1526 (SB1) and 2492 kg ha^{-1} (UA1). Average yield for all estates is 2117 kg ha^{-1}. Ranges between minimum and maximum yields are from 1474 to 2611 for the estates, and from 77 to 4562 kg ha^{-1} for the sections, showing a substantial heterogeneity at this level. To further underpin this notion, Table 2.3 provides a summary of yields and the G, E, and M variables for TR1 in 2004. Age ranged between 9 and 73 years, pH between 4.3 and 5.6, organic carbon content between 1.7 and 2.5%, and yield between 1341 and 3349 kg ha^{-1}.

Estate	*Estate Level*				*Section Level*			
	Min	*Max*	*Mean*	*years*	*Min*	*Max*	*Mean*	*Years*
SB1	1494	1563	1526	1998-2007	541	2670	1532	2004-2007
UA1	2215	2611	2492	1998-2007	1142	3848	2492	1998-2007
UA2	2211	2556	2343	1998-2007	805	3836	2343	1998-2007
TR1	1801	2531	2048	1998-2007	434	4242	2048	1998-2007
TR2	2054	2470	2343	1998-2007	77	4562	2356	2000-2007
DR1	1785	2334	2037	1998-2007	188	4402	2042	1999-2007
DR2	1960	2131	2029	1998-2007	380	3395	2022	2002-2008
Averages	1931	2314	2117		582	3851	2119	

Table 2.2: Descriptive tea yield statistics for the different gardens at estate and section level (kg ha^{-1}). Estate level data are for the period from 1998 until 2007, whereas section data are collected for a limited number of years, as specified.

	Genotype	Management	Environment						
Section No.	*Area (ha)*	*Cultivars*	*Age (Years)*	*N (kg ha^{-1})*	*P (kg ha^{-1})*	*K (kg ha^{-1})*	*pH*	*OC (%)*	*Yield (kg ha^{-1})*
A	11.33	TV-9, TV-26, Dangri	44	110	30	70	4.9	1.7	2025
B	6.74	Assam	49	120	30	120	4.5	2.1	1874
C	7.27	Assam	52	100	20	100	4.3	1.7	1280
D	10.36	TV-1, 18, 22, 23	17	150	50	150	4.4	2.5	1687
E	4.8	Tingamira	34	160	50	160	4.5	1.9	2060
F	6.03	Assam	54	120	30	120	4.5	1.6	1656
G	13.32	Tingamira, TV-9	34	160	50	160	4.6	1.8	2790
H	6.98	Assam, TV-9, TV-26	73	130	30	110	4.6	2.1	2790
I	17.63	Dangri, TV-1, TV-9	32	110	30	70	4.6	1.6	1341
J	7.26	Assam, TV-26	68	120	30	100	4.8	1.9	1942
K	7.7	TV-20, 22, 23, 26, 28	9	150	50	90	4.7	2.5	2064
L	11.36	TV-1, 17, 22, 23, 26	10	165	50	100	5.6	2.1	3132
Average				132.9	36.5	115.3	4.6	2.03	2182
**Std. Dev.*				22.8	11.4	31.1	0.34	0.31	579.34

***Standard Deviation**

Table 2.3: Sectionwise data of the TR1 tea estate showing the cultivars, age of the plantations, NPK application, soil pH and organic carbon, and the yield in 2004. In this year no pruning was applied.

2.3.2 Yield and Rainfall at Estate Level

The analysis on climatic factors is restricted to rainfall, as a quick scan revealed that no significant relationship exists between yield and temperature or yield and sunshine hours. Figure 2.3 shows how annual rainfall differs between years and between estates, 1998 being very wet and 2007 very dry. SB1, with the lowest yields (Table 2.2), has a much lower average annual rainfall than all the other estates. Application of Eq. [2.1a] revealed a positive linear relationship between rainfall and mean yield for the two estates in Terai (TR1, TR2), and a negative relation for DR1 (Table 2.4a). As Dooars is the wettest area in 7 out of the 10 observed years, excessive wetness may be a reason for this. A regression analysis [2.1b] for all estates shows a positive linear effect and no significant quadratic effect (Table 2.4a). The overall analysis showed that rainfall does have an effect on tea yield over different estates in different regions with a likely average yield increase of 495 kg ha^{-1}. From Eq. [2.1c], we noticed that linear and quadratic effects are not significant and of much smaller size, even though the R^2 value is very high (Table 2.4b).

Estate	*n*	R^2	*Intercept, β_0*	*Rainfall, β_1*	*Rainfall², β_2*
SB1	10	0.001	1430	0.009	
UA1	10	0.072	2596	-0.031	
UA2	10	0.193	2490	-0.048	
TR1	10	0.411	1460	0.169*	
TR2	10	0.665	1781	0.197**	
DR1	10	0.453	3245	-0.279*	
DR2	10	0.135	1569	0.112	
All estates	70	0.249	495	0.883***	-0.000106

Table 2.4a: Linear relation between tea yield and rainfall at the estate level combining different years (n = number of years). In this table and in the subsequent tables the following legend is applied: *: significance at p = 0.05, ** significance at p =0.01, ***: significance at p = 0.001.

n	R^2	*Root MSE*	*Mean Yield*
70	0.995	183.7	2129

Estate	*Parameter Estimate*	*Standard Error*	*Pr > | t |*
Rainfall, β_1	0.031	0.037	0.410
Rainfall^2, β_2	-3.02$_{10}$-6	4.73$_{10}$-6	0.525

Table 2.4b: Linear relations using a generalized linear model between tea yield, rainfall and rainfall^2 corrected for different estates.

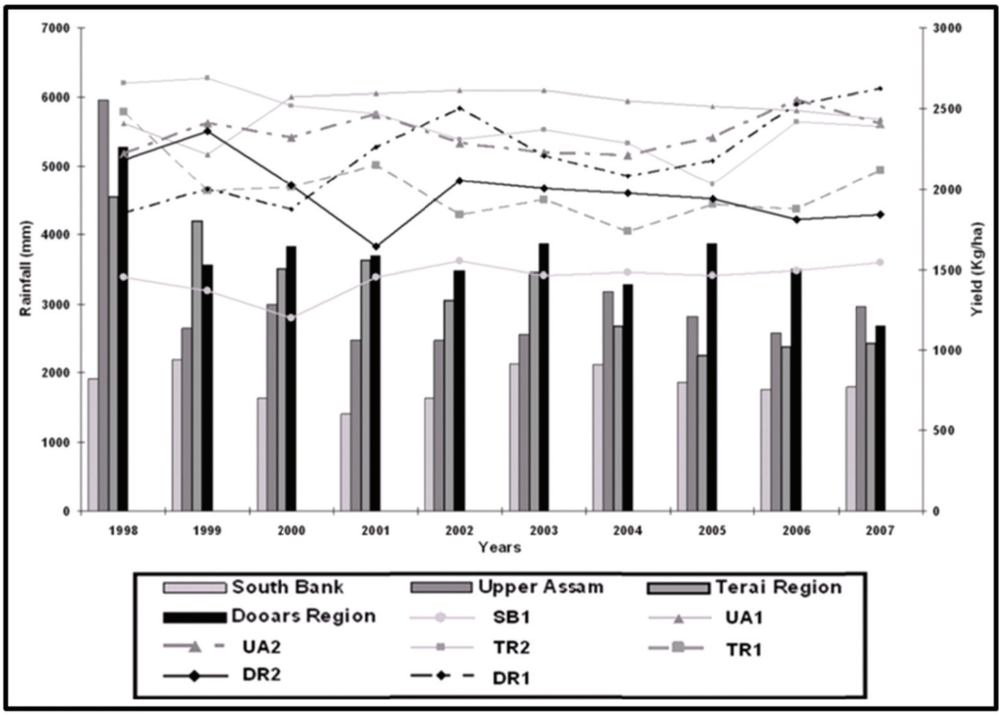


Figure 2.3: Ten year yield and rainfall amounts across seven tea estates. Lines represent tea yield from the seven estates and bars represent rainfall.

2.3.3 Soil pH and Organic Carbon at Section Level

Soil pH for the four estates with soil data ranged between 4.5 and 4.8 while the soil organic carbon percentages for the four estates were 1.0% (SB 1), 1.8% (TR 1), 2.1 (DR 1), and 2.2% (DR 2). The R^2 values are very low throughout. Results of the sectionwise regression analysis [2.2] shows a significant positive effect of pH and organic carbon in SB1 while a significant positive effect of organic carbon could be observed in TR1 (Table 2.5).

Estate	*Mean pH*	*Mean OC*	R^2	*Intercept,* β_0	*pH,* β_1	*OC,* β_2
SB1	4.79	0.979	0.157	179	183*	557***
TR1	4.64	1.757	0.147	-1617	538	578**
DR1	4.52	2.193	0.083	5457	-681	-22
DR2	4.49	2.145	0.027	2128	49	-184

Table 2.5: Linear relations between tea yield, soil pH and organic carbon at the section level for individual estates. The positive between yield and pH is significant at SB1 when considered jointly with OC.

2.3.4 Pruning Analysis

An analysis of variance [Eq. 2.3] shows a predominantly significant and negative effect of the individual pruning regimes on yields (Table 2.6a). The negative effect implies that individual pruning regimes decreases tea yield. LOS and LS did not show any effect on yield. In estate DR2, no significant effect could be observed for the different pruning regimes.

The analysis between pruning (η = 1) and non-pruning (η = 0) shows a significant negative effect for different pruning regimes at estate level (Table 2.6b), although the R^2 value was relatively low throughout. All the estate showed significant negative effect. The overall estate level pruning analysis showed that frequent pruning results in yield loss due to heavy crop loss. The least square difference (LSD) test was done between the major pruning regimes DS, LOS, LP, LS, and MS. The multiple comparisons (Table 2.6c) revealed that pruning types LOS is significantly different from types DS, LP, LS, and MS, which did not show significant differences among themselves.

Estates	*Prune, η*					
	Intercept, β_0	*DS*	*LOS*	*LP*	*LS*	*MS*
SB1	1373	-391**		-589***		632
UA1	2365	-132		-551***		-259
UA2	2091	-617***		-774***		-575*
TR1	1919	-324***	117	-462***	-360	-444*
TR2	2032	-512***		-728***	-107	-602***
DR1	1855	-103		-517***		-344**
DR2	1987	-202		-9		-76

Table 2.6a: Estimated effects of 5 individual pruning regimes (DS, LOS, LP, LS and MS) on tea yield at the section level for individual estates. Each number shows the difference in yield of the pruned sections with the unpruned sections. Statistical testing is done with the t-test.

Estates	*n*	R^2	*Intercept,* β_0	*Prune,* η
SB1	75	0.177	1843	-470***
UA1	79	0.078	2714	-350*
UA2	79	0.390	2836	-745***
TR1	596	0.069	2255	-336***
TR2	315	0.274	2749	-717***
DR1	439	0.076	2230	-380***
DR2	261	0.016	2150	-163*

Table 2.6b: Estimated effect of pruning on tea yield at the section level for individual estates: $\eta = 0$ for non-pruning and $\eta = 1$ for pruning.

Prune	*'j'*			
'i'	LOS	LP	LS	MS
DS	-437			
LOS		583	477	565
LP				
LS				

Table 2.6c: Multiple comparisons testing between different pruning regimes. Empty cells indicate non-significant effects. LOS (i.e. different deviating regimes) provides significantly higher yields than other pruning regimes.

2.3.5 Age Analysis

The sectionwise regression analysis [Eq. 2.4a] reveals that plant age has a negative, linear effect on tea yield for all estates (Table 2.7a). At the same time though, Figure 2.4 suggests a parabolic relationship, with production peaks generally falling in the period between 20 and 40 years. The generalized linear model [2.4b] relates age and age^2 to yield, shows effects for several estates, but apparently gives no better fit than the linear approach (Table 2.7b). R^2 values are low throughout.

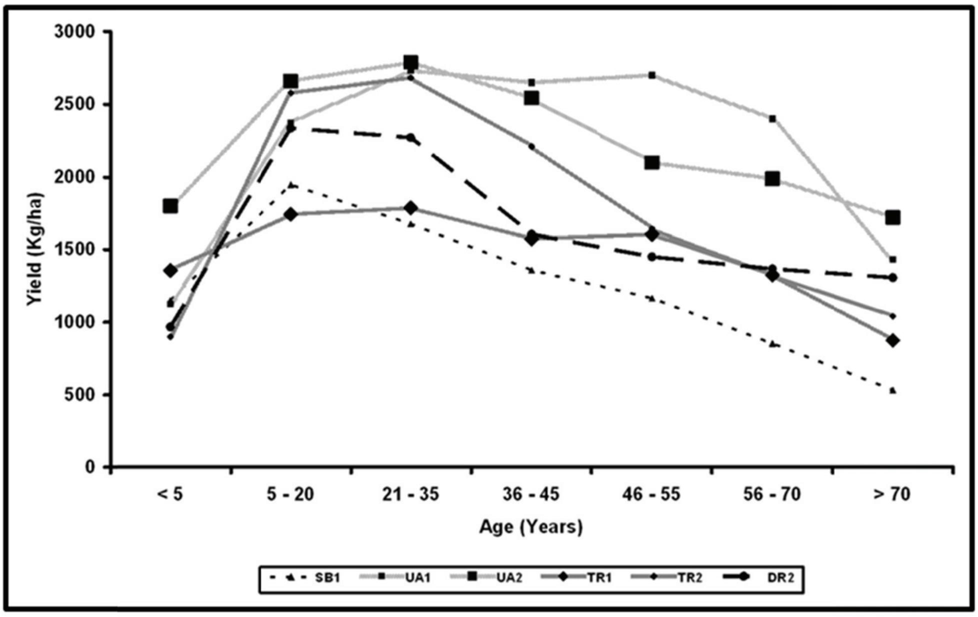


Figure 2.4: Relation between tea yield and age groups of tea plants at the seven estates. Yield shows a clear optimum between 20 and 40 years for age and declines afterwards.

Estates	*n*	R^2	*Intercept,* β_0	*Age,* β_1
SB1	110	0.236	1845	- 10.24***
UA1	80	0.009	2619	- 4.70
UA2	80	0.188	2797	- 6.30***
TR1	596	0.001	2083	- 0.81
TR2	311	0.029	2520	- 4.11**
DR2	253	0.211	2400	- 8.86***

Table 2.7a: Linear relations between tea yield and age of plantations at the section level for individual estates.

Estates	*n*	R^2	*Intercept,* β_0	*Age,* β_1	*Age²,* β_2
SB1	110	0.252	1734	1.426	- 0.154
UA1	80	0.071	1924	53.230*	- 0.994*
UA2	80	0.249	3385	- 36.520**	0.237**
TR1	596	0.019	2401	- 18.040***	0.184***
TR2	311	0.030	2473	- 1.592	- 0.024
DR2	253	0.212	2429	- 10.404*	0.082

Table 2.7b: Linear and quadratic relations between tea yield and age of sections at for individual estates. Maximum tea yield occurs at UA1 at 27 years of age. At the other estate no significant quadratic relation with a negative squared age term was observed.

2.3.6 Fertilizer Analysis

The sectionwise regression analysis [Eq. 2.5], jointly including N, P, and K application, revealed positive significance in four estates for N, and three estates for K application, out of a total of six estates. For P, the picture was mixed (Table 2.8).

Estates	*n*	R^2	*Intercept*, β_0	*N*, β_1	*P*, β_2	*K*, β_3
SB1	65	0.397	- 537	17.78	1.83	3.29**
UA1	67	0.116	811	9.97*	- 3.57	3.85
UA2	58	0.119	975	8.02*	4.82	0.65
TR1	366	0.329	- 68	16.59***	- 7.17*	1.17
DR1	439	0.307	708	5.10**	2.77	6.35***
DR2	274	0.394	938	- 0.80	14.80**	6.33***

Table 2.8: Linear relations between tea yield and N, P and K applications at the section level for each estate individually. Estate TR2 could not be analyzed as identical NPK applications were reported.

2.3.7 Age/Fertilizer Analysis

Applying [Eq. 2.6], effects of age and NPK fertilizer application are combined (Table 2.9). Although R^2 values are reasonable (0.146 - 0.637), the combined model does not reveal more than the two separate models.

Estate	*n*	R^2	*Intercept*, β_0	*Age*, β_1	*N*, β_2	*P*, β_3	*K*, β_4
SB1	61	0.637	141	- 10.86***	16.0*	- 3.45	2.55**
UA1	67	0.146	1153	- 9.66	10.6	- 6.31	2.74
UA2	58	0.244	1719	- 5.80	5.7	1.56	1.61
TR1	366	0.330	-71	0.1	16.6***	-7.15*	1.17
DR2	219	0.369	969	-4.4***	11.7*	0.35	-1.35

Table 2.9: Linear relations between tea yield and Age, N, P, and K at the section level for each estate individually. Estate DR1 was not included because of missing age information. Estate TR2 could not be analyzed as identical NPK applications.

2.3.8 Within Estate Spatial Analysis

The spatial autoregression (SAR) analysis was carried out applying the models [2.7a] and [2.7b] for TR1, while using the 2004 yield data (Figure 2.5; Table 2.10a). Variation in yield was observed within different sections with varying N applications. Higher yields were obtained at higher N rates (Figure 2.5c). Table 10a also shows a significant positive effect of N application. Inclusion of N as an explanatory variable leads to a decrease in lambda 'λ'. A spatial effect could be observed with the spatial range parameter λ ranging between – 0.019 for N and 0.007 for NPK for the different models. None of the values however is significant at the 0.05 level. An F value of 3.736 with a significance level of 0.0002 for the full model indicates that N has a clear and positive effect on yield. This agrees with the ordinary linear regression (Table 2.10b) results, for example providing equations as

$$Y_S = 1737$$

and

$$Y_S = -464 + 4.66\, Age + 16.56\, N + 1.91\, P - 1.51\, K$$

for the intercept model and the full model respectively, while the SAR analysis (Table 2.10a) results provides the equation as

$$Y_S = 1751$$

and

$$Y_S = -469 + 4.67\, Age + 16.59\, N + 1.89\, P - 1.51\, K$$

for the intercept model and the full model respectively. The two models showed differences between yield, age and NPK applications where minor yield differences of 1737 and 1751 could be observed in the OLS and SAR respectively. Age and NPK effects were found to be almost similar with slight differences. The two equations confirm the similarities between the OLS and SAR analysis.

SAR Model	*Intercept, β_0*	*Age, β_1*	*N, β_2*	*P, β_3*	*K, β_4*	*λ*	*F Stat.*	*p value*
Yield	1751					0.140		
N	-408		17.11***			-0.019	7.157	0.0000
Full model	-469	4.67	16.59***	1.89	-1.51	0.007	3.736	0.0002***

Table 2.10a: Linear relations between tea yield and management factors at the section level of estate TR1 in 2004 using the SAR Model. The first row is a model without explanatory variables; the next four rows are individual models with different explanatory variables, whereas the bottom row shows estimates for a model including all effects.

OLS Model	*Intercept, β_0*	*Age, β_1*	*N, β_2*	*P, β_3*	*K, β_4*
Yield	1737				
Full model	-464	4.67	16.56***	1.91	-1.51

Table 2.10b: Linear relations between tea yield and management factors at the section level of estate TR1 in 2004 using the OLS Model.

2.3.9 Combined Estates Spatial Analysis

Our final analysis considers the relationship between yield and the age and fertilizer variables using model [2.7a] for a single year (2004), combining the different estates. The linear mixed modeling analysis uses coordinates for the centers of the different sections and estimated variograms. We observe a relatively strong spatial dependence for the reduced model, in which the nugget (2.47×10^5) is more than twice the value of the sill parameter (1.04×10^5), and the estimated range equals 435 m (Table 2.11). In the full model, the clear spatial structure disappears. The sill (0.2×10^5) is reduced to less than 10% of the nugget parameter (3.0×10^5). The decrease of the AIC is small, indicating that the effect is limited in relation to the number of introduced parameters. Comparing the estimated effects with those from the ordinary linear regression analysis, we again observe a significantly positive N effect, i.e. an increase in yield with increasing N values of 13.35 kg yield ha^{-1} per kg N ha^{-1}, a highly significantly negative Age effect, i.e. lower yield with increasing age, and a negative K effect ($p = 0.07$) in the LMM model. Spatial variation is observed within the sections indicating that other explanatory variables may be involved, such as age of the plantations, pest infestations, diseases, waterlogging, and soil stress.

Models	*n*	*Intercept, β_0*	*Age, β_1*	*N, β_2*	*P, β_3*	*K, β_4*	*Nugget*	*Sill*	*Range*	*AIC*
OLS	181	1134	-5.161**	8.36	0.076	-0.701				2784
LMM	181	898	-4.195**	13.35***	-0.795	-3.546	299300	28500	1531	2767
OLS	251	830		8.49						3886
LMM	251	647		10.33***			247400	104400	436	3870

Table 2.11: Estimated ordinary least squares (OLS) and linear mixed model (LMM) output relating tea yield to age and NPK fertilizer application. A joint analysis is applied at the section level using data from all estates in 2004.

2.4 Discussion

This study focuses on information available at two different scales from seven tea estates in north eastern India. The scope of the study is largely set by the availability of data made available to us for a period of 10 years. The tea estates within the different regions analyzed in this study use different cultivars. Vegetative propagation offers improved clonal tea varieties targeted for desired traits (Othieno, 1981; Seurei, 1996). Other reasons for yield stagnation may include the presence of allelopathic chemicals such as caffeine and theobromine in old plantations, arising from the pruning's and leaf litter mulch that hinder nutrient uptake

(Owuor, 1996; George and Singh, 1990). These chemicals inhibit seed germination and subsequent radical growth and in vitro growth of tea plants (Owuor et al., 2007).

Although the estates use different cultivars, their detailed information could not be used in the analysis due to non-availability of data. As sections within the estates are frequently facing replanting on a gap-filling basis, the present study is not based on a controlled researcher-managed environment. Also, since this replanting took place on a per plant basis, the changes were not being monitored even on a section basis. Changes in plant density as a result of replanting, and the number of shade trees per section, were not available either. Also, replaced plants were not always of the same variety as their predecessors. In fact, the entire range of varieties observed in the seven estates, include clonal varieties such as TV-1, TV-9, TV-26, etc. and seedling variaties such as Assam, Tingamira, Rajgarh, Dangri, etc. As new varieties are planted as they develop, it was decided that average age of plants in a section as reported by estate management could be taken as the independent variable, and used as a proxy for genotype. This is not an ideal research situation, but it was the best we could get from the estate managers. Similar complications in this field are mentioned by Francis et al. (2002), who used different methods to study the phenotypic stability of twenty tea genotypes for six years. As stand age increased, yields generally decreased, but yield fluctuations between genotypes were substantial, and the response was not consistent across the sites for all genotypes indicating the need to test clones at multiple sites over longer periods of time. Wachira (2002) also demonstrated that the yield responses of tea genotype widely varied within different regions.

Different researchers have reported on G, E, and M variables that influence tea yields. On temperature, for example, Tanton (1982) gives an optimum range of 18 to 20 °C, Carr and Stephens (1992) use a wider range of 18 to 30 °C, but Barua (1989) stated that tea grows best from 13 – 30 ^{0}C. The growth rate of tea is lower at higher elevations and low temperatures but it is ideal for good quality tea (Odhiambo et al., 1988; Owuor et al., 1990; Robinson and Owuor, 1992). In Central Africa, fifty five percent annual tea loss was due to tea mosquito bugs (Ratan, 1984) while thirty percent yield loss was reported from Kenya (Sudoi, 1995), whereas Pethiyagoda (1964) and Smith et al. (1993) have suggested that clonal differences in numbers of dormant (banjhi) shoots may be more important than shoot growth in determining tea yields at low temperatures.

Average estate yields ranged between 1526 (SB 1) and 2492 (UA 1) kg ha^{-1}, but at the section level, minimum and maximum values ranged between 77 and 4562 kg ha^{-1}. The yields at the very low ends may be due to the replanting. Table 2.3 also shows that heterogeneity within one estate, for one year, and for all variables studied, can be quite high. Also, for the year 2007 as a whole, Assam had an average tea yield of 1534, Dooars of 1950, but Terai of 3202 kg ha^{-1}, again showing major differences. The data also show that tea yields > 4 tons ha^{-1} can be attained.

We used a data driven statistical approach by applying standard regression analysis with yield as the dependent variable, and two more advanced spatial statistical methods to account for possible spatial dependencies. This is most likely the cause for the relatively low R^2 values. Different models were compared to analyze the variations at the estate level in different regions. Linear and quadratic analysis has been carried out on the available rainfall data to see the effect of rainfall on yield. Tea plants thrive best under high and evenly distributed rainfall of at least 1500 mm per year, and a dry season of not more than three months. At the equator, the ideal monthly rainfall distribution will be 90 to 180 mm and the crop yield falls below 60 mm (Carr and Stephens, 1992). It is also estimated that non-shaded tea transpires upto 2200 mm water ha^{-1} yr^{-1} (Katikarn and Swynnerton, 1984; Anandacoomaraswamy et al., 2000) depending on the area. In our study, however, annual rainfall totals were used as environmental parameters, hiding from view seasonal differences. Kamau (2008) also found seasonal rainfall differences in years to have a marked effect on tea yields.

The choice for a regression based statistical approach is apparent from the amount of data collected. This choice is motivated by considering tea yield as the one continuous dependent variable that depends on linear, quadratic, and discrete explanatory variables. An essential choice has been the scale of observation in space and time. Some models (model 1.1) combined data across estates; some models (models 2.2 – 2.6) combined data across time periods, whereas other models (models 7) analyzed the data of a single year and one estate only. Any choice for a combination of data has been motivated by the questions to be addressed, by the scale of the process as well as by the availability of the data. Rainfall (model 1.1) was considered at the estate level, age, pH, organic carbon, fertilizers, and pruning (models 2.2 – 2.7) at the section level. Such effects should be assessed irrespective of more global estate effects. In all these models, the time has been taken as the replicate, assuming the absence of global change and of effects twined with year.

Spatial dependence of the data could only be included at the section level, i.e. within individual estates. Although it may exist as well between estates, there would be little use to incorporate this, because of the relatively low number of estates and major differences between them. At the section level, spatial dependencies should be included. Data availability only allowed us to do so for fertilizers and age. Inclusion of the spatial dependence resulted into differences in estimated effects. For example, we found a significant 16.6 vs. 10.3 kg ha^{-1} N application for the two spatial models 2.7, respectively, and 8.3 kg ha^{-1} N application for the non-spatial model 2.6. The explanation is that the major sources of spatial variation in the tea yield are explanatory variables at the section level and possibly also at the within-section level. We may hypothesize that inclusion of spatial dependencies for the other variables may lead to minor changes in parameter size effects and their significance as well. At an even finer scale level, i.e. at the within-section level when analyzing individual plants, spatial dependence may have a much larger effect and should be included (Stein et al., 2000).

Responses to pH were virtually absent, which may be due to the limited pH range (4.5 – 4.8). Estate SB1 (with lowest rainfall, soil fertility, and yields) showed that the combination of pH and organic carbon had a significant effect on tea yields. Regression coefficients were low throughout though, testifying to the uncontrolled research conditions. Organic carbon was also highly significant in TR1, but not in the Dooars estates. Since the two estates in Dooars had average organic carbon contents > 2%, we may conclude that this value is a useful threshold when evaluating inherent soil fertility. Kamau (2008) found in Kenyan tea plantations that NPK stocks increase with the age of the plantations. He also concluded that ageing of tea plantations results in the accumulation of high C and NPK stocks that could maintain yield stability under adverse weather conditions. The rate of increase differs between genotypes.

The age and N (and to a lesser extent K) fertilizer effects were among the clearest, but need a sharper genotype-focus when looking at the results of Kamau (2008) in Kenya. He found that clonal tea responds better to N irrespective of age while old seedling tea does not. He further stated that N management should be on the basis of yield ability of tea bushes as defined by genotype-density combinations and age classes. On age and fertilizer, Owuor and Odhiambo (1994) stated that the response of tea bushes to N increases till the age of 30 years followed by a decline. Up to 30 year old plantation, higher rates of 200 kg N ha^{-1} yr^{-1} can be applied. Younger plantations should be applied with 150 kg N ha^{-1} yr^{-1} while aged plantations should be applied with 50 kg N ha^{-1} yr^{-1}. This would help in maintaining the tea quality and prevent against pests damage. This provides insights for management decisions in India too.

Pruning is an agronomic practice in the production of leaves for the manufacture of black tea (United Planters Association of Southern India, UPASI, 2002). It is done to maintain the plucking table and to enhance production by increasing branching (Ravichandran & Parthiban, 1998) in order to attain greater number of tender leaves (Satyanarayana et al., 1994) and avoiding the plants to attain tree heights. The results as presented in table 2.6a were counter-intuitive, as apparently a lower yield is obtained after pruning than before. This might indicate that continuous pruning results in severe crop loss and yield reduction. We followed several sections during the past 10 years, one example being shown in Figure 2.6, confirming the statistical calculations in which decline in yields could be observed when different pruning regimes are applied to a particular section. Explanations for the decline in yield after pruning are that the pruning is done more often without following proper pruning regimes and recommended pruning cycle. Lack of proper information on pruning to the staffs of the estates may be another reason for such a decline. Applying pruning to old sections might also reduce yield because recovery of old bushes after pruning depends on the health of the bushes.

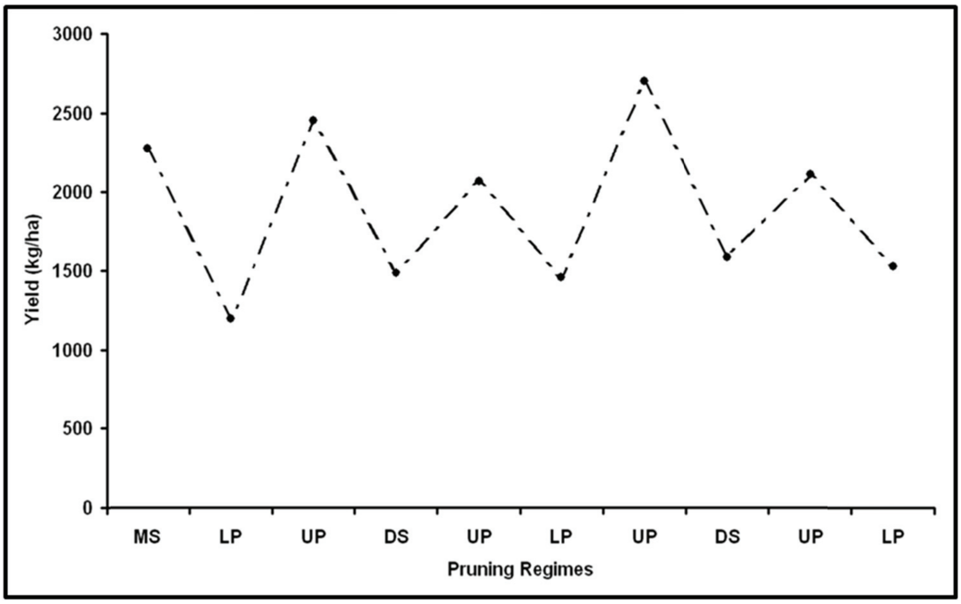


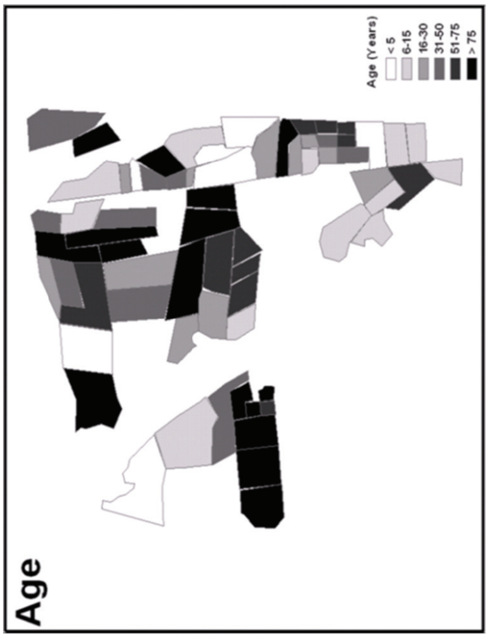
Figure 2.6: Effect of different pruning regime on tea yield from 1998 – 2007 for one section of a tea estate UA1.

This study focused on explaining the variation of tea yield in different regions of North East India. For such an analysis, more detailed information like identification of factors limiting improvements in the productivity of existing tea, or the improvement of factory or transport capacity, and likely distribution of yield throughout the year has to be taken into consideration (Matthews and Stephens, 1998a). Modeling approaches, although scarce for tea, may come in handy, as was done for Tanzania by the CUPPA-Tea model (Matthews and Stephens, 1998b). The CUPPA Tea (Cranfield University Plantation Productivity Analysis for Tea) Model simulates the growth and yield of tea. The model can be used to estimate the potential yield and seasonal distribution of yields when water, nutrients, pests and diseases are not limiting. It models yield responses of tea to climate, weather, and management inputs, with particular emphasis on understanding the physiological mechanisms involved. The model simulates the growth processes of the tea bush, taking into account the effects of water, temperature, sunlight, humidity, and nutrients. Secondary data sets such as those used for the current study are less appropriate, as they often do not match the input requirements of the models, but a primary data collection campaign can be organized such that the required data is collected. The Tanzania-developed model could then be both calibrated and validated for Indian conditions.

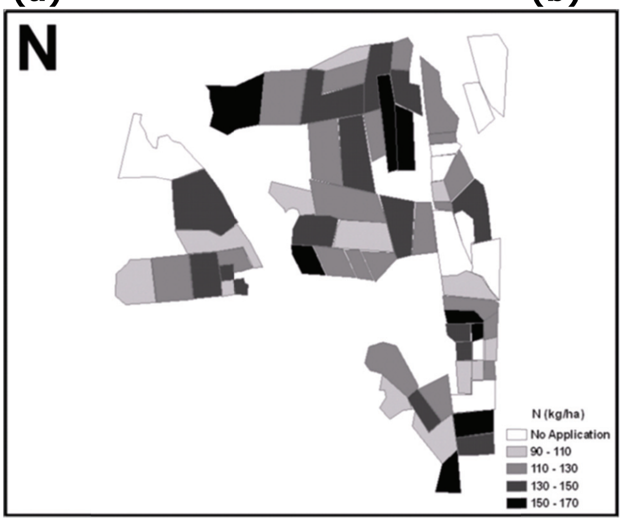
2.5 Conclusions

The conclusions of this study are based on a routinely collected data set from seven estates during 10 years. To these data an extensive statistical analysis was carried out. From this study, it was concluded that substantial agronomic monitoring is required to stimulate the tea sector in North East India. More specifically, we conclude that:

1. At the estate level, major differences occurred between the estates analyzed, due to variation in management practices and uncontrolled environmental factors. Rainfall analysis did not reveal a large effect among tea yields except in one region where a negative rainfall effect is likely to be due to excessive wetness.
2. Yield variation at the estate level is due to age of the tea plants at the section level: tea yield decreases with an increasing age at the section level. A further analysis at the individual plant level may be required to get more specific information.
3. At the section level a positive yield response to N fertilizer exists. The yielding ability of the tea bushes may be due to the heterogeneity within the sections both with seedling and clonal tea, plant population density, age of the plantations, and good management practices.
4. Pruning shows a negative effect on tea yield as a decline in yield occurs in the year after pruning. On the relatively short time period for this study, pruning did not show any benefit. On a longer term, however, it may have a more positive effect on tea yield.
5. Statistical modeling with straightforward methods is indispensable to extract relevant information from available data. Modeling spatial dependencies is relevant at the section level, giving more precise estimates. A collection of several years of data is valuable to quantify effects irrespective from individual years.



(a) **(b)**



(c)

Figure 2.5: Maps of estate TR1 showing sectionwise yield (a), age (b) and N application (c) in 2004

3

A wavelet based approach for monitoring tea plantation

This chapter explores the application of remote sensing in monitoring the different stages of replantation using spatial data at different spatial scales. Wavelets such as Haar, Daubechies and the Symlets were extensively used to extract patterns and were compared at different levels of decomposition. The extracted patterns were identified and analyzed using topographic and hydrological parameters.
This chapter is revised and resubmitted in the *International Journal of Remote Sensing* for publication as "A wavelet based approach for monitoring plantation crops (Tea: Camellia sinensis) in Northeast India."

Abstract

This study analyzes the monitoring of tea replantation using LISS III and CARTOSAT – 1 images. Monitoring identifies four phases of replantation and rejuvenation, starting at the time of uprooting and finishing when new plants are planted. Study area is the Dooars region in Northeast India. The Perpendicular Vegetation Index (PVI) and Perpendicular Soil Index (PSI) were derived. Haar, Daubechies and the Symlets wavelets were used to extract information at different scales. In a multi-resolution study, the wavelets are compared at different levels of decomposition. Topographic and hydrological parameters are included. Informative patterns for each stage of replantation were selected at individual sections within the estate, on the basis of spatial correlation. The study shows that levels 3 and 4 gave superior information as compared to the other levels. The anisotropic autocorrelation gave constant spatial variation at different scales and in different directions. The selected patterns were weakly correlated with slope, flow accumulation and CTI. Management activities and small variation in elevation proved less efficient in explaining the extracted patterns. Hydrological processes could be evaluated using cross correlations. The asymmetric Daubechies-4 wavelet gave the best results for extraction of fine features, whereas the symmetric Symlets-8 wavelet best represented extraction of smooth features. Although a strong quantitative linear relationship between the extracted patterns and topographic parameters could not be established, we conclude that wavelets are useful to extract patterns and interpret spatial variations observed at different phases of tea replantation.

3.1 Introduction

In agricultural scenarios, management activities are guided by changes in crop and soil conditions that are most likely to vary within the field. Quantifying patterns of crops and soil conditions during the growing seasons increasingly helps in proper management and decision making. Therefore, patterns extracted from remote sensing images may be useful to support such quantification, for example, by applying wavelets. Patterns are the non-random distribution and arrangement of low and high values (Epinat et al., 2001).

This study considers the use of remote sensing as a tool to better understand the causes for decline in tea yield in India (Dutta et al., 2010). Attempts to monitor diseased tea areas in India using remote sensing showed that plantations could be monitored and that diseased areas could be delineated despite the presence of shade trees (Dutta et al., 2008). An important activity taking place to reduce the decline is the replantation at individual sections within tea plantations. Tea replantation considers the chain from 1) uprooting an existing section, 2) leaving the section bare, 3) planting of Guatemala grass and 4) replanting a section with young tea plants. This study explores the different replantation stages through the use of remote sensing technology.

So far, no work has been done on monitoring replantation by means of remote sensing. Replantation is an important activity, aiming at increasing the yield of tea estates thereby achieving quality in the process. Various criteria's such as age of bush, health, yield, and vacancy percentage determine whether tea bushes are being uprooted (Dutta, 2006). A remote sensing based monitoring system for tea replantation would help simultaneously cover large areas. In this study, wavelets are used to monitor the different stages of replantation and rejuvenation in the tea growing areas of India using multiscale pattern analysis. In a Fourier and wavelet analysis, spatial transformations are done by creating linear combinations of orthogonal function of spatial frequency and distance to summarize pixel values of a particular spectral band (Schowengerdt, 1997). Mallet et al., 1997, proposed the adaptive discrete wavelet transform (DWT) for reducing the dimensionality in the classification of multi spectral data and optimizing the discriminatory information present in the image.

Wavelets have been applied in a pattern analysis for various crops. Initially, Verhagen et al., 2000 used wavelets in a study on potato yield patterns to distinguish between spatial patterns and allowing a quantitative approach for its classification. Schmidt and Skidmore (2003**)** used wavelets and confirmed that increased spectral resolution of hyperspectral sensors can improve the mapping of floristics while Cosh and Brutsaert (2003) examined the spatial structure of vegetation density at the land surface. Later, Choua et al., 2007 found wavelet analysis a good tool for identifying and describing crop features while Li et al., 2008 successfully discriminated tea varieties by comparing different wavelet transform models. Blackburn et al., 2008 quantified chlorophyll concentration by applying wavelet analysis to leaf reflectance spectra for accurate predictions of chlorophyll concentration. More recently, Martinez and Gilabert (2009) monitored vegetation dynamics from NDVI time series using a multi resolution analysis based on wavelet transform. Cheng et al., 2010 also used continuous wavelet analysis for detection of green attack damage by mountain pine beetle.

The objective of the research described in this paper is to monitor spatial patterns of vegetation and bare soil occurring during tea replantation and to better understand the causes of the patterns. A pattern analysis based on wavelets was applied to multi-temporal satellite data at different resolutions. The results of the three wavelets Haar, Daubechies (db4) and Symlet (sym8) were then compared and the patterns extracted. The study is carried out at two Indian tea estates where the different stages of replantation were available. The standard wavelet functions such as Daubechies (db4), Symlet (sym8) and Haar were being applied in this study.

3.2 Replantation

Tea is a mono-cultured crop with little inter culture operation and without crop rotation. The mono-culture of tea causes a condition of improper soil functioning known as soil sickness (Barua, 1969). To improve the field conditions, uprooting and replanting of old and degraded plantations with high yielding cultivars (Kamau, 2008) are being carried out. Sections where the tea plants reach the economic life age (> 50 years) and where a decline in yield and quality of tea is observed are uprooted and a new generation of young tea is planted. The targeted sections are those yielding less than 65 percent of the average of the sections within an estate, those with more than 25 percent vacancies, those that are noticeably below garden mark in quality and the 2.5 percent oldest tea sections. Replantation has four major stages (Figure 3.1):

Stage 1: Uprooting (Up) starts by uprooting of tea plants and shades trees. The sections are left barren during approximately 3 months. A land planning is done by means of contour surveys, identification of catchments and marking of the drainage lines.

Stage 2: Young Guatemala (YG): young Guatemala grass is planted as a rehabilitation crop after ploughing and levelling the land.

Stage 3: Mature Guatemala (MG): After the Guatemala grass has remained in the field during approximately 24 months it is cut at 25 – 30 cm from the ground and used as mulches. After 3 months the section is leveled again, manure is added to the soil and drains are dug.

Stage 4: Replanting (Rp). Finally, tea seedlings are planted, at a plant spacing of 60 cm in rows separated by 90 cm in hilly areas and by 105 cm in plain areas. Shade trees are also planted at 12m x 12m spacing. Replantation usually starts in October and it takes three years to complete.

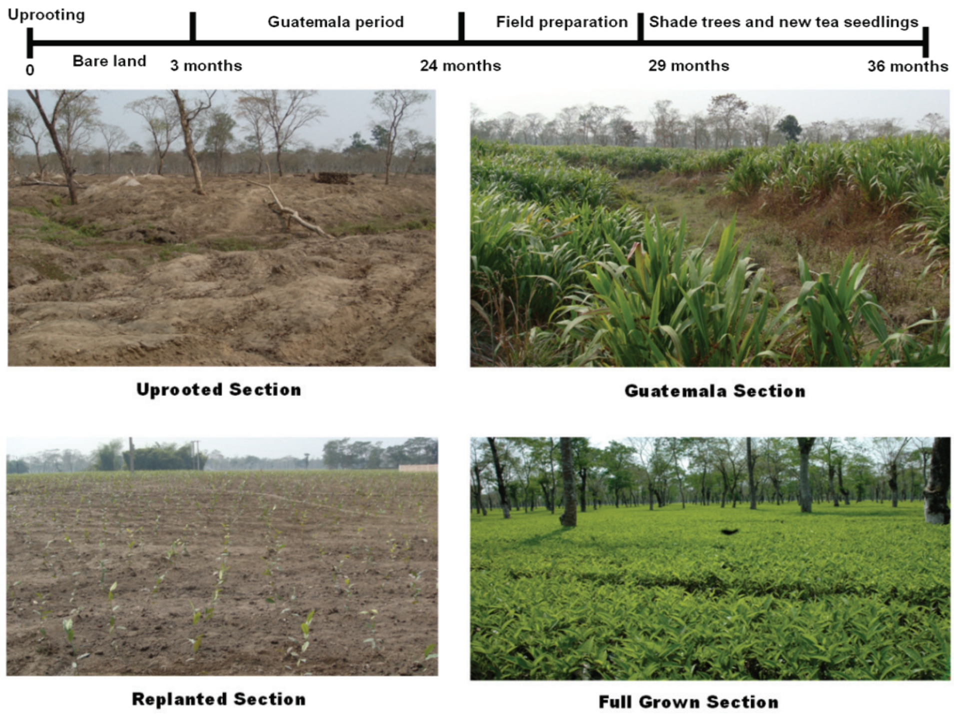


Figure 3.1: Graph showing the different stages of replantation in a section of an estate

3.3 Materials and methods

3.3.1 Study area

In Northeast India, two estates were selected for this study. Both are located in the Dooars region, at the foothills of the eastern Himalayas (Figure 3.2). The region has an altitude of 1750 m in the north and 90 m in the south. Half the area is hilly, whereas the other half is made up of plains. It has hot summers and monsoon rains whereas winters are cold and foggy. Dooars has an annual tea production of 142 million kg with an average annual yield of 1950 kg ha^{-1} in 2007 (Tea Statistics Annual Report, 2007). The first estate, labeled as DR1, has an area of 962.41 ha and is located at an altitude of 90 m above mean sea level. The second estate labeled as DR2 has an area of 432.12 ha and is located at 530 m above mean sea level. Both estates have undertaken replantation.

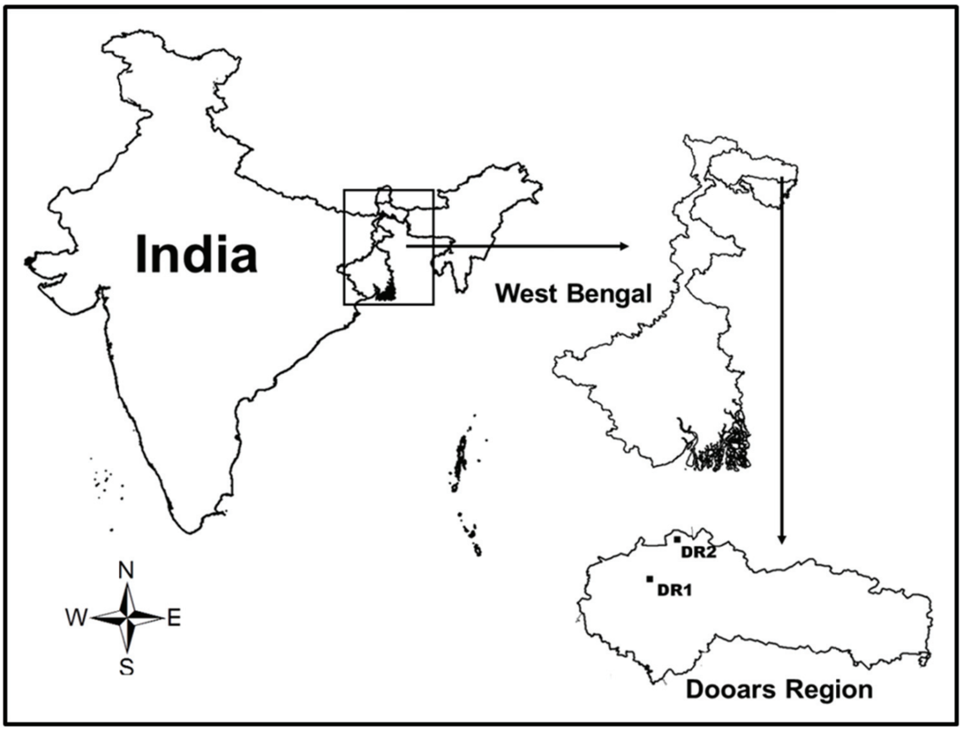


Figure 3.2: Locations of the tea estates used in this study within the tea growing regions of North East India.

3.3.2 Data acquisition

A LISS III image acquired on 9th December 2005 was used for estate DR1 and DR2 (Young and Mature Guatemala respectively). One CARTOSAT – 1 image acquired on 26 December 2005 was used for estate DR2 and one acquired on 18 April 2008 for estate DR1. These images were also used for DEM generation. The three images were merged and resampled to a 2.5 m resolution. LISS III image consists of 4 spectral bands: green (0.52µm-0.59µm), red (0.62µm- 0.68µm), near infra-red (0.77µm-0.86µm) and middle infra-red (1.55µm- 1.70µm). Its revisit time is 24 days with a 141 km swath and a spatial resolution of 23.5 meter. The stereoscopic images of CARTOSAT – 1 were generated by capturing the same area at 5° tilt in AFT band and 26° tilt in FORE band. The panchromatic CARTOSAT – 1 image covers 30 km swath at 2.5 m ground resolution.

A high resolution Google Earth image acquired on 26 October 2006 was used for DR2 (replanting stage) and one acquired on 17 December 2006 for DR1 (uprooting stage). Both images were georeferenced using UTM projection and were re-sampled to a 1 m resolution. A geometric correction was done with more than 30 ground control points, collected from Google Earth and accurately located in the image.

Tea yield data are available at the estate level and for individual sections. Estate level yield data from 1998 until 2007 are available for both estates. Sectional yield data for DR2 are available between 2002 and 2008 and for DR1 and between 1998 and 2007. Climatic data (rainfall, temperature, sunshine hours) are collected routinely at the estate level.

3.4 Methods

Each estate is divided into different sections, typically of a size between 10 and 15 ha. Sections contain tea plants of different varieties, of a different age, and are managed on an individual basis. In DR1 and DR2, the replantation stages were monitored from the time of uprooting until replanting using multi temporal datasets. From DR1, an Uprooted (Up) section with an area of 13.07 ha was selected, whereas from DR2, a Young Guatemala (YG) section (11.66 ha), a Mature Guatemala (MG) section (9.61 ha) and a Replanted (Rp) section (9.61 ha) were selected. The slope, flow accumulation, compound topographic index, and correlation maps were also generated for each section. The subsets of the sections were taken from the perpendicular vegetation indices (PVI) images generated from Google Earth and fused images and wavelets were applied to observe the patterns. The generated slope, flow accumulation, compound topographic index (CTI), and correlation maps were then compared to understand the nature of the patterns observed within the sections.

In this study, monitoring was done using the sections from two different estates at different time periods. Different images at different spatial resolutions were used for different sections to observe their patterns using wavelets.

3.4.1 Perpendicular Vegetation Index (PVI)

Google Earth images provide spectral information but could not provide information on radiance since the reflectance in any measureable unit is restricted due to image compression, colour balance and stretch for visualizations. Therefore, we used the perpendicular vegetation index (PVI) to measure the changes from the bare soil reflectances caused by vegetation. It gives an indication of vegetative cover independent of the effects of the soil. (Richardson and Wiegand, 1977). In calculating PVI of a surface with vegetation, the reflectance in the red and NIR ranges are measured and plotted. The PVI is the perpendicular distance of the measured point from the soil line, defined as:

$$PVI = \frac{NIR - (a \times R - b)}{\sqrt{1 + a^2}} \qquad [3.1]$$

where NIR = Near Infrared band (band giving highest reflection to vegetation)

R = Red (band giving lowest reflection to soil)
a = slope of the soil line
b = gradient of the soil line.

Based on the concept of PVI, soil index was drawn among the set of spectral bands which shows highest variation between vegetation and soil. To calculate PVI, a linear regression line was drawn between the highest dry and wet vegetation points in the feature space. All other points were shifted towards this regression slope line, by calculating the euclidean distance between the points and the perpendicular intercept to the regression line. Based on this the soil index was designed to enhance the soil brightness called the Perpendicular Soil Index (PSI) which was calculated for the Up section at 1 m resolution and decimated to level 6 to give a coarse resolution of 64 m on the ground.

3.4.2 Generation of Digital Elevation Model (DEM)

A DEM was generated using CARTOSAT – 1 stereo data. After a radiometrical correction using the rational polynomial coefficients (RPC) model and georeferencing using the RPC files and UTM projection, a polynomial adjustment model is computed for each image. Accuracy of the DEM was assessed using ground control points from the Google Earth images. Tie points were generated using automated image matching techniques and their ground coordinates were calculated during the triangulation. The location accuracy of the points and the accuracy of the triangulation were assessed. The points with a higher error were eliminated and new control points with more accuracy were used. A DEM was generated for both estates followed by generation of a slope map, a flow accumulation map, a compound topographic index (CTI) map and correlation maps were generated.

The CTI is a steady state wetness index and is a function of both the slope and the upstream contributing area per unit width orthogonal to the flow direction (Yang et al., 2005). It is based on the equation:

$$CTI = \ln\left(\frac{As}{\tan\beta}\right) \qquad [3.2]$$

where '*As*' is the specific catchment area [area (m^2) per unit width orthogonal to the flow direction], and β is the slope angle expressed in radians (Gessler et al., 1995). The CTI is correlated with several soil attributes such as horizon depth, silt percentage, organic matter content and phosphorus (Moore et al., 1993). A correlation map was generated to find the correlation between slope, flow accumulation and CTI. The mean and standard deviation of 3 × 3 pixel sliding window was calculated on the two.

3.4.3 Wavelet Analysis

Wavelets convert data into different frequency components, and then study each component with a resolution matched to its scale. Two functions play a key role in wavelet analysis, the scaling function *'ϕ'* and the wavelet *'ψ'* (Boggess and Narcowich, 2001). Mallat (1989) and Meyer (1985 – 86) formulated the concept of multiresolution analysis.

Let V_j be the approximation spaces, for j = ….., -2, -1, 0, 1, 2,….. be a sequence of subspaces of functions in $L^2(R)$. The collection of spaces $\{V_j, j \in Z\}$ is called a multiresolution analysis with scaling function ϕ if the following conditions hold:

a. (nested) $V_j \subset V_{j+1}$
b. (density) $\overline{\cup V_j} = L^2(R)$
c. (separation) $\cap V_j = \{0\}$
d. (scaling) The function $f(x)$ belongs to V_j if and only if the function $f(2^{-j}x)$ belongs to V_0.

(orthonormal basis) The function ϕ belongs to V_0 and the set $\{\phi(x-k), k \in Z\}$ is an orthonormal basis (using the L^2 inner product) for V_0.

Wavelet functions are generated by the dilations and translation of a mother function $\psi_{j,m,n}(x, y)$.

$$\psi_{j,m,n}(x, y) = 2^{-j/2}\psi\left(2^{-j}x - m, 2^{-j}y - n\right) \tag{3.3a}$$

A scaling function $\phi_{j,m,n}(x, y)$, the father wavelet function, is responsible for improving the coverage of wavelet spectrum and is given by

$$\phi_{j,m,n}(x, y) = 2^{-j/2}\phi\left(2^{-j}x - m, 2^{-j}y - n\right) \tag{3.3b}$$

where the dilation parameter *j,* a scale factor as a power of 2, determines the width of wavelets, *m* is a translation parameter and *n* is the shift index responsible for the location of wavelet function along the x and y-axis.

In wavelets, the approximation crystal also contains the low-frequency content of the signal and the highest energy distribution; hence it's the most important part of the signal which gives identity to it. The high-frequency content of the input signal is delineated in the detail crystals which gives the quality to the signals. High frequency means the signal which varies at a very short range giving fine scale information. It seeks to analyze the data between frequency mean and the highest frequency that one can detect in the data. The process iterate only on the approximation crystal i.e., each level is calculated by passing the previous approximation coefficients through a high and low pass filters that decomposes the input signal into next four lower scale. The approximation window then becomes narrower with every dilation step and high frequency component occupying wide range of decimated frequency. After each decimation the input signals are represented as four separable two-dimensional wavelet crystals, one approximation and three detailed functions (in horizontal, diagonal and vertical direction). In this study we consider three types of wavelet functions: Haar, Daubechies and Symlets wavelets.

Haar Wavelets

The Haar wavelet is a sequence of rescaled square-shaped functions which together form a wavelet family or basis. The Haar sequence is the first known wavelet basis and has been extensively used in the theory of wavelets.

The Haar scaling function (Burrus et al., 1998) is defined as

$$\phi(x) = \begin{cases} 1, for 0 < x < 1 \\ 0, elsewhere. \end{cases} \qquad [3.4a]$$

The Haar mother wavelet is therefore given by

$$\psi(t) = \begin{Bmatrix} 1, for 0 < t < 1/2 \\ -1, for 1/2 < t < 1 \\ 0, otherwise \end{Bmatrix} \qquad [3.4b]$$

Haar scaling function [4a] generates the subspaces V_j consisting of the space of piecewise constant functions of finite support whose discontinuities are contained in the set of integer multiples of 2^{-j}. This verifies that $\{V_j, j \ge 0\}$ together with Haar scaling function ϕ satisfies the definition of multiresolution analysis. So Haar wavelet is the function of

$$\psi(x) = \phi(2x) - \phi(2x-1) \qquad [3.4c]$$

Daubechies Wavelets

Daubechies wavelets (1988) form a family of orthogonal wavelets characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis. The scaling function equals (Boggess and Narcowich, 2001):

$$\phi(x) = \sum_k p_k \phi(2x-k) \text{ where } p_k \text{ are the coefficients.} \qquad [3.5a]$$

Once the p_k have been identified and ϕ has been constructed then the associated wavelet is given by:

$$\psi(x) = \sum_{k \in Z} (-1)^k p_{1-k} \phi(2x-k) \qquad [3.5b]$$

The Daubechies scaling and wavelet functions are continuous but not differentiable. Daubechies also showed that for every *N* there will be *2N* non-zero, real scaling coefficients $p_0, ..., p_{2N-1}$, resulting in a scaling function and wavelet that are supported on the interval $0 \le t \le 2N-1$. The corresponding degree *2N – 1* polynomial

$P_N(z) = \frac{1}{2} \sum_{k=0}^{2N-1} p_k z^k$ has the factorization:

$$P_N(z) = (z+1)^N \overline{P_N}(z) \qquad [3.5c]$$

where P_N is $N-1$ and $P_N(-1) \ne 0$. Therefore, the associated wavelets have precisely *N* vanishing moments. The scaling function ϕ_N and wavelet ψ_N generated by P_N have Fourier transforms as the coefficients of P_N are real, $P_N(-z) = P_N(-\bar{z})$, leading to the equations:

$$\overline{\phi_N}(\xi) = \frac{1}{\sqrt{2}} \prod_{j=1}^{\infty} P_N\left(e^{-i\xi/2^j}\right) \qquad [3.5d]$$

$$\overline{\psi}_N^{(k)}(0) = (-e^{-i\xi/2} P_N)\overline{\phi_N}(\xi/2) \qquad [3.5e]$$

Symlets Wavelets

Symlet wavelets are a variation of Daubechies wavelets proposed by Daubechies in 1992. An orthogonal, compactly supported wavelet of finite length with linear phase filters is impossible to construct. The purpose of the variation to the Daubechies wavelets was to create a wavelet of the same size and same number of vanishing moments as the Daubechies wavelet, but with near linear phase filters. Because of its near symmetry this wavelet was called the Symlet wavelet.

3.5 Results

3.5.1 Up Section

The section was undulating with an elevation of 87 – 90 m and a slope of 20%. Patterns extracted from the uprooted section were correlated with slope, compound topographical index (CTI), and the flow accumulation (Figure 3.3a). From the digital elevation model, central and northern part of the section was found to be at a higher relief as compared to the other part of the section. Flow accumulation showed the natural drainage pattern of the section based on flow directions. Compound topographic index (CTI) was used to study the effects of topography (Moore et al, 1993). Perpendicular Soil Index (PSI) indicates the presence of healthy vegetation in the western side of the section. The patterns follow the drainage lines. Correlation with DEM and CTI showed that DEM was more correlated than CTI.

A wavelet was applied to the Perpendicular soil index (PSI). PSI calculated at 1 m resolution was decimated to level 6 to give a coarse resolution of 64 m on the ground (Table 3.1). Patterns could not be extracted from level 5 and 6 due to coarser resolution and loss of information. Correlations between all six levels of the Daubechies4 (db4) wavelet and the PSI image decreased from 0.71 and 0.62 at level 5 and 6, respectively. By going down the levels, we observed that high frequency details were reduced and the correlation of the input image goes down.

Between level 4 and 5, correlation reduced from 0.87 to 0.76, showing loss of information beyond level 4 and 5. This may be due to the extraction of patterns by removing the noise in the form of high frequency details. At the upper levels, crystals of each level were found to be highly correlated which apparently decreases as we go down the level. The sym8 gave almost similar results at the first four levels (Table 3.2). The differences increase when going down the levels as shown by the flattening and more pronounced shape of the wavelets. Flat and linear nature of the section allowed db4 and sym8 to extract patterns (Figure 3.4a). The sym8 wavelet at level 4 had a comparatively large range for the wavelet coefficients. The extracted pattern at this level was analyzed by topographical and hydrological characteristics of the section. Elevation within the section ranges between 87 and 90 m. The soil index ranges between -6.9 to 14 with a mean of 7.02. After generalization by the Sym8 wavelet the mean ranged at level 4 between -2.7 and 10.28, with standard deviation of 1.5.

	a1 db4	*a2 db4*	*a3 db4*	*a4 db4*	*a5 db4*	*a6 db4*	*PSI*
a1 db4							
a2 db4	0.97						
a3 db4	0.92	0.94					
a4 db4	0.87	0.86	0.91				
a5 db4	0.76	0.8	0.85	0.90			
a6 db4	0.65	0.69	0.73	0.77	0.87		
PSI	0.98	0.96	0.9	0.83	0.71	0.62	1

Table 3.1: Correlation matrix between different levels of approximation with the input Perpendicular Soil Index of the uprooted section

	PSI	*A4haar*	*A4db4*	*A4sym8*
PSI				
A4haar	0.75			
A4db4	0.87	0.9		
A4sym8	0.87	0.92	0.99	

Table 3.2: Correlation matrix for different wavelets at level 3 with the input Perpendicular Soil Index of the uprooted section

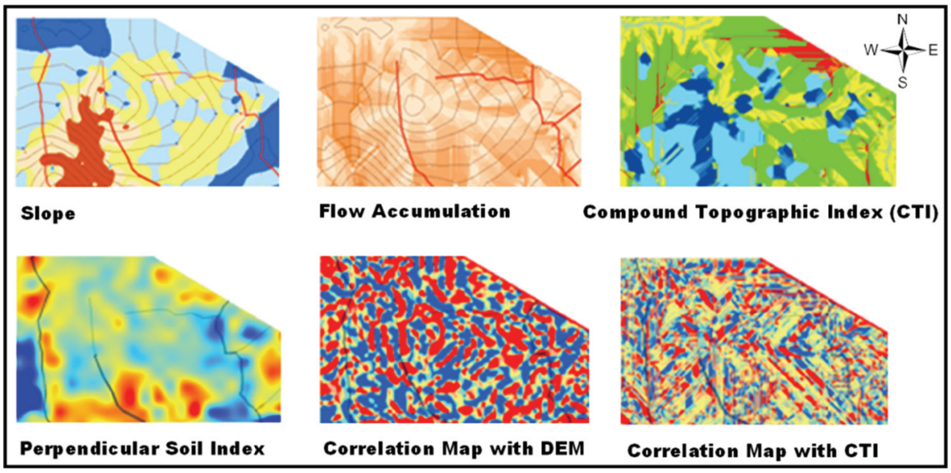


Figure 3.3a: Patterns extracted from Sym8 wavelet and correlated with different maps

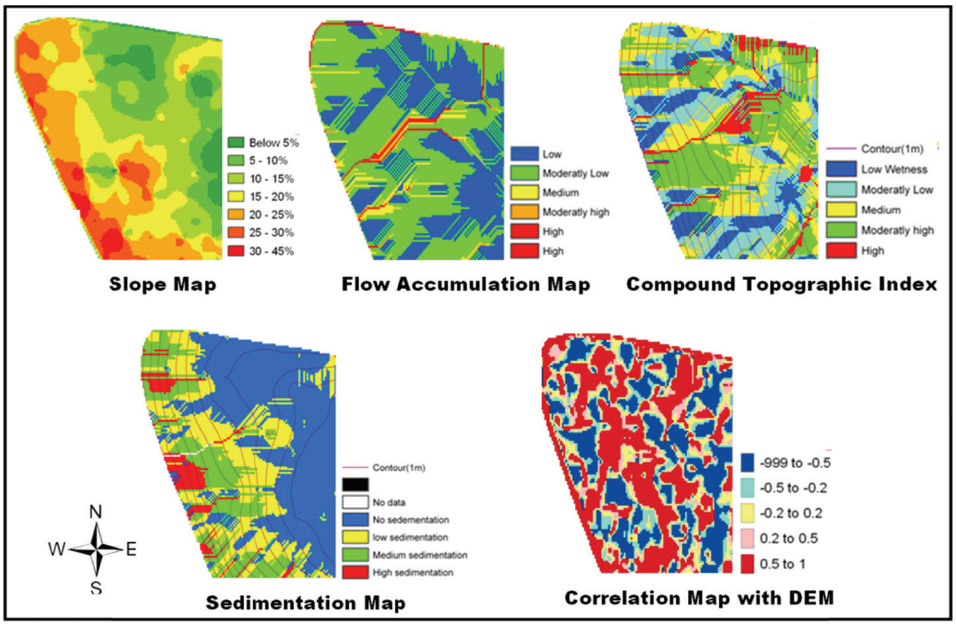
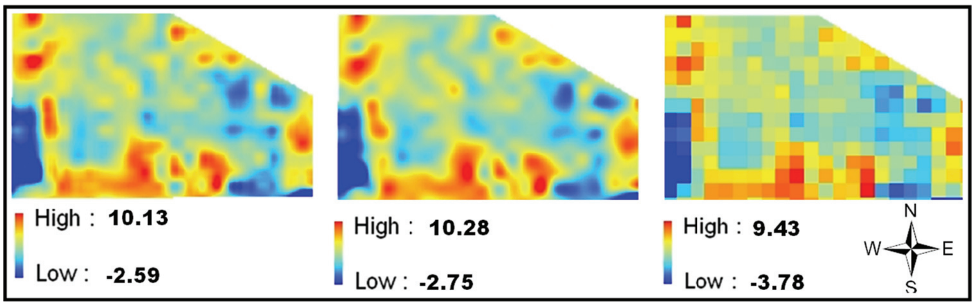


Figure 3.3b: Patterns extracted using sym8 wavelet and correlated with different maps



a. Daubechies (db4) b. Symlet (sym8) c. Haar

Figure 3.4a: Approximation by db4, sym8 and Haar wavelets in an uprooted section (a, b, and c)

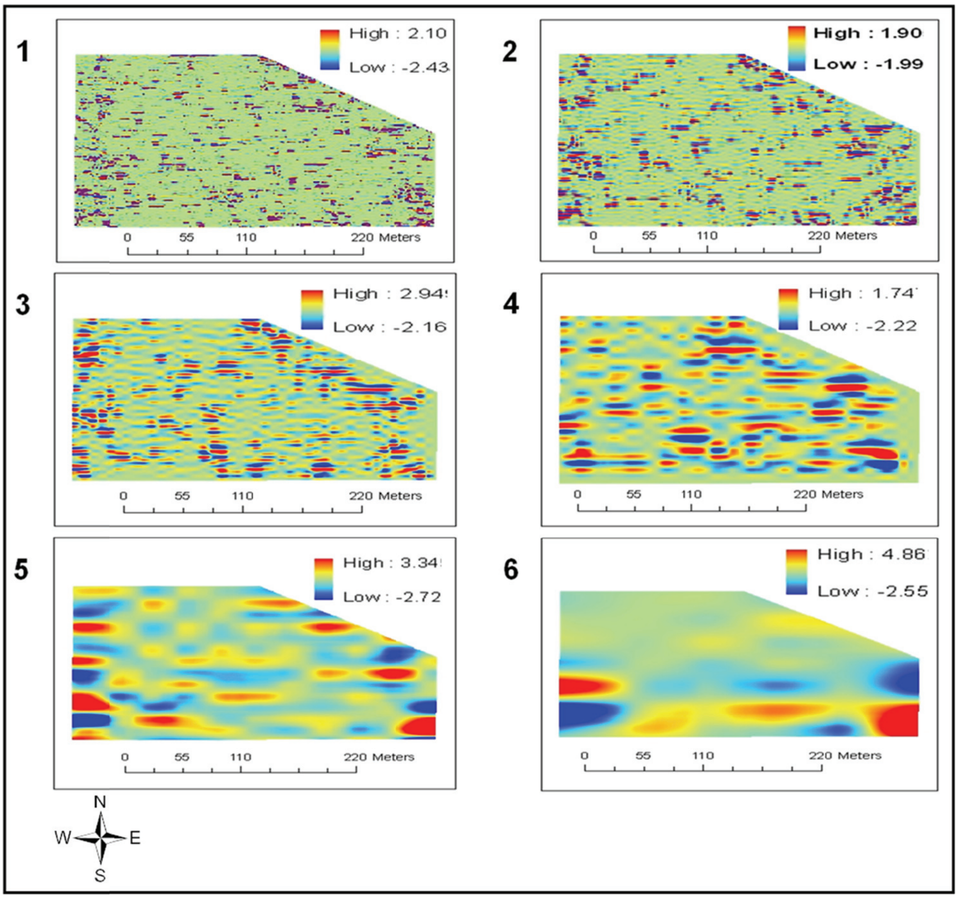


Figure 3.4b: Horizontal details at six levels of decimation by db4 wavelet

Fine frequency wavelet coefficients captured detailed information in the horizontal, vertical and diagonal direction from level 1 to 6. Details were extracted at different scales in horizontal directions using the db4 wavelets. Noise could be observed at level 1 whereas levels 5 and 6 provide generalized information about the changes in horizontal direction for which it was not used for further analysis. Therefore, patterns were extracted using level 3 and 4 (Figure 3.4b). Wavelets show variation at six different spatial scales whereas autocorrelation gives constant values, extent and magnitude of variation. Level 2, 3 and 4 shows spatial correlation wavelet coefficients up to 8, 15 and 35 pixels corresponding to 4 m, 8 m and 16 m on ground respectively. Fine variation could be observed at level 2 with respect to distance while the extent of spatial correlation was less.

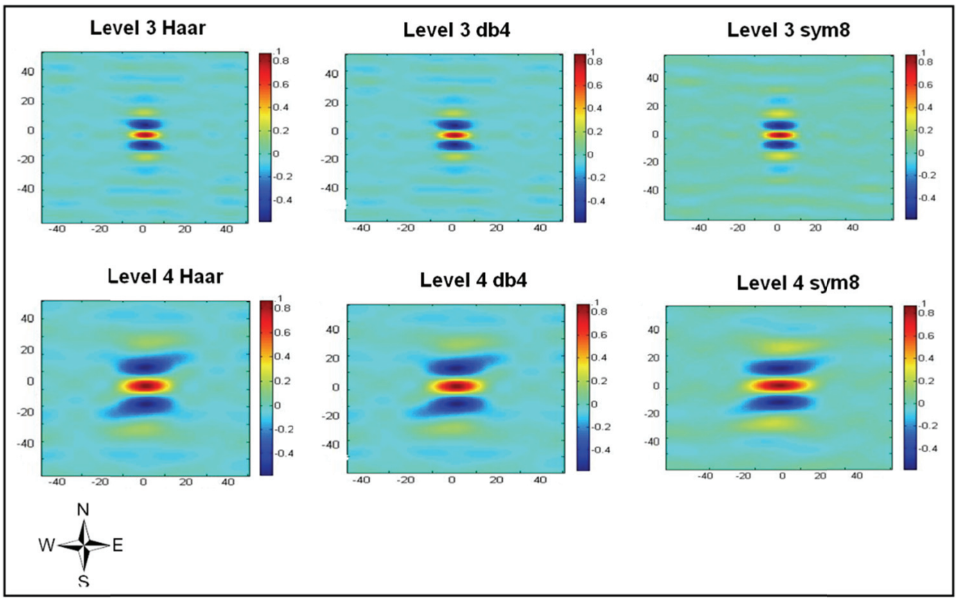


Figure 3.4c: Horizontal anisotropy by Haar, db4 and Sym8 in level3 and 4 of decimation

Therefore, for all three wavelet functions, anisotropic autocorrelation was derived at levels 3 and 4. In Figure 3.4c, repetivity is observed at level 3 and strong horizontal structure was absent. This corresponds to some weak repetivity of features at 8 m on the ground. The autocorrelation surface for db4 and sym8 wavelets shows a higher spatial correlation than the Haar wavelets. The correlation of sym8 and Haar using the input

PVI image was higher than db4 (Table 3.3). Higher repetivity was observed in the horizontal direction of sym8 as compared to db4 and Haar but the autocorrelation value was low (Figure 3.4c). Horizontal features of level 3 of sym8 were better represented in this section compared to level 3 of db4 and Haar.

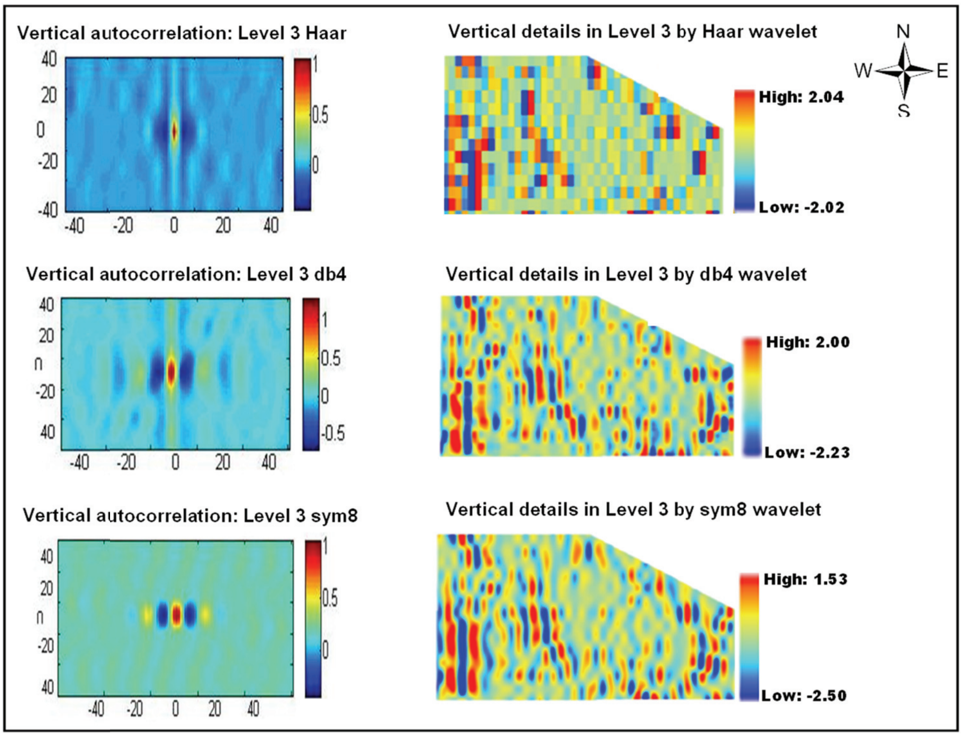


Figure 3.4d: Vertical details at level-3 by Haar, db4 and sym8

The horizontal features extracted by the sym8 wavelet at level 3 depict the track lines in this section. Further information was extracted and analyzed using vertical details (Figure 3.4d). The sym8 wavelet at level 3 gives better results compared to db4 and Haar in the vertical direction with a repetivity of 30 m distance indicating the presence of tracks drawn by the farmers. The vertical line on the south west of the section shows changes due to presence of vegetation. Diagonal details extracted from sym8 level 3 were better than db4 and Haar and it best represents diagonal features on the field which repeats at 15 m distance (Figure 3.4e). These patterns were not observed in the input image indicating that features exist diagonally in the section. Due to the smoothness and symmetric nature of the section, sym8 gives the best representation of the details in this section.

	PVI	*h3db4*	*h3haar*	*h3sym*	*h4db4*	*h4haar*	*h4sym*
PVI							
h3db4	0.01						
h3haar	0.19	0.01					
h3sym	0.18	0.03	0.24				
h4db4	0.02	0.00	0.01	0.02			
h4haar	0.22	0.00	0	0.17	-0.05		
h4sym	0.22	0.04	0.29	-0.03	0.08	0.39	

Table 3.3: Correlation between different wavelets at level 3 and level 4

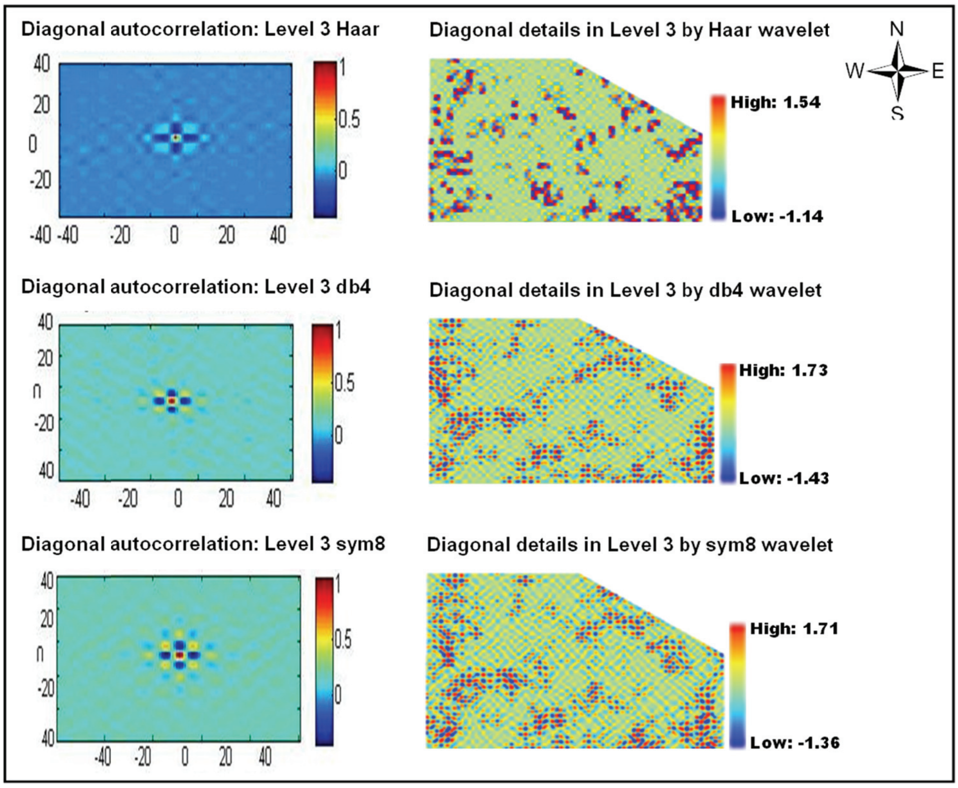


Figure 3.4e: Diagonal details at level-3 by Haar, db4 and sym8 wavelets with their respective anisotropic maps

3.5.2 YG Section

The elevation of the section ranged between 412 to 424 m above mean sea level with a slope of 45%. The extracted patterns were correlated with slope, flow accumulation and compound topographic index (CTI) of the section (Figure 3.3b). Eastern part of the section is at higher elevation while the northern and eastern part has the least flow accumulation. CTI showed the wetness within the section. Higher sedimentation was observed in the western part indicating greater variability in vegetation. The topographical relations observed were better. Flow accumulation was found to be correlated while slope, wetness, and sedimentation showed a weak correlation.

The PVI for this section has a mean and a standard deviation of 7.34 and 1.8, respectively. The PVI is calculated at 2.5 m resolution from LISS III – Cartosat fused image. Figure 3.5a shows a red region with indicating vegetation, and reflecting healthy soil while the blue region shows low vegetation reflecting stressed soil conditions. The PVI image was decimated upto level 6. Because loss of information increased from level 4 onwards, attention focused on levels 2 and 3, using the Haar, db4 and sym8 wavelets. It was also observed that from level 3 onwards, information loss was more having less than 90% correlation with PVI while at level 4; information further gets reduced to 40 m ground resolution. So only level 2 and 3 were considered and compared. The db4 and sym8 wavelets provided a similar approximation but the sym8 has larger range and a higher correlation with the input PVI image ranging between 0.90 – 0.95. As at level 3, the sym8 wavelet best represents the vegetation in this section, and was considered for further analysis (Figure 3.5a). It has a mean and a standard deviation of 7.3 and 1.6 respectively indicating the absence of fine features. The image could be generalized at 20 m ground information.

Fine details of the section were extracted at different levels and compared to obtain directional information. The ploughing direction was a major feature in this field. Clear horizontal lines with strong horizontal autocorrelation were observed in the image. Level 1 wavelets of Haar, db4 and sym8 gave strong horizontal autocorrelation. Level 2 of db4 gave the best information about the horizontal repetivity of the features at 10 m ground distance. Beyond level 3, no correlation was observed (Figure 3.5b). Strong features were not observed from vertical and diagonal directions but repetivity was found in the vertical direction at 45 m ground distance (Figure 3.5c). Figure 3.5d shows the features extracted by db4, level 2 for horizontal direction, level 3 for diagonal direction and level 3 sym8 for vertical direction.

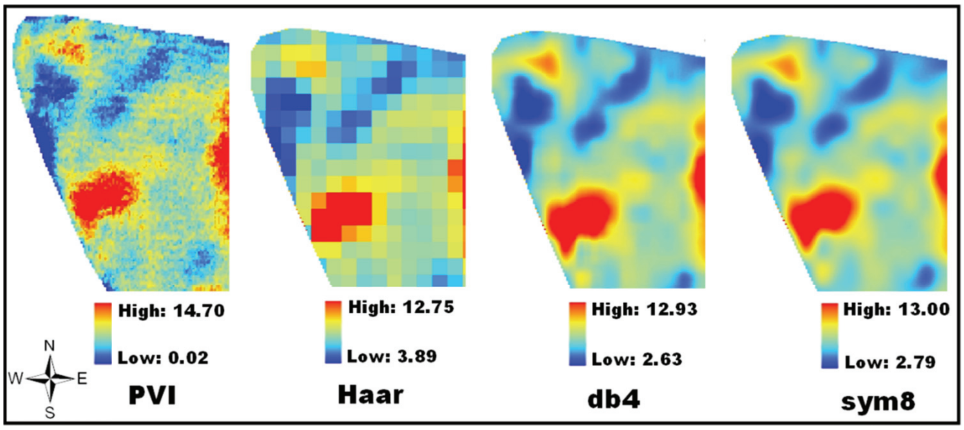


Figure 3.5a: Approximation by Haar, db4 and sym8 wavelets for a young Guatemala section

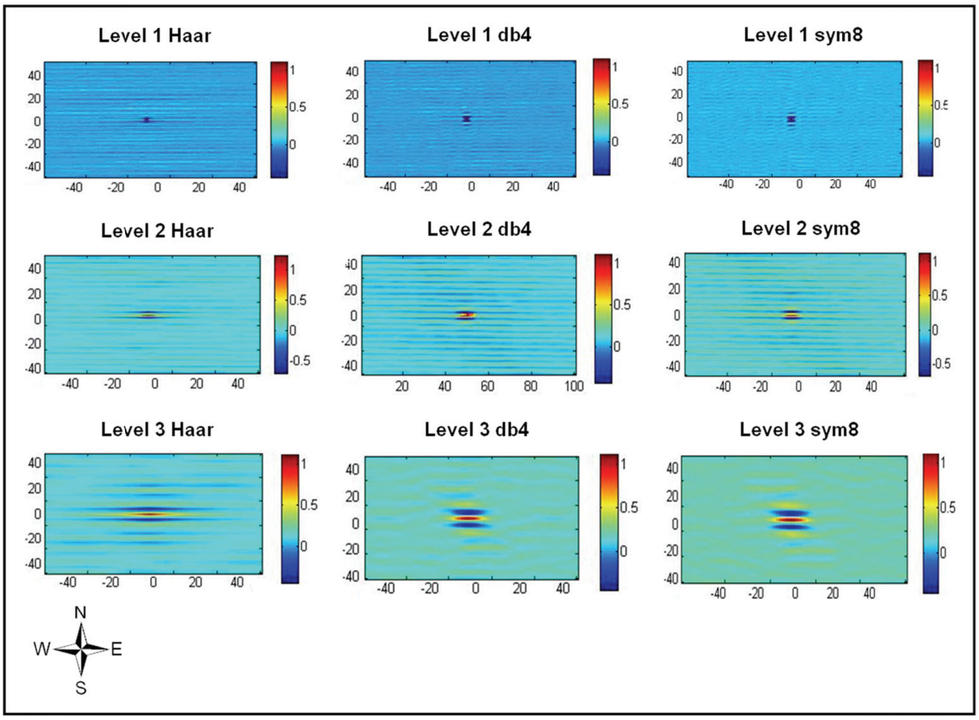


Figure 3.5b: Horizontal autocorrelation of section 18 by Haar, db4 and sym8 wavelets

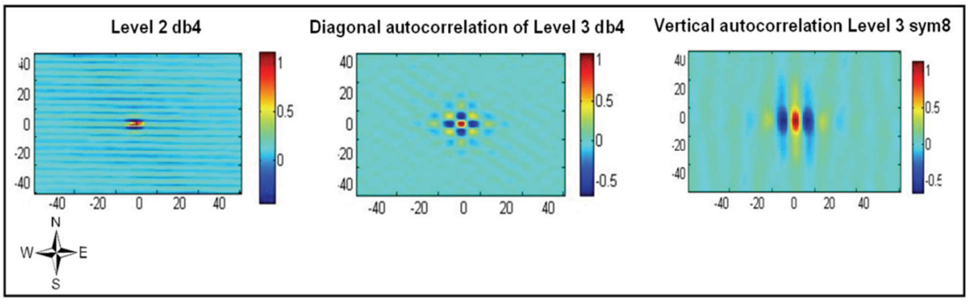


Figure 3.5c: Anisotropic autocorrelation in horizontal, vertical and diagonal direction in YG section

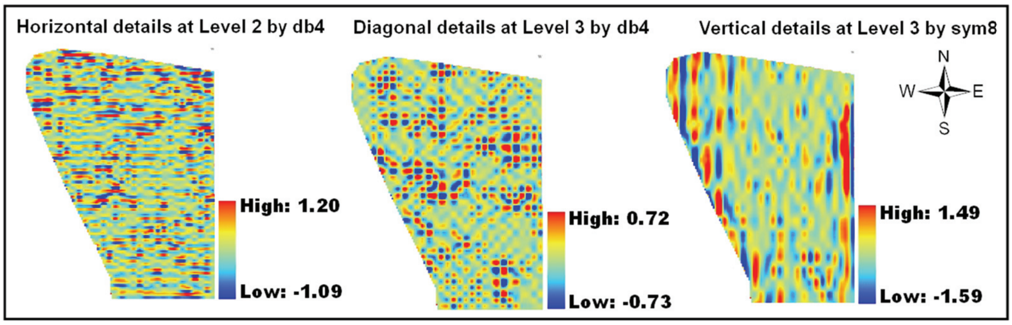


Figure 3.5d: Horizontal, Vertical and Diagonal details of YG section

3.5.3 MG Section

The section has an elevation of 345 – 356 m and a slope of 44%. The slope and the sedimentation of the section were 10 – 12% correlated with Guatemala variations (Figure 3.6e). North eastern part of the section shows low vegetation. Changes in pattern could be observed between mature Guatemala and replanted section. Topographic parameters and drainage networks contribute significantly in pattern extraction. The two main drain lines show an inverse relation to vegetation while the other field drains are positively related to the vegetation in both the stages of replantation. The Guatemala section has better vegetation cover with more flow accumulation. The north eastern part of the section showed stress which may be due to soil condition.

The PVI in this section has a mean and standard deviation of 0.79 and 0.844, respectively, thus indicating less variation within the section than the earlier sections. The PVI is calculated at 2.5 m resolution. The PVI image (Figure 3.6a) was decimated and correlated with the input image. Level 3 gave better results at 2.5 m pixel size corresponding to 40 m ground information. Using the Haar, db4 and sym8 wavelets, 3D mesh plots were drawn for level 3 (Figure 3.6a). The db4 and sym8 wavelets gave similar correlations with the PVI image. The plot reveals that db4 is more similar to the input PVI image than the other wavelets.

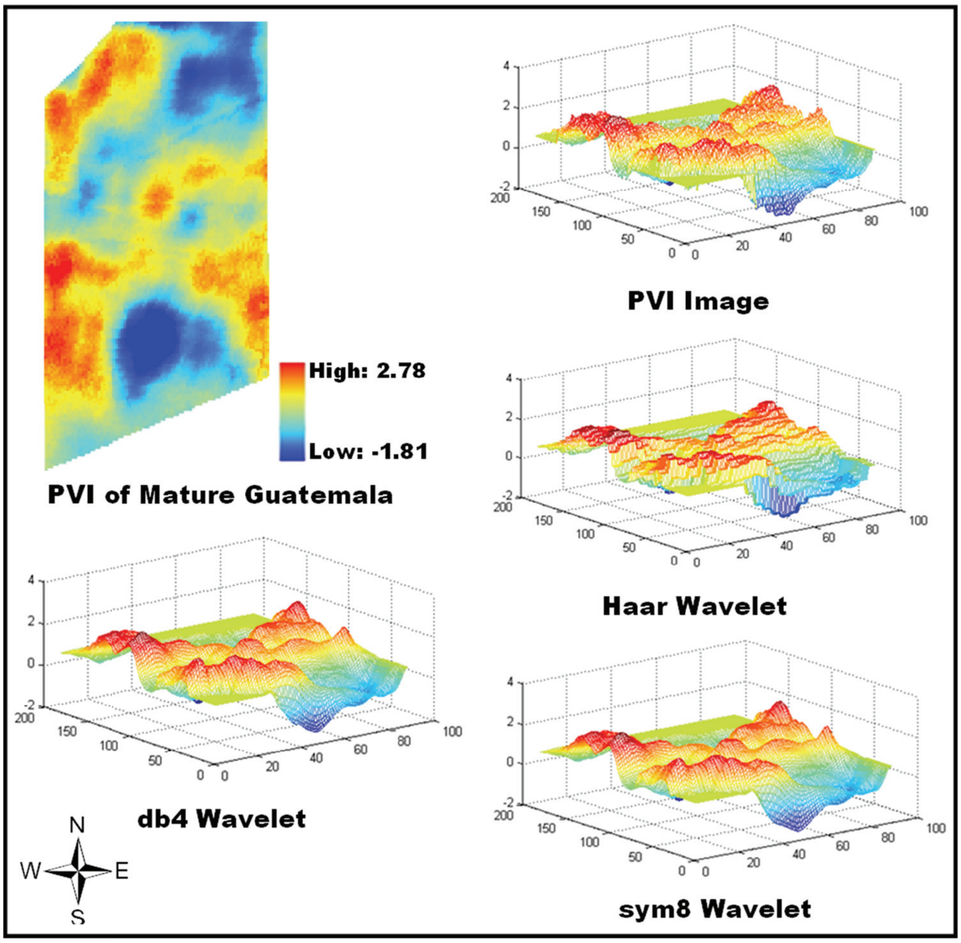


Figure 3.6a: PVI image and 3D mesh plots of a Mature Guatemala section

Fine frequency wavelet coefficients show that this section has many details. Prominent patterns could be seen in the diagonal direction which may be due to lopping. At level 2, features were observed diagonally at 10 m distance on the ground (Figure 3.6b). Level 4 has diagonal spatial correlation with repetivity of 20 pixels (corresponding to 50 m ground distance) (Figure 3.6b).

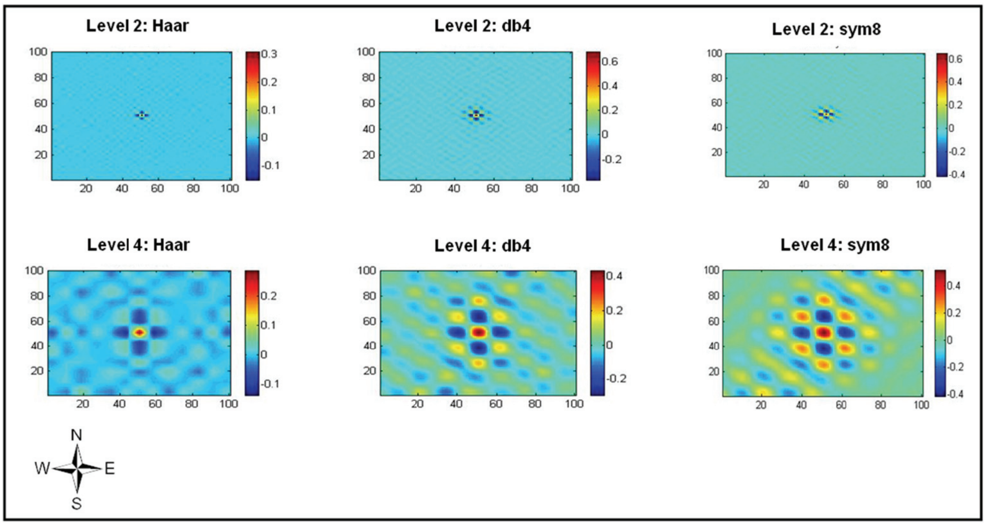


Figure 3.6b: Autocorrelation of Section under Guatemala in diagonal direction.

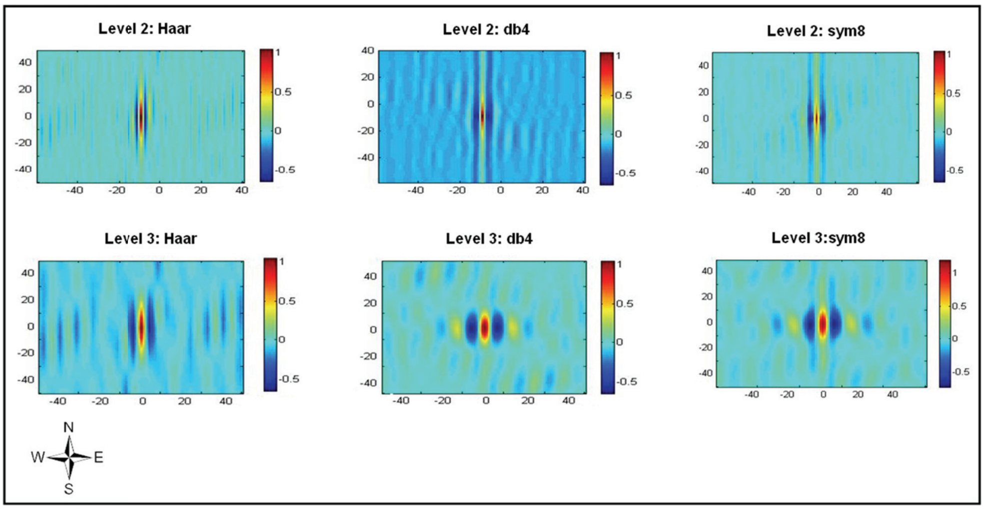


Figure 3.6c: Autocorrelation of Section under Guatemala showing vertical and horizontal details

Comparing the three wavelets, it was observed that db4 could extract pattern in diagonal and horizontal direction while sym8 could extract patterns in vertical directions (Figure 3.6c). Autocorrelation map shows some repetivity at level 2 in vertical directions at 10 m resolution at 15 m ground distance (Figure 3.6d) while weak repetivity was observed at level 3 in horizontal and vertical directions at 10 m resolution at 25 m ground distance. Fine details of the MG section could also be observed from level 4 of different wavelets in horizontal, vertical and diagonal directions.

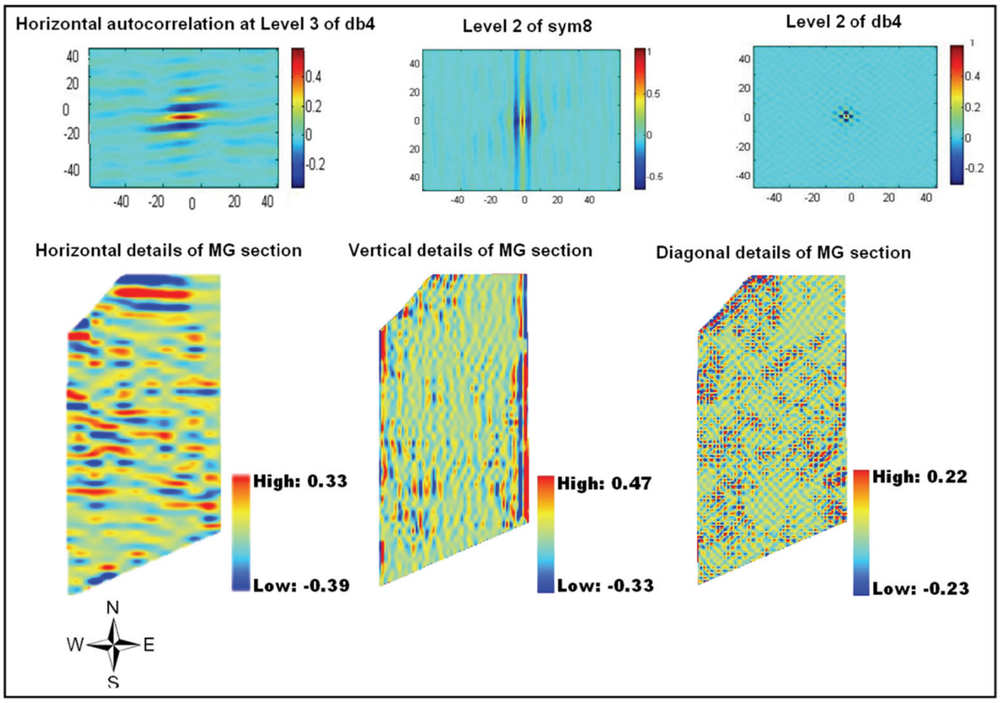


Figure 3.6d: Autocorrelation, vertical, horizontal and diagonal details of MG section

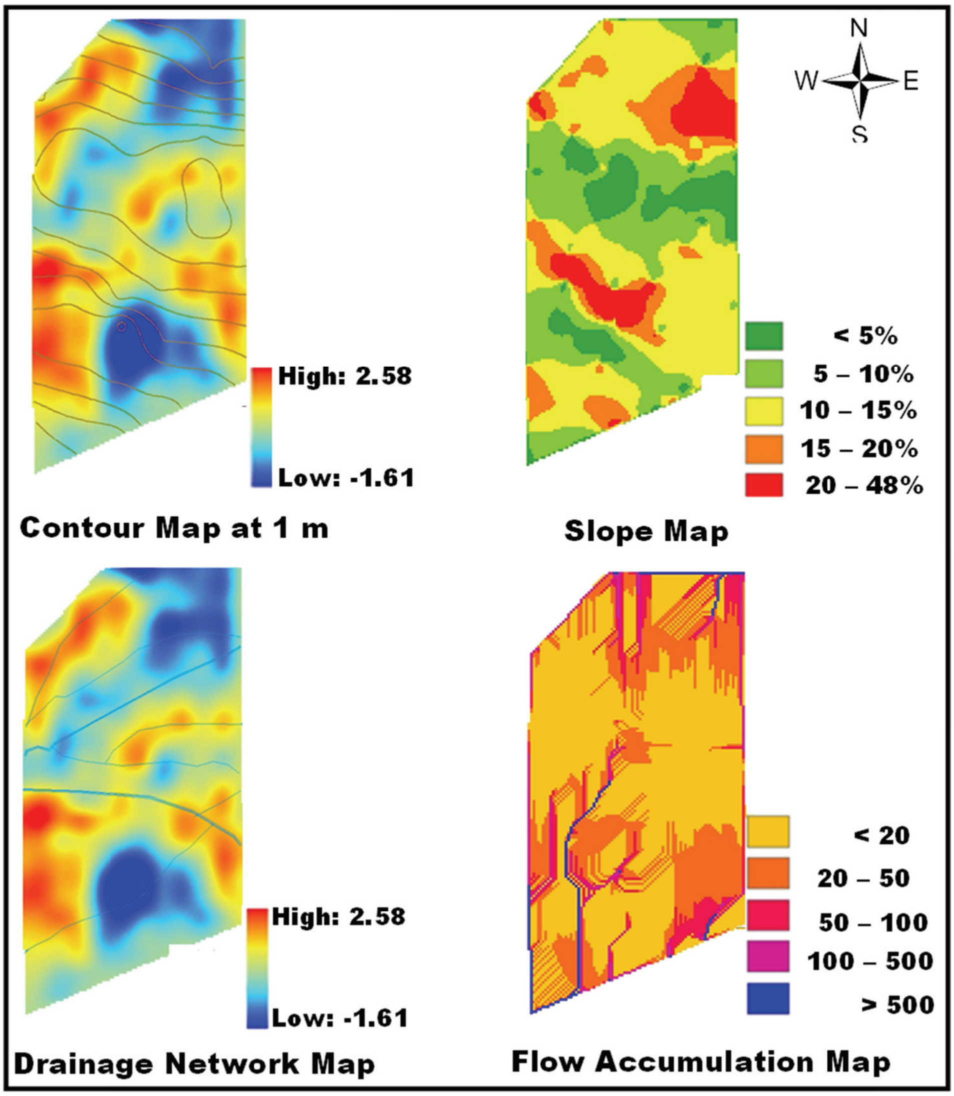


Figure 3.6e: Section showing the contour lines, slope map, drainage network map and flow accumulation map of the Guatemala stage, ready to replant stage

3.5.4 Rp Section

The sectional details are same with the MG section as it was the same MG section but after replantation. The PVI for this section, replanted with 14600 tea plants, has a mean and standard deviation of - 9.38 and 1.86 respectively. The PVI was calculated at 1 m resolution. The section has a low vegetation cover as the young tea plants planted in rows shows high variability in PVI. All the three wavelets (Haar, Daubechies and

Symlets) were decimated at different levels. Level 4 has a correlation of 0.89, whereas at level 5 the correlation equals 0.73, thus showing a loss of information at level 5. At each level, the db4 and sym8 wavelets are equally correlated with the input PVI image. The sym8 wavelet gives a better performance than the db4 at level 3 due to its symmetric shape. Similar mesh plots of sym8 and db4 were obtained (Figure 3.7a). Therefore, the db4 wavelet was applied at 16 m generalization of the section. The mean of db4 was same with the input PVI image but standard deviation varied from 1.86 to 1.5.

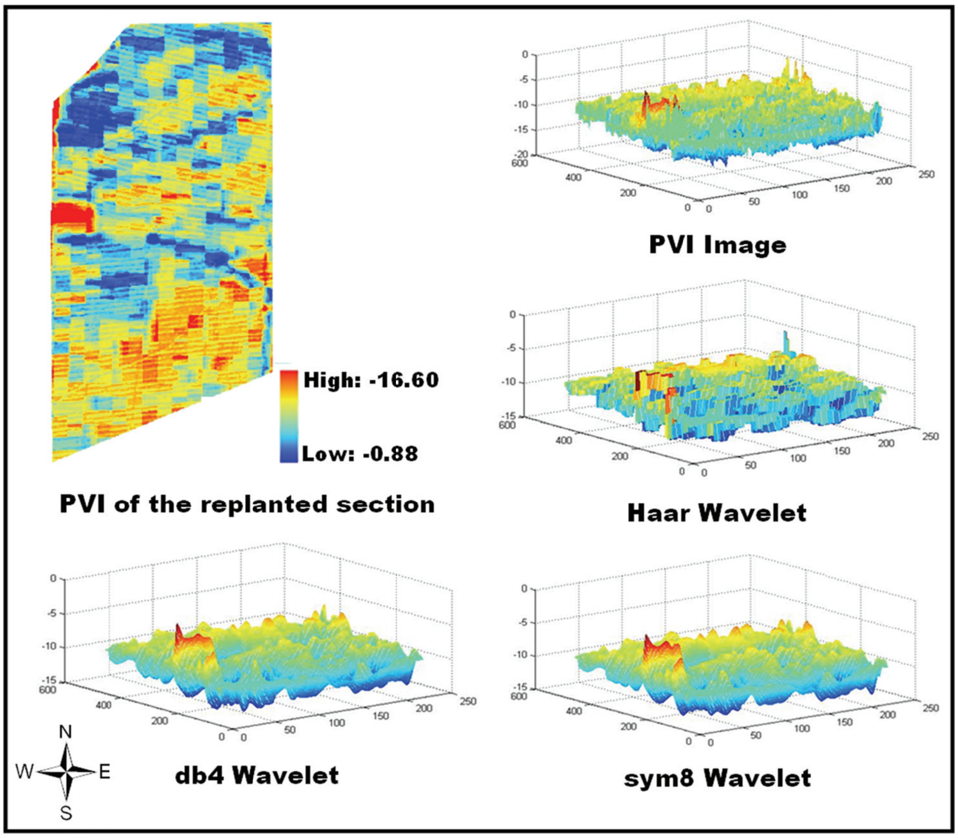


Figure 3.7a: PVI image and 3D mesh plots of a replanted section

Fine frequency wavelet coefficients when analyzed gave significant information in the detailed crystals (Figure 3.7b). From anisotropic autocorrelation, prominent horizontal features could be extracted. Level 2 of db4 and sym8 gave equally good results (Figure 3.7c). Strong repetivity could be observed in horizontal crystals at 5 m ground distance, caused by the ploughing lines to prepare for transplanting seedlings.

Table 3.5 and Table 3.6 show the most suitable levels at different resolutions and most suitable wavelets for different stages of replantation.

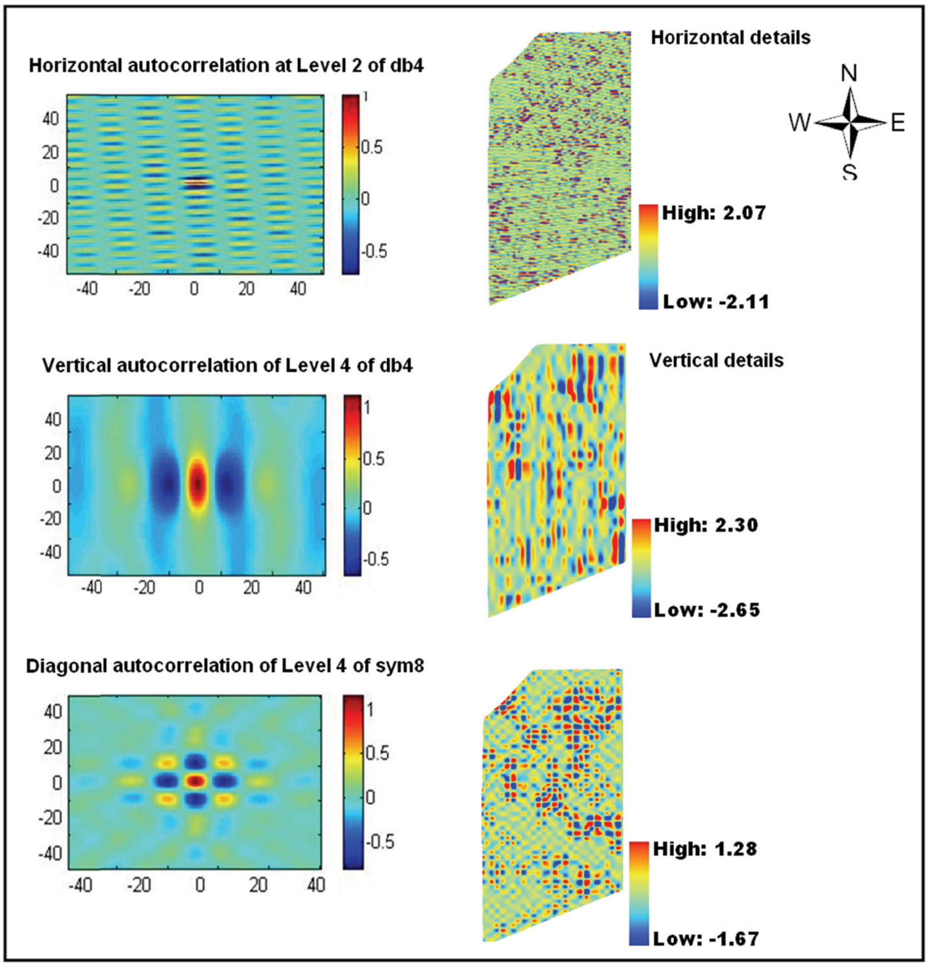


Figure 3.7b: Horizontal, vertical and diagonal details of the Rp section with their respective anisotropic autocorrelation

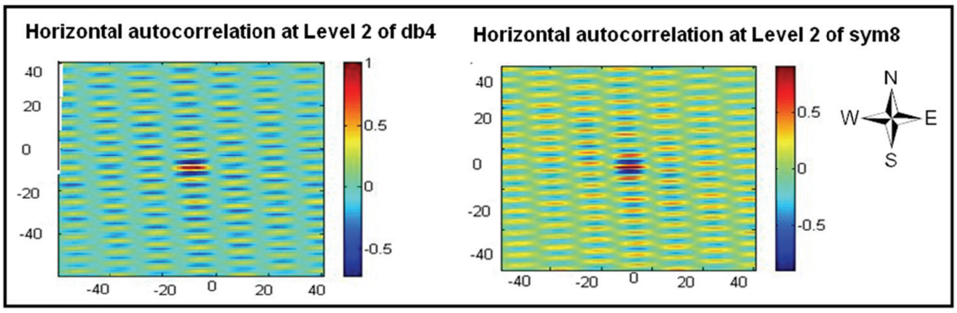


Figure 3.7c: Horizontal direction autocorrelation of Rp Section

3.5.5 Topographic Influence/Assessment

A quantitative analysis was carried out to compare the correlation between the different stages of replantation along with the topographic parameters like slope, wetness, sedimentation, and flow accumulation with their approximations (Table 3.4). Elevation has the largest correspondence with the field pattern whereas slope is inversely related to vegetation. The correlation of hydrological influence on vegetation due to elevation or slope was found to be very weak. Therefore, cross correlation was performed to explain the relationship. The MG section showed a stronger topographical relationship. Extracting pattern using wavelet analysis could provide useful information in implementing proper planting programme and also the measures that needs to be undertaken.

Stage of Replantation	*DEM*	*Slope*	*Flow accumulation*	*Sedimentation index*	*Wetness index*
Just after uprooting	11%	5%	2.50%	6%	6%
Young Guatemala	9%	6%	12%	2.70%	8%
Mature Guatemala	20%	10%	8%	12%	1%
Replanted tea seedlings	3%	1.50%	1.50%	1.20%	1.70%

Table 3.4: Pearson correlation coefficient between the approximation crystal for each stage and DEM, Slope, Wetness index and Sedimentation index of the respective section

3.6 Discussion

The study focuses on identifying patterns within the sections during the different stages of replantation and rejuvenation. Different levels of information were obtained using wavelets. Information at different scales was analyzed using the multiresolution analysis. The study showed that decimation of level 3 and 4 gave more amount of information compared to the other levels.

Wavelets were applied on different images at different resolutions. When the section was bare, generalization was observed at 16 m resolution. The wavelets therefore could reveal unobservable patterns within the sections. Repetivity features at 20 m and 30 m distance in horizontal and vertical directions respectively could be observed in the UP section indicating those features to be management lines. YG section showed strong horizontal features at 10 m distance. The MG section was generalized at 20 m resolution because the variations were smoother when the section was covered with vegetation. The last two phases of replantation (MG and the Rp section) were from the same section so temporal changes within the section could be observed. Horizontal features observed at 5 m distance at 4 m ground resolution may be due to soil pathogens, shade tree effects, soil nutrient deficiencies and management activities. Hence fine information could be extracted using wavelets.

Remote sensing images and relevant ground truth could contribute to assess, analyze, monitor and model the characteristics of tea bush growth. To achieve timely and accurate information on the status of crops, an up-to-date crop monitoring system may provide accurate information. The earlier and more reliable the information, the greater is the value (Hamar et al., 1996, Reynolds et al., 2000). Remote sensing offers an efficient and reliable means of collecting the information required, in order to map tea type and acreage and also the structure information on the health of the plantations. The spectral reflectance of a tea field always varies with respect to the phenology, stage type and crop health and these could be well monitored and measured using the multispectral sensors. It would allow the planters to detect stress associated with moisture deficiencies, insects, fungal and weed infestations and to take effective measures. Remote sensing will further help tea planters to identify areas within an estate which are experiencing difficulties, in order to apply, for instance, the correct type and amount of fertilizer, pesticide or herbicide. Using this approach, the planter will not only improve the productivity but will also reduce input costs and minimizes environmental impacts.

Among the three wavelets considered for the study, only db4 and sym8 could extract patterns whereas the Haar wavelet gave less satisfactory results. Results obtained from db4 and sym8 show some interesting differences, mainly because the sym8 wavelet is almost symmetric with sixteen coefficients and db4 is asymmetric and has only eight coefficients. The pattern observed with sym8 is mainly due to its long support size. Db4 wavelet is more suitable for crystals having fine pattern at a lower separation. Regular and smooth patterns were observed with sym8, indicating that sym8 could extract low frequency detailed information. At different approximation levels, complexities disappeared and the hydrological influence of vegetation was obtained. As pedogenesis occurs in response to water movement the spatial distribution of topographic attributes that characterize these flow paths also capture the soil variability (Moore and Hutchinson 1991).

Attributes chosen to perform the analysis were: elevation, slope, flow accumulation, sedimentation index and CTI. Correlations were calculated between the parameters and the different levels at each stage of replantation. The expected relations between soil wetness, slope and vegetation could not be obtained. The section under mature Guatemala showed significant spatial dependence. The cross correlation shows a 75 – 100 m range of spatial dependence in the mature Guatemala section indicating the presence of spatial structure in the field that can be modeled with other parameters. No pixel to pixel correlation could be observed among the vegetation patterns obtained from wavelets decimated images and different topographical and hydrological parameters. The study found that the selected pattern of the different sections was weakly correlated with the wetness index, flow accumulation, sedimentation index and slope with correlations between 0.1 and 0.2 with elevation. Also, the cross correlation was strong at 40 m. The linear relationship between the extracted pattern and topographic parameters was found to be weak.

Soil physical and chemical properties including soil moisture cause a large variation within fields. Wavelets can help to delineate site specific management zones and to decide areas which require intensive soil sampling to obtain a complete picture of the soils and vegetation in a section. Wavelet provides more affluent warehouse for spatial analysis, as it operates locally and characterizes both low and high frequency resolution information simultaneously.

The boundary pixel problem is still a major shortcoming of wavelets. In this study, the irregular shape of the field had to be handled by replacing the 'no-data' by the image mean in order to decrease the biasness caused by abrupt change in frequency. The images were then decimated to filter variation at several spatial scales. Patterns were extracted for each stages of replantation thereby providing a platform for spatial analysis.

Wavelet could delineate site specific management zones to get a better understanding about the soil and vegetation status within the section. The study showed that for a better analysis, multi-temporal data for the same section at different stages of replantation should be done along with their coordinates that could help in correlating soil properties with other spatial dataset. The patterns of soil development and its properties varies with topography which gives a relationship allowing prediction of soil attributes from landscape position at larger scale. The study further showed the most suitable levels at different resolutions and most suitable wavelets for different stages of replantation (Table 3.5 and Table 3.6).

Stage of Replantation	*Approximation*	*Horizontal*	*Vertical*	*Diagonal*
Just after uprooting	Level-4 (16m)	Level-3(8m)	Level-3(8m)	Level-3 (8m)
Young Guatemala	Level-3 (20m)	Level-2(10m)	Level-3(20m)	Level-3(20m)
Mature Guatemala	Level-3(20m)	Level-3(20m)	Level-2(10m)	Level-2 (10m)
Ready to replant tea seedlings	Level-4(16m)	Level-2(4m)	Level-4(16m)	Level-4 (16m)

Table 3.5: The levels for different stages of replantation at different resolutions

Stage of Replantation	*Approximation*	*Horizontal*	*Vertical*	*Diagonal*
Just after uprooting	Db4/ Sym8	Sym8	Sym8	Sym8
Young Guatemala	Db4/ Sym8	Db4	Sym8	Db4
Mature Guatemala	Db4/ Sym8	Db4/sym8	Sym8	Db4
Ready to replant tea seedlings	Db4/ Sym8	Db4	Db4	Db4

Table 3.6: The different wavelets that are applied during the different stages of replantation

Uprooting and replanting is inevitable and the stumbling block of gestation period must be addressed by monitoring the stages of replantation. The system should cover large areas at a time and simultaneously. The wavelets applied shows that patterns could be extracted at different levels and the different stages of replantation could be monitored. But the patterns derived from each individual section representing the stages of replantation vary from one another. The uniformity in the patterns could not be obtained because the patterns were extracted from different sections spread over two different estates. Monitoring a single section from the time of uprooting till replanting could give more consistent patterns at the different stages which would help us compare the evolving patterns from the same section during different stages of replantation at different time periods.

3.7 Conclusions

From this study it was concluded that wavelets such as Haar, db4 and sym8 could extract patterns from different stages of replantation. Daubechies (db4) and symlet (sym8) could give better results as compared to Haar. The results of Daubechies (db4) and Symlet (sym8) are similar due to their compactness at upper levels, as dilation increases; shape of wavelet comes into play and becomes more prominent at lower levels. Increase in dilation makes the shape of wavelet more prominent at lower levels. The symmetrical sym8 wavelet could reveal smooth details, whereas the db4 wavelet isolated fine details and signal discontinuities. Differences between db4 and sym8 increase when decreasing the level because the wavelet becomes more flattened and its shape becomes more pronounced.

The study further concluded that the selected patterns of the fields were weakly correlated with slope, flow accumulation and CTI. A strong quantitative linear relationship between the extracted patterns and topographic parameters could not be established. The low vegetation variability was associated with areas that have either a steep slope or a low flow accumulation. The study further showed that the influence of the various hydrological processes related to vegetation, accurate DEM, drainage information and soil properties like pH, organic carbon could be properly evaluated using cross correlation. Further attempts should also involve monitoring a single section from the time of uprooting till planting of new tea seedlings.

4

Integrating satellite images and spectroscopy to measuring green and black tea quality

This chapter explores different methods for determining and monitoring tea quality using GIS data and remotely sensed NDVI and Near Infrared (NIR) spectroscopy. NDVI was extracted from ASTER data. The study focused on monitoring green and black tea quality parameters using remote sensing, spectroscopy and statistical models and to investigate the relations existing between them.

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Abstract

This study quantifies the effects of green leaf and black tea parameters that influence tea quality in Northeast India. It was motivated by a decline in tea quality that is of concern to tea growers. The rationale of the study is to identify the different parameters that have a significant influence on liquor brightness and other variables measuring tea quality. Here, we investigate several methods for estimating tea quality based on tea quality data, near infrared spectroscopy and remotely sensed data (NDVI). Attention focused on two high yielding clones (TV1 and S3A3). NDVI was obtained from ASTER images. Statistical analysis shows that liquor brightness is affected by the levels of caffeine content, theaflavins and catechins. Relationships exist between quality parameters and remote sensing in particular for the S3A3 clone. NDVI has a positive relation with caffeine, theogallin EC, and ECG. NIR is negatively related to caffeine, theogallin, and catechins. We conclude that NDVI and Near Infrared (NIR) spectroscopy have a large potential to be used for monitoring tea quality in the future while NDVI under the conditions of maximum biomass during active growth stage of tea could monitor foliar biochemical parameters for assessing tea quality.

4.1 Introduction

Tea is made from tender shoots of *Camellia sinensis* (L.) O. Kuntze (Hara et al., 1995; Wright et al., 2002). It is a leading cash crop in world agriculture (Dutta et al., 2010). Its production has increased from 850 million kg between 2000 and 2003 to 980 million kg between 2004 and 2007. Main tea producing countries are China, India, and to a lesser degree Sri Lanka, Kenya, and Indonesia. With the increasing world population, the tea market is expected to grow further (Tea Statistics Annual Report, 2007). In India, however, stagnation in tea production and decline of tea quality are occurring, which are major problems to the tea industry (Dutta, 2006). Several factors attribute, such as old age of tea bushes, declining soil health, and increased incidence of pests and diseases, all resulting in deterioration of tea quality.

Factors like colour, appearance, flavour and mouth feel jointly make up the quality of tea. Formation of orthoquinones, bisflavanols, theaflavins and thearubigins from the catechin precursors takes place during enzymic fermentation (Roberts, 1958a,b). Caffeine plays a vital role in tea quality characteristics such as briskness and other taste properties (Dev Choudhury et al., 1991; Hilton and Ellis, 1972; Roberts, 1962; Sanderson, 1972) and it is an important parameter for quality evaluation (Khokhar and Magnusdottir, 2002; Owuor et al., 1986; Yao et al., 2006). Liquor brightness and total colour of black tea are critical quality attributes, used in the tea trade to rank and price black teas (Biswas et al., 1973; McDowell et al., 1991). During black tea processing, theaflavins (TF) and thearubigins (TR) and other polymerization products are formed (Roberts, 1962; Sanderson et al., 1972). The attractive colour of tea infusion is due to TF which is an important quality index of black tea giving a bright colour and brisk taste of the liquor (Sanderson et al., 1976). TR contributes to total colour i.e. the colour of black tea and possibly also to the liquor brightness. The major tea leaf catechins include epicatechin (EC), epicatechin gallate (ECG), catechin (+C), epigallocatechin (EGC) and epigallocatechin gallate (EGCG) (Obanda et al., 2001) contributing to the astringent taste of tea (Ding et al., 1992; Kuhr and Engelhardt, 1991). ECG and EGCG are the main residual catechins in black tea (Obanda et al., 2001).

Understanding the spectral characteristics of tea plants is important in monitoring tea plantations by remote sensing (Rajapakse et al., 2002).

They developed an empirical model between Normalized Difference Vegetation Index (NDVI) and LAI of the tea canopy and revealed that different tea clones have unique spectral characteristics depending on the tea canopy structure, size, greenness and maturity of the leaves. Understanding the spectral characteristics of tea plantations is important for monitoring the growth of plants and estimating tea-yield using remote sensing methods. The spectral characteristics of a plant canopy largely depend on the composite spectral response of leaves and soil background (Richardson and Wiegand, 1977). Reflectance signals of vegetation in the visible and near-infrared are used to detect distribution, health and productivity of plants (Buschmann and Nagel 1993; Rajapakse et al., 2002). Hall et al., 1988 used near infrared (NIR) spectroscopy to determine theaflavins and also to measure the overall tea quality. Near-infrared spectroscopy provides a rapid method for the simultaneous estimation of the moisture content, theaflavin content and overall quality of black tea. NIR spectroscopy also helps monitor tea manufacturing process thus enabling better control of withering, fermentation and drying stages. With the help of available field information, Remote Sensing (RS) and Geographical Information System (GIS) have become powerful and successful for monitoring crop growing status and estimating crop yield in agriculture. At the same time, the demand for monitoring quality has become more urgent. Therefore, attention has been given towards monitoring and estimating crop quality through remote sensing and GIS. In this way, we can relate nitrogen or other bio-chemical contents present in leaves or stems and remotely sensed parameter derived from satellite imagery. Temporal remotely sensed data can also be used to estimate crop quality by retrieving bio-chemical contents in leaves or stems. Correlations between these contents and quality indicator indicate the quality of grains or rootstalks (Pan et al., 2004).

The important chemical constituents which influence the taste and flavour in tea brew are polyphenols, caffeine, sugars, organic acids, volatile flavour compounds and amino acids. Phenolic compounds of tea, such as theaflavins and thearubigins, are important from an intrinsic quality point of view. These are responsible for the colour, flavour and brightness of tea. Caffeine is responsible for the briskness. The volatile flavour compounds of tea and their variation in composition due to geographical and other process variables are of paramount importance from a quality point of view. It is also known that the chemical and quality variations occur due to the variation in the genetic make-up of the plants, even when they are grown under similar conditions in one environment (Owuor et al., 2008).

Tea quality should maintain the ISO standards so that the expectations of the consumers are met (Scott, 2004). Methods for sampling tea should follow the ISO 1839 while liquor preparation for use in sensory tests should follow ISO 7516 standards (ISO Focus, 2004). Quality monitoring is usually done through laboratory analysis. Vegetation indices obtained by remote sensing and NIR spectroscopy have not been used in monitoring tea quality.

The present study aims to investigate methods for estimating tea quality based on tea quality data, near infrared spectroscopy and remotely sensed data (NDVI). These methods are then explored when developing an approach to monitor tea quality. The study is applied to a tea estate in the Assam region in India.

4.2 Materials and Methods

4.2.1 Study Area

The study area is located in the Jorhat district, at South Bank region of Assam in India (Figure 4.1). Jorhat, the second largest town in Assam, is situated in the South Bank at 26.75° N latitude and 94.22° E longitude. It has an average elevation of 116 m. The district spreads over an area of 2,851 m^2. Summer temperature ranges between 15 and 28°C, and winter temperature between 7 and 18°C. Summers are accompanied by the monsoon showers leading to an average annual rainfall of 2244 mm. There are approximately 135 tea estates including ‘out’ gardens that occupy an area of 2690 km^2 (Jorhat District Profile: National Informatics Centre, Government of India). This study is carried out in the Tocklai experimental tea estate of Tea Research Association. At this estate, data at the section level are available, whereas the estate owns laboratory facilities for quality analysis.

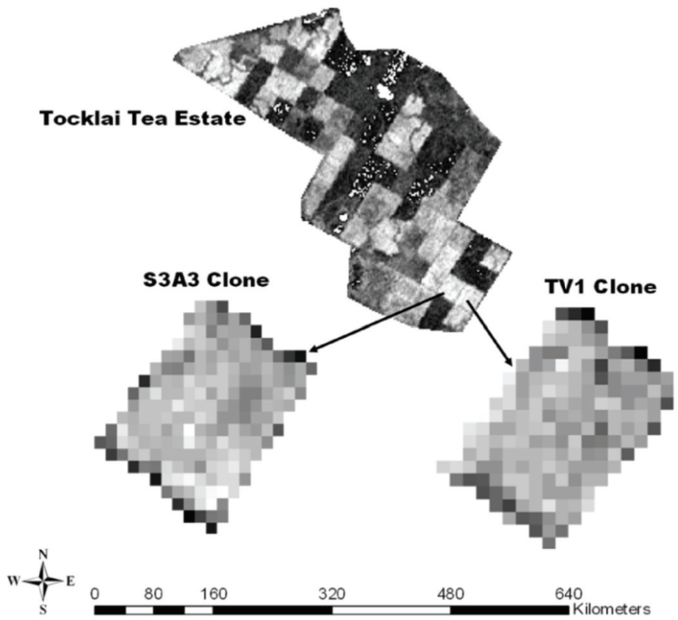

Figure 4.2: NDVI map showing the sections of clone S3A3 and TV1 of Tocklai Tea Estate, Assam, Northeast India

4.2.2 Data Used

Leaf Collection

Leaves were collected from the two clones TV1 and S3A3 that were planted in two sections. These clones were selected on the basis of good fermenting ability. Plucking was carried out at a 7 days interval, starting at the 20th April and ending at the 15th June. Both clones were plucked between 2 and 3 pm. The plucking method followed was the two leaves and a bud. In total, 1 kg of leaves was plucked by the same pluckers who maintained 65 – 75% leaf fineness.

Quality of the leaf samples was analyzed with special reference to total polyphenols content and catechins profile. Green leaf samples from the experimental plots were processed for CTC black under controlled environment of processing in Environment Controlled Manufacture

(ECM) system. Black tea was analyzed for their quality parameters both from the first and the second flush of tea leaves.

Satellite Data

For this study, an ASTER image acquired on 26th June, 2009 was used for Tocklai tea estate. The ASTER (L1B) scene covers an area of approximately 60 km by 60 km. The image was georeferenced to the WGS-84 datum and Universal Transverse Mercator (UTM) projection. The zone assigned is 46. The scenes are rotated from true north to produce a smaller dataset.

The image was geometrically corrected to compensate for the distortions and degradations caused by the errors due to variation in altitude, velocity of the sensor platform, variations in scan speed and in the sweep of the sensors field of view, earth curvature and relief displacement. The random distortion are corrected by selecting sufficient number of ground control points with correct coordinates from GPS points, which can be accurately localized in the satellite image. Using the transformation function, it determines the correct coordinates for the distorted image positions and forms an undisturbed output grid. Each cell in the new grid is assigned a grey level according to the corresponding pixel in the original image and the process is called resampling. Therefore, the image was resampled to assign the DN values to the transformed grid by using nearest neighbor (NN) interpolation algorithm, because NN closely preserves the spectral information of the original image. For this study, the first three bands in the visible and near infrared part of the spectrum (15m) were used.

4.3 Methods

4.3.1 Chemical analysis

The tea quality analysis is carried out in several steps. The Environment Controlled Manufacture (ECM) was used for the manufacture of black tea. The leaves were passed through the Crushing Tearing Curling (CTC) rollers, and dried in leaf dryers. The dried leaves are put in the fermenting trays and are placed inside the (ECM). The ECM is an integrated and controlled miniature factory for the manufacture of black tea for quality analysis. The tea is subjected to the conditions of the actual tea factory and provides samples from a single clone for early quality assessment, giving enough samples for tasting. For our quality analysis, tea was subjected to controlled conditions with a fermentation time of approximately 45 minutes. On completion of fermentation, the processed tea is taken out of ECM and transferred to the wither moisture for approximately 30 minutes for black tea preparation. Once the tea dries completely, sieves of different sizes is use to grade the tea. The graded tea is further analyzed using High Performance Liquid Chromatography (HPLC) for quality assessment.

The HPLC is based on the principle that several chemical constituents are responsible for maintaining the quality of fresh tea leaf. The most important ones are polyphenols, catechins (+C), epicatechin (EC), catechingallate (CG), gallocatechin (GC), epicatechingallate (ECG), gallocatechingallate (GCG), epigallocatechin (EGC), and epigallocatechingallate (EGCG). Theaflavins (TF) and thearubigins (TR) are the major quality attributes of CTC black tea formed from enzymatic oxidation. TF, TR, total soluble solids, total polyphenols and caffeine are estimated for assessing black tea quality. Catechins such as EGCG, ECG, EGC, +C, EC, GC, GCG, total polyphenols, caffeine, and total soluble solids are analyzed using standard chemicals (Sigma Aldrich) and methods to assess green tea quality. The total polyphenols content is determined using a spectrophotometer. An infusion is prepared from black tea by extracting sample with boiled water in a thermo flask with occasional shaking over 10 mins. TF's are extracted with ethyl acetate in separating funnel in the presence of disodium hydrogen phosphate as fixing agent. TF and TR are then estimated by following the method of Ullah et al., 1984. Peak height in the form of different curves for different polyphenols, and catechins observed in HPLC mainly depends on elution property of a compound and varies from compound to compound. The reason for getting different peak height of the catechins was measured. Peak heights of different compounds could not be compared from one chromatogram. So it should always be compared between two analyses. Thus peak height of one compound in the samples of different cultivars or same cultivar at different dates should be compared.

4.3.2 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is used to identify vegetation conditions. The NDVI is traditionally used to extract vegetation abundance from remotely sensed data (Tucker, 1979). It divides the difference between reflectance values in the visible red and near infrared wavelengths by the overall reflectance in those wavelengths:

$$NDVI = {(NIR - VR)}\big/{(NIR + VR)}$$

where *NIR* and *VR* are reflectance in near-infrared and visible red regions, respectively (Rajapakse et al., 2002).. The NDVI is calculated for each tea section.

Phenology and vigour are the main factors that affect NDVI. NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation contains large quantities of chlorophyll. They absorb most of the visible light that hits it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation (right) reflects more visible light and less near-infrared light (NASA Earth Observatory).

In this study, the NDVI was generated from the ASTER image for the area under study (Tocklai tea estate). The NDVI image was generated using ENVI software while the NDVI values were extracted using the ERDAS Imagine software. The ENVI and the ERDAS software have a NDVI module where the image file could be converted to the NDVI image. Using the 'Transform' and the 'NDVI' tools in ENVI, the spectral bands of the original image is assigned and the NDVI model is run. Hence the NDVI image is generated. The entire estate was then masked out from the NDVI image and the two sections within the estate containing the two clones of TV1 and S3A3 were identified. The sections were then masked out and each section was divided into 9 grids. From each of these grids, the NDVI values were extracted using the 3×3 pixel extraction method (Dutta, 2006) and the means of the NDVI values for the two sections were determined. The average NDVI values were then used for further analysis by comparing it with different green leaf quality parameters.

4.3.3 Near Infrared (NIR) Spectroscopy

Tea quality was also evaluated by using the NIR spectroscopy for nine tea samples of each of the TV1 and S3A3 clones both in field as well as in laboratory conditions. At the field level, NIR spectra for green leaves were measured using NIR Flex N – 500 whereas for black tea it was measured during HPLC analysis. Samples of 6 g were collected at a 7 day interval. Reflectance NIR spectra were recorded over the range of 1100 – 2500 nm. Linear regression was done to find the relations between different green leaf and black tea parameters and assess their quality.

4.3.4 Statistical Analysis

A linear regression analysis and a stepwise regression analysis were carried out to establish relationships among the tea chemical parameters and NDVI and NIR for green and black tea samples. The sample size consists of 9 samples for each clones (TV1 and S3A3) for both green leaf and black tea quality parameters.

Different quality parameters were used to derive relations for the two clones. Here we assigned estate as *e*, and the sections within estate as *s*. As regards to the notation, we used subscript 'e' to denote the estate specific parameter and brackets were used for the scale in space and time of observation. All parameters are given by Greek symbols and coefficient β is used for continuous effects.

For the brightness of black tea $B_e(s,t)$, , the following models were explored:

$$B_e(s,t) = \beta_0 + \beta_1 \cdot Cf(s,t) + \varepsilon(s,t) \qquad [4.1a]$$

$$B_e(s,t) = \beta_0 + \beta_1 \cdot EC(s,t) + \varepsilon(s,t) \qquad [4.1b]$$

$$B_e(s,t) = \beta_0 + \beta_1 \cdot EGCG(s,t) + \varepsilon(s,t) \qquad [4.1c]$$

$$B_e(s,t) = \beta_0 + \beta_1 \cdot Tot.C(s,t) + \varepsilon(s,t) \qquad [4.1d]$$

$$B_e(s,t) = \beta_0 + \beta_1 \cdot NIR(s,t) + \varepsilon(s,t) \qquad [4.1e]$$

where $Cf(s,t)$ is the caffeine content, $EC(s,t)$ is the epicatechin content, $EGCG(s,t)$ is the epigallocatechingallate content, $Tot.C(s,t)$ is the total catechin content present in green tea leaves, and $NIR(s,t)$ is the near infrared reflectance from green tea leaves.

For Theaflavins $TF_e(s,t)$ the following models were explored:

$$TF_e(s,t) = \beta_0 + \beta_1 \cdot EC(s,t) + \varepsilon(s,t) \quad [4.2a]$$

$$TF_e(s,t) = \beta_0 + \beta_1 \cdot EGCG(s,t) + \varepsilon(s,t) \quad [4.2b]$$

For Thearubigins $TR_e(s,t)$ of black tea the following relations were explored:

$$TR_e(s,t) = \beta_0 + \beta_1 \cdot EC(s,t) + \varepsilon(s,t) \quad [4.3a]$$

$$TR_e(s,t) = \beta_0 + \beta_1 \cdot EGCG(s,t) + \varepsilon(s,t) \quad [4.3b]$$

For the caffeine content $Cf_e(s,t)$ of green tea leaves we explored the relation

$$Cf_e(s,t) = \beta_0 + \beta_1 \cdot LM(s,t) + \varepsilon(s,t) \quad [4.4]$$

where $LM(s,t)$ is the leaf moisture present in green tea leaves.

For the total colour $TC_e(s,t)$ of black tea we explored the following relations

$$TC_e(s,t) = \beta_0 + \beta_1 \cdot TF(s,t) + \varepsilon(s,t) \quad [4.5a]$$

$$TC_e(s,t) = \beta_0 + \beta_1 \cdot TR(s,t) + \varepsilon(s,t) \quad [4.5b]$$

and the multivariate model

$$TC_e(s,t) = \beta_0 + \beta_1 \cdot TF(s,t) + \beta_2 \cdot TR(s,t) + \varepsilon(s,t) \quad [4.5c]$$

where $TF(s,t)$ is the theaflavin content and $TR(s,t)$ is the thearubigin content of black tea.

For the green leaf parameters $GLP_e(s,t)$ we explored the relations

$$GLP_e(s,t) = \beta_0 + \beta_1 \cdot NDVI(s,t) + \varepsilon(s,t) \quad [4.6a]$$

$$GLP_e(s,t) = \beta_0 + \beta_1 \cdot NIR(s,t) + \varepsilon(s,t) \quad [4.6b]$$

where $NDVI(s,t)$ is the normalized difference vegetation index and $NIR(s,t)$ is the near infrared spectroscopy.

Finally, for the black tea parameters $BTP_e(s,t)$ we explored the relation

$$BTP_e(s,t) = \beta_0 + \beta_1 \cdot NIR(s,t) + \varepsilon(s,t) \qquad [4.7]$$

In all the above equations, $\varepsilon(s,t)$ are the independent errors in section s and at time t.

Further, three integrated models were constructed that were analyzed using a stepwise regression procedure. The first model relates Britghness of black tea to four chemical constituents of the clones; the second model relates the caffeine content of green tea to the chemical parameters of green tea, whereas the third model relates the caffeine content of green leaf to reflectance values:

$$B_e(s,t) = \beta_0 + \beta_1 \cdot TF(s,t) + \beta_2 \cdot TR(s,t) + \beta_3 \cdot TC(s,t) + \beta_4 . Cf(s,t) + \varepsilon(s,t) \qquad [4.8a]$$

$$Cf_e(s,t) = \beta_0 + \beta_1 \cdot LM(s,t) + \beta_2 \cdot Tg(s,t) + \beta_3 \cdot Tb(s,t) + \beta_4 \cdot GA(s,t) + \beta_5 \cdot EGC(s,t) + \beta_6 \cdot EGCG(s,t) + \beta_7 \cdot ECG(s,t) + \beta_8 \cdot C(s,t) + \beta_9 \cdot EC(s,t) + \beta_{10} \cdot Tot.C(s,t) + \varepsilon(s,t) \qquad [4.8b]$$

$$Cf_e(s,t) = \beta_0 + \beta_1 \cdot LM(s,t) + \beta_2 \cdot NDVI(s,t) + \beta_3 \cdot NIR(s,t) \qquad [4.8c]$$

where $Tg(s,t)$ is the theogallin, $Tb(s,t)$ is the theobromine and $GA(s,t)$ is the Gallic acid content while the other notations are given above.

The full forms for all the above abbreviations are given below:

Abbreviations	*Full form*
B	Liquor brightness
+C	Catechins
EC	Epicatechin
CG	Catechingallate
GC	Gallocatechin
ECG	Epicatechingallate
GCG	Gallocatechingallate
EGC	Epigallocatechin
EGCG	Epigallocatechingallate
TF	Theaflavin

(Continuation of abbreviations)

Abbreviations	*Full form*
TR	Thearubigin
Tg	Theogallin
Tb	Theobromine
GA	Gallic acid
Cf	Caffeine
LM	Leaf Moisture
TC	Total colour
Tot. C	Total catechin
GLP	Green leaf parameter
BTP	Black tea parameter
NIR	Near infrared spectroscopy
NDVI	Normalized difference vegetation index

4.4 Results

4.4.1 Laboratory Analysis

The results of the chromatographs from the first and the second flush of tea leaf show that there exist differences between the caffeine content and ECG, +C, EC, EGCG and EGC. The results showed that the elusion property of a compound varies from compound to compound. When the caffeine content of the first and the second flushes of the two clones S3A3 and TV1 were compared, increase in caffeine content during the second flush could be well observed (First flush: S3A3 = 16.433; TV1 = 16.436 & Second flush: S3A3 = 17.044; TV1 = 16.45). Higher peaks of EGCG could also be observed during the two flushes (First flush: S3A3 = 19.017; TV1 = 19.03 & Second flush: S3A3 = 19.732; TV1 = 18.878). Higher levels of ECG content was observed during the second flush (First flush: S3A3 = 9.087; TV1 = 9.064 & Second flush: S3A3 = 9.56; TV1 = 9.584). The catechins of green tea leaves for the two clones used in this study have shown the variations in the composition of catechins during the first and the second flush. Results have demonstrated that the clones used in this study have wide differences in flavan-3-ol (catechins) composition, suggesting large genetic variations. Significant differences in the levels of all individual flavan-3-ols, suggests that the quality potentials of these clones could be different leading to variations in the individual theaflavins composition in the black teas.

4.4.2 Linear Regression Analysis between Green and Black Tea Parameters and NDVI and NIR

The results of the linear regression models (4.1) – (4.5) are shown in Table 4.1 and Table 4.2 for the two clones. For S3A3 we observe some clear relations. Model (4.1a) shows a significant negative effect of caffeine content on brightness. This indicates that a higher level of caffeine lowers brightness. Further from model (4.1a), it was also observed that caffeine decreases with the maturity of crop shoots (R^2 = 0.478). Model (4.1b) shows a significant negative effect of Epicatechin (EC) showed with brightness. This indicates that brightness reduces with higher levels of EC (R^2 = 0.707). EGCG has a significant negative effect on liquor brightness for S3A3 (R^2 =0.491), as shown by model (4.1c). From model (4.1d) we observe that the total catechin has a significant negative relationship with brightness (R^2 = 0.492). And finally, from model (4.1e) we observe a significant positive effect of near infrared (NIR) on brightness (R^2 = 0.598). In contrast to S3A3, clone TV1 did not show any significant relation with the different parameters. Further, applying the models (4.2a), (4.2b), (4.3a), (4.3b), (4.4), (4.5a), (4.5b) and (4.5c) did not show any significant effects between the different parameters for the two clones.

The results of the linear regression between the green leaf and black tea parameters using NIR and NDVI values shows that NIR and NDVI could predict the quality of tea (Table 4.3). When NIR values as explanatory variables were linearly regressed using model (4.6b) against the different green tea parameters as dependent variables for clone S3A3, it was observed that NIR has a significant negative effect on caffeine, Theogallin, EGCG and ECG, with R^2 ranging between 0.105 and 0.782. Similarly, when NDVI values were used as explanatory variables against the green leaf parameters using model (4.6a) for clone S3A3, significant positive effects of Theogallin and ECG are observed, with R^2 values ranging from 0.121 to 0.674.

The linear regression model (4.6b) shows that NIR has a significant positive effect on Gallic acid for green leaf parameters of clone TV1, whereas a significant negative effect could be observed for EC. The regression model (4.6a) shows a significant positive effect of the NDVI over caffeine and EC. The results are given in Table 4.4.

Finally, model (4.7) did not show any significant relations on black tea parameters for both clones S3A3 and TV1 (Table 4.5).

4.4.3 Stepwise Regression for Caffeine and Brightness

Results of the stepwise regression are given in Table 4.6. Applying model (4.8b), it was observed that ECG has a significant positive effect on caffeine content in TV1 (R^2 = 0.526), whereas a significant positive effect could be observed on caffeine content in S3A3 when EGCG was used as an explanatory variable (R^2 = 0.794). Similarly, stepwise regression [model (4.8a)] for black tea parameters and caffeine showed that brightness is affected by caffeine and theaflavins content. A significant negative effect of caffeine on brightness could be observed in S3A3 with a moderate R^2 value of 0.478 while a significant positive effect of theaflavins on brightness could be observed in TV1 with a high R^2 value of 0.638.

Results of the stepwise regression model (4.8c) showed a significant negative effect of NDVI over caffeine content in clone TV1 with an R^2 value of 0.466 while a significant negative effect of NIR could be observed over caffeine content in clone S3A3 with an R^2 value of 0.702. This shows that NDVI and NIR could establish relationships with green leaf parameters.

Legend applied: *: significance at p = 0.05, ** significance at p =0.01, ***: significance at p = 0.001 (The legend applied is same for all the tables)

Models	*Intercept*	*R^2*	*Caffeine*	*EC*	*EGCG*	*TC*	*TF*	*TR*	*NIR (GL)*	*NIR (BT)*	*LM*
1 (a)	29.38	0.121	-1.51								
1 (b)	23.2	0.017		-0.81							
1 (c)	24.08	0.018			-0.225						
1 (d)	24.93	0.021				-0.144					
1 (e)	4.47	0.035							3.81		
1 (e)	18.15	0.001								0.868	
2 (a)	1.66	0.009		0.049							
2 (b)	1.44	0.044			0.029						
3 (a)	18.87	0.384		-1.5							
3 (b)	14.72	0.044			0.14						
4	-8.38	0.132									0.172
5 (a)	5.09	0.132					1.13				
5 (b)	9.37	0.049						-0.142			
5 (c)	5.82	0.134					1.05	-0.036			

Table 4.1: Linear relations between green leaf and black tea parameters for clone TV1

Models	*Intercept*	*R²*	*Caffeine*	*EC*	*EGCG*	*TC*	*TF*	*TR*	*NIR (GL)*	*NIR (BT)*	*LM*
1 (a)	33.84	0.478	-2.2*								
1 (b)	27.2	0.707		-1.91**							
1 (c)	33.43	0.491			-0.797*						
1 (d)	33.23	0.492				-0.37*					
1 (e)	1.204	0.598							5.06*		
1 (e)	10.86	0.05								3.12	
2 (a)	2.16	0.149		-0.069							
2 (b)	2.38	0.1			-0.028						
3 (a)	17.02	0.039		-0.341							
3 (b)	15.31	0.011			0.09						
4	2.96	0.004									0.021
5 (a)	5.55	0.087					0.95				
5 (b)	4.41	0.32						0.187			
5 (c)	5.82	0.134					1.05	-0.036			

Table 4.2: Linear relations between green leaf and black tea parameters for clone S3A3

Note: NIR (GL): NIR (Green Leaf)
NIR (BT): NIR (Black Tea)

Models	*Indicators*	*Caffeine*	*Tg*	*Tb*	*EGC*	*EGCG*	*ECG*	*+C*	*EC*	*GA*
6 (a)	*Intercept*	-5.2	-5.67			-16.09	-11.66			-0.34
	NDVI	42.49	31.82*			122.54	74.29**			1.83
	R²	0.246	0.589			0.262	0.674			0.121
6 (b)	*Intercept*	12.27	5.59	2.18	14.44	33.56	14.01	-2.49	7.71	
	NIR	- 1.72**	- 0.88***	-0.37	-2.05	- 4.08**	- 1.92***	0.79	-1.32	
	R²	0.702	0.782	0.136	0.255	0.698	0.779	0.11	0.21	

Table 4.3: Linear relations between green leaf parameters of clone S3A3 with NDVI and NIR

Models	*Indicators*	*Moisture*	*Caffeine*	*ECG*	*+C*	*EC*	*Tg*	*Tb*	*GA*	*EGCG*	*+C*
6 (a)	*Intercept*	49.43	-194.49	-135.5	-19.05	-159.41					
	NDVI	123.85	1051.50*	826.55	145.7	760.39*					
	R²	0.145	0.466	0.207	0.327	0.488					
6 (b)	*Intercept*					120.06	-11.32	20.61	-5.22	-126.5	-3.26
	NIR					- 22.51*	4.91	-3.93	1.34*	50.78	4.01
	R²					0.455	0.161	0.327	0.536	0.176	0.263

Table 4.4: Linear relations between green leaf parameters of clone TV1 with NDVI and NIR

Note: Tg: Theogallin
Tb: Theobromine
GA: Gallic Acid

Clones	*Models*	*Indicators*	*Thearubigins*	*Theaflavins*	*Total Color*	*Brightness*
S3A3	7	*Intercept*	1.6	1.46	8.25	10.86
		NIR	3.59	0.14	-0.19	3.12
		R^2	0.114	0.016	0.003	0.05
TV1	7	*Intercept*	42.53	0.37	-7.55	18.15
		NIR	-6.35	0.33	3.52	0.87
		R^2	0.32	0.021	0.237	0.001

Table 4.5: Linear relations between black tea parameters of clone S3A3 and TV1 with NIR

Clones	*Models*	*Indicators*	*R^2*	*Intercept*	*Cf*	*TF*	*EGCG*	*ECG*	*NIR*	*NDVI*
S3A3	8 (a)	Brightness - AI	0.478	33.84	- 2.20*					
	8 (b)	Caffeine - AI	0.794	0.72			0.319***			
	8 (c)	Caffeine - Moist - NDVI - NIR	0.702	12.27					- 1.72**	
TV1	8 (a)	Brightness – AI	0.638	4.76		9.75**				
	8 (b)	Caffeine - AI	0.526	15.55				0.614*		
	8 (c)	Caffeine - Moist - NDVI - NIR	0.466	-194.49						- 0.24*

Table 4.6: Stepwise regression between brightness and black tea parameters, caffeine and green tea parameters and caffeine and moisture – NDVI – NIR of clone S3A3 and TV1

Note: Cf: Caffeine
TF: Theaflavins
AI: All Indicators
Moist: Moisture

4.5 Discussion

Tea is made from the young tender shoots of two leaves and a bud. Quality of tea depends on the different chemical constituent present on the leaves. Tea quality also depends on the cultivars used, plucking standards, pruning types and also on the fermentation.

This study presents a comparison of chemical parameters of green tea leaf and black tea of two different clones grown and processed under similar conditions with that of NIR spectroscopy and NDVI. Normally it is observed that factors affecting the growth rate of tea plants normally lead to variations in chemical compositions and their quality (Robertson, 1983; Owuor, 1995). The negative effect of caffeine confirms that a higher level of caffeine content lowers tea liquor brightness which was further indicated through the NIR spectroscopic analysis. The caffeine contained in tea flush is higher in spring and gradually decreases with the growth of leaves. The caffeine contents in 1st and 2nd leaf (3.4% in dry weight) are higher than that in the mature leaf (around 1.5% in dry weight) (Zhen et al, 2002). A further higher level of caffeine also contributes to bitterness in tea which results in reducing the astringency of tea due to interaction with bitter caffeine. Theaflavins are formed by the enzymatic oxidation and condensation of catechins. The formation of theaflavins during fermentation reaches a maximum and then declined. For CTC tea, this maximum usually occurred between 90 – 120 min. It was generally recognized that the theaflavins plays an important role in determining the quality of black tea infusion, described by tea tasters as 'brightness' and 'briskness' (Roberts, 1962; Hilton & Ellis, 1972). However, the contribution made by these compounds to quality differs with individual theaflavins. Xiao, (1987) reported that withering process have an obvious impact on theaflavins and thearubigins. A positive impact of theaflavins on liquor brightness was also observed. Analysis has also shown that ECG and EGCG have a positive impact on caffeine content in green leaves. A higher level of ECG and ECGC increases the bitterness and astringency. The threshold value of catechins is around 12 – 17×10^{-4} M [(+)-EC, (-)-EGC] in free type catechins, and 4×10^{-4} M [(-)-ECG, (-)-EGCG] in gallate type catechins (Yamanishi, 1992). Beyond this threshold level, caffeine content increases resulting in increased bitterness and lowering liquor brightness. While the clone S3A3 showed clear effects between the different parameters, it was observed that the clone TV1 did not show any effects between the parameters when carrying out a linear analysis. But stepwise regression did show clear positive effects of ECG over caffeine and theaflavins over brightness indicating that increase levels of ECG and theaflavins have impact on the caffeine and brightness levels of TV1.

Magoma et al. (2000) demonstrated the genetic variability of tea clones. The different level of theaflavins and catechins emphasizes the large genetic variation in the clones used in this study. The formation of theaflavin requires a reaction between a trihydroxyflavan–3–ol and a dihydroxyflavan–3–ol (Nakagawa & Torii, 1965; Robertson, 1983). The correct balance and amount of the trihydroxyflavan-3-ols and dihydroxyflavan-3-ols are therefore necessary to ensure maximum formation of the theaflavins, one of the key chemical quality parameters of black tea (Deb & Ullah, 1968; Hilton & Ellis, 1972; Hilton & Palmer-Jones, 1975; Wright et al., 2000, 2002). Although, in the two clones used in this study, their levels were higher, they could be the limiting factor in theaflavins formation as they run out faster. It is also speculated that the very high levels of EGCG in the green leaf of two clone's causes a flooding effect of EGCG quinones during fermentation, leading to formation of other products, such as thearubigins (Wright et al., 2002). No significant correlation could be observed between green leaf biochemical parameter and black tea liquor colour in this study. The results presented here demonstrated that green leaf biochemical parameter's enhances the plain black tea quality by higher amounts of theaflavins and brightness and low levels of thearubigins. It is also found that EGCG of green tea leaf could be used to predict quality of plain black tea both during the first and the second flush.

NIR has a significant negative relation with green leaf parameters. For every parameter such as caffeine, theogallin, theobromine, EGC, EGCG, ECG, Gallic acid, +C and EC assessed, it showed that near-infrared (NIR) spectroscopy could provide a rapid method for simultaneous estimation of the green leaf parameters and overall quality of green leaf but it was not clear from the analysis whether NIR spectroscopy could assess the overall quality of black tea as the black tea parameters of the two clones when assessed did not show any effects. The ability to rapidly monitor these parameters in tea provides a further means of final product quality control during the buying, importing or blending stages. This technique may be appropriate for the continuous monitoring of the tea manufacturing process, thus enabling better control of the withering, fermentation and drying stages.

NDVI is considered to be a measure of plant productivity (Sellers, 1985; Tucker and Sellers, 1986) and is sensitive to vegetation parameters such as the green leaf area index, the fraction of absorbed photo synthetically active radiation and the percentage of the ground surface covered by vegetation. Pan et al., 2004 developed create correlation models for retrieving bio-chemical content in stems and leaves or other remotely sensed parameters that indicate nutritional status and environmental stresses using normalized differential vegetation index (NDVI). It was observed that system integrated remote sensing with GIS, is an important part of digital agriculture, and that its successful application will expend the application of remote sensing and GIS in agriculture. Several optical indices have arisen by relating leaf biochemical constituent concentrations with hyperspectral data. Many studies have focused on the investigation of effective hyperspectral chlorophyll indices (Carter, 1994; Gitelson and Merzlyak, 1997; Vogelmann et al., 1993; Zarco-Tejada et al., 2001, 2005), while carotenoids (Gitelson et al., 2002; Sims and Gamon, 2002) and water content (Penuelas et al., 1993) have also been examined. Moreover, many recent studies that used hyperspectral data focused on improving the commonly and widely used Normalized Difference Vegetation Index (NDVI) and on developing new indices aiming to compensate for soil background influences (Bannari et al., 1996; Qi et al., 1994; Rondeaux et al., 1996), and atmospheric effects (Karnieli et al., 2001; Kaufman and Tanre, 1992). Canopy reflectance in the visible and near infrared is strongly dependent on both structural (i.e. amount of leaves per area, leaf orientation, canopy structure) and biochemical properties (i.e. chlorophylls, carotenoids) of the canopy (Jacquemoud et al., 1996; Zarco-Tejada et al., 2001). High spectral and spatial resolution satellite sensors with large swath width that would be capable of frequent global coverage would be an interesting advance in vegetation remote sensing (Stagakis et al., 2010). This kind of data would offer great possibilities for multiple applications and analyses that could expand the present capabilities of accurate ecosystem monitoring and improve our understanding of global vegetation state, processes, change and dynamics. Results from our study also show that relationships exist between green leaf quality parameters and NDVI indicating that NDVI could be used for monitoring tea quality thereby confirming that concentration of foliar biochemical parameters can be monitored using NDVI under the condition of maximum biomass during the active growth stage (April – October) of tea. Multispectral sensor can be used to measure the canopy reflectance of tea. Green leaf chemical parameters when analyzed using NDVI, polyphenolic substances present in green leaf shows positive effects indicating that these chemical substances could determine tea quality. NDVI was found to be positively correlated with the green leaf parameters such as Gallic acid, EC, Caffeine, Theogallin and EGCG. It reveals that NDVI could be an indicator of quality of green tea.

From this study, it was observed that remote sensing can play an important role in assessing tea quality. New remote sensing multispectral and hyperspectral sensors could generate vast amounts of data in a cost effective manner and at higher spatial and spectral resolutions. Hyperspectral and multispectral images, consisting of reflectance from the visible, near infrared and mid-infrared regions of the electromagnetic spectrum, can be interpreted in terms of physical parameters and are useful for operations such as stress mapping, fertilization and pesticide application and irrigation management (Liaghat and Balasundram, 2010). High resolution satellite data could be an important indicator for monitoring tea quality. The study further observed that the application of remote sensing is site specific which means that for monitoring tea quality, a section should be free from shade tree effects to avoid the interference of reflectance between the tea canopy and shade trees. For this, further attempts should be made using high resolution microwave data such as Risat (1 m) that has the ability to penetrate through clouds and shade trees. Availability of remote sensing data for the same date of leaf collection is another important factor that would ensure effective monitoring of tea quality parameters. Attempts to study at individual plant level should be made by using very high resolution data such as Geo Eye (0.41 m) and SPOT (2.50 m). More frequent observations would result in effective monitoring of tea quality from time to time. Trials should also involve resolution merging techniques to monitor quality. Further attempts should include different clones and their quality parameters analyzed at different time periods to see their effects.

4.6 Conclusions

The factors influencing tea quality are complex. Since direct or indirect remote sensing methods can't realize the estimation of tea quality so the effective linkage between remote sensing retrieval models and agronomic models should be established. The integration of remote sensing and GIS is an important part of digital agriculture, and its successful application specially in monitoring tea quality will expend the application of remote sensing and GIS in the plantation sector. In this study, the green leaf and black tea parameters were evaluated through linear and stepwise regression analysis to find if there exist any relationships between different chemical parameters. It leads to the conclusion that:

1. Relationships could be established between remote sensing and green leaf and black tea quality parameters in particular for one of the clones investigated in this research
2. NDVI and Near Infrared (NIR) spectroscopy could be used for monitoring tea quality. Statistical analysis using NDVI and NIR shows clear effects between different tea quality parameters. Positive effects of NDVI on caffeine, EC, theogallin and ECG could be

observed while NIR analysis showed clear negative effects on caffeine, theogallin, EGCG, ECG, Gallic acid and EC.

3. The study further shows that foliar biochemical parameters for measuring tea quality can be monitored using NDVI under the condition of maximum biomass during the active growth stage of tea.
4. Statistical analysis also showed that liquor brightness is affected by the levels of catechins, theaflavins and caffeine contents. Theaflavins contributes to brightness and colour of black tea liquor.
5. The study reveals that higher levels of epigallocatechingallate (EGCG) and epicatechin (EC) and lower levels of caffeine contents reduce the liquor brightness. Stepwise regression also shows that change in any quality parameter level affects caffeine content. Higher levels of EGCG and ECG, results in increase caffeine content in green leaf. Further it also shows that liquor brightness is affected by theaflavins and caffeine contents.

5

A Statistical and Modelling Approach for Analysing Factors Determining Tea Productivity

This chapter quantifies the effects of different yield-determining factors on tea yield. A field trial was executed in 2007, 2008 and 2009 at Tocklai Tea research station. Data were also used to calibrate the CUPPA Tea model developed by the University of Cranfield for Tanzanian conditions.
This chapter is revised and resubmitted in *Experimental Agriculture* for publication as: “Analysis of factors that determine tea productivity in North-Eastern India: A combined statistical and modelling approach”.

Abstract

The effects of a number of genotypic, environmental and management factors on tea yield are quantified and modelled, using a three year (2007 – 2009) field trial in Assam, North-East India. The study followed combined statistical analysis and modelling approach to get insight of the factors that limit tea productivity and which will enable us to correctly interpret the data, verify assumptions and to reach valid conclusions. Plantation age had a significant negative (R^2 = 0.77) and fertilizer application a significant positive effect on tea yield (R^2 = 0.69 for urea; R^2 = 0.62 for rock phosphate and R^2 = 0.74 for muriate of potash). Monthly rainfall had a significant positive effect on monthly yields (R^2 = 0.43). Rainfall was more strongly associated with tea yields, when rainfall in month x was related to the tea yield of month x + 1 (R^2 = 0.49). The statistical analysis done for the hypothetical situation that the fields were fully planted shows an improved correlation of monthly rainfall x and tea yield of month x + 1 (R^2 = 0.58). Adjusted yields and fertilizer applications also correlated better than actual yields.

The study further reports the simulation results of CUPPA Tea Model in Northeast India to find out how well predicted and observed values for tea production matched. The results obtained shows close correspondence between predicted and observed yields indicating that the model could be used on contrasting soil types, genotypes, and also on daily, weekly and monthly weather data. Observed and predicted yields of seedling, clonal and mixed tea showed a strong fit for the year 2007, 2008 and 2009 with a correlation of 0.72, 0.98, 0.95 (seedling tea), 0.90, 0.97, 0.93 (clonal tea) and 0.87, 0.98, 0.94 (mixed tea), respectively. When forcing the data points to the $y = x$ line, R^2 turned out to be 0.51. However, it can be further calibrated and validated for Northeast Indian conditions, if more required input parameters are collected in a series of plantations. This model seems useful for proper strategic planning of a tea estate.

5.1 Introduction

Tea is a leading cash crop in world agriculture. The main tea producing countries are China, India and to a lesser degree Sri Lanka, Kenya and Indonesia (Tea Statistics Annual Report, 2009). Tea in Northeastern India is grown in four major regions: Assam, Terai, Dooars and Darjeeling. With an annual tea production of 480 million kg in 2007, Assam covers approximately 17% of the world's tea production (Tea Statistics Annual Report, 2007). Decline in tea production and of tea quality are seen as major problems by the tea industry in India.

In Kenya, an important tea exporting country, Kamau (2008) performed research on the productivity and resource use in ageing tea plantations, and observed that significant differences in the mean tea yield were mainly due to differences in management practices, use of tea genotypes, and age of the plantations. It was also concluded that further improvement in tea productivity should take into account the interactions between Genotype (G), Environment (E), and Management (M) as was found in food crops (Spiertz et al., 2007). Based on this approach, Dutta et al. (2010) investigated the effects of age (a proxy of G since varietal information was not sufficiently distinct to be used), rainfall, soil organic carbon and pH (E), and NPK fertilizer application and pruning regime (M) on tea yields in seven tea plantations, over a 5 to 10 year period between 1998 and 2007. They found that tea yield was weakly correlated with rainfall ($R^2 = 0.25$), and with soil organic carbon (SOC); $R^2 = 0.10$) on estates where SOC > 2%. Plant age had a negative ($R^2 = 0.28$) and N fertilizer application a positive effect ($R^2 = 0.30$) on tea yield. Combined analysis of the effect of age and fertilizer application gave higher regression coefficients than separate analysis (R^2 values ranging between 0.15 – 0.64). The pruning analysis remained inconclusive.

The analysis of these secondary data triggered the setting up of a field trial to further investigate the relations between tea yield and G, E, M parameters, as well as the use or development of a tea production model. Neither ongoing field studies on tea growth and production, nor simulation models describing tea growth and production seem to abound. The only model described in recent literature is known as CUPPA Tea, developed in Tanzania (Matthews and Stephens, 1998b,c). The model was developed with a range of crop, soil and water parameters to provide a dynamic simulation of tea growth and production. Many parameters in this model are hard to measure on a routine basis, whereas others, such as fertilizer use are not fully functional, which makes rapid validation less easy. The model has earlier been successfully validated for conditions in Tanzania and Zimbabwe (Matthews and Stephens, 1998b,c), and has also been used to study the influence of irrigation potential on tea yield in Northeast India (Panda et al., 2003).

The objective of the research in this paper is to analyse factors affecting tea productivity through statistical and modelling approach. The study reports on a three year (2007-2009) agronomic field trial on tea in Assam, India. The factors looked into are based on the earlier analysis of secondary data (Chapter 2), and include variety (clonal vs. seedling), and age (G); rainfall, temperature, soil pH, and organic carbon (E); tea bush density, and fertilizer application (M). As a number of sections contained considerable gaps, the analysis was repeated for 'adjusted' yields, considering 100% coverage of sections by tea bushes. Next, the results were used to perform a calibration of the CUPPA Tea Model for the conditions in Assam. A sensitivity analysis was carried out to check the robustness of the CUPPA Tea model.

5.2 Materials and Methods

5.2.1 Study Area and Field Data

The study was carried out in the Tocklai Experimental Tea Estate of Tea Research Association (TRA) located at Jorhat district in the South Bank region of Assam in Northeast India (Figure 5.1). Jorhat is situated at 26.75° N latitude and 94.22° E longitude. The site has an average elevation of 116 m with summer temperature ranging between 15 and 35°C, and winter temperature between 7 and 18°C. Summers are accompanied by heavy monsoon showers with the area receiving an average annual rainfall of 2244 mm. There are 135 tea estates in the area.

The estate has an area of 205 ha out of which 118 ha is under tea. It has 11 sections with the area of each section ranging from 4 to 14 ha. The sections contain tea plants of different cultivars (Table 5.2) and are managed on an individual basis. Tea yield data were collected both at the estate and at the section level for 2007, 2008 and 2009. Daily rainfall data were collected by the weather station of TRA. Soil pH and soil organic carbon (SOC) data were collected in 2007 only for the topsoils (0

– 15 cm) of all sections. Soil samples were collected using random sampling method (Dang, 2007). The pH was measured by the standard potentiometric method with glass electrode (Jackson, 1973), whereas organic carbon was determined by the wet digestion method (Walkley and Black, 1934; Jackson, 1973; Tandon, 1993). Fertilizer (urea, rock phosphate and muriate of potash (MOP)) were applied for all three years at the section level. Gaps (vacancies), cultivars, bush spacing and plant age were also recorded at the section level.

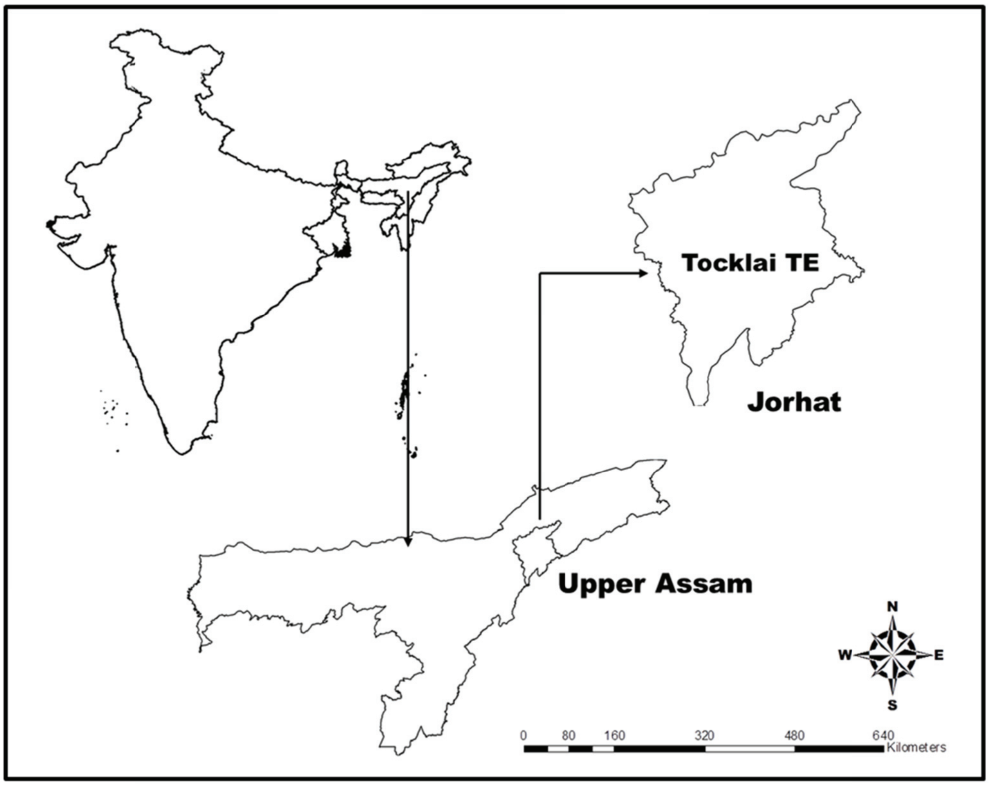

Figure 5.1: Location of Tocklai Experimental Tea Estate

5.2.2 Statistical Analysis

Descriptive statistics have been calculated at the section level for each year. The mean was calculated as the sum of the annual yields $Y(s,t)$ where $Y(s,t)$ is the yield in year t and section s, divided by the number of years and the number of sections. The standard deviation was also calculated as a measure of variability within a dataset.

Secondly, a correlation analysis was carried out both for actual and adjusted yields at the section level. Adjusted yields are analysed by considering 100% coverage of sections by tea bushes.

Thirdly, a linear regression analysis has been carried out for actual and adjusted yields with monthly rainfall as the explanatory variable at the section level:

$$Y\_t(\mathrm{s},m) = \beta_0 + \beta_1 \cdot rain(t,m) + \varepsilon(t) \qquad [5.1]$$

where, $Y\_t(s,m)$ is the section specific monthly yield (m) for year (t) = 2007, 2008 and 2009, $rain(t,m)$ is the monthly rainfall and $\varepsilon(t)$ is the error, assumed to be independent. A similar analysis was carried out with the rainfall of one month (x) as the explanatory variable and the yield of the following month ($x + 1$) as a dependent variable.

A section-wise linear regression analysis was carried out to see the effects of the explanatory variables age, vacancy, pH, SOC, and fertilizer application. In the parallel run, yields were adjusted by considering that vacancies within the sections do not exist.

Yield and Age: This model is written as:

$$Y(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \varepsilon(s,t) \qquad [5.2]$$

where $Age(s,t)$ is the age of the plantations in section s in year t while $\varepsilon(s,t)$ is the error assumed to be independent.

Yield and Vacancy: This model is written as:

$$Y(s,t) = \beta_0 + \beta_1 \cdot Vac(s,t) + \varepsilon(s,t) \qquad [5.3]$$

where $Vac(s,t)$ is the number of vacancies within the sections s in year t while $\varepsilon(s,t)$ is the error assumed to be independent.

Yield and pH and SOC: First, a linear model was implemented to relate pH with yield at the section level:

$$Y(s,t) = \beta_0 + \beta_1 \cdot pH(s,t) + \varepsilon(s,t) \qquad [5.4a]$$

where $pH(s,t)$ is the pH in the section s in year t. Similarly, a model for SOC equals

$$Y(s,t) = \beta_0 + \beta_1 \cdot SOC(s,t) + \varepsilon(s,t) \qquad [5.4b]$$

where $SOC(s,t)$ is the amount of organic carbon at section s in year t.

Yield and Fertilizers: The following model was applied:

$$Y(s,t) = \beta_0 + \beta_1 \cdot FERT(s,t)\ ) + \varepsilon(s,t) \qquad [5.5]$$

where $FERT(s,t)$, are the amounts of urea (U), rock phosphate (RP) and muriate of potash (MOP) applied to section s in year t. $\varepsilon(s,t)$ are independent and identically distributed (i.i.d.) random variables.

Finally, a section-wise multiple regression analysis was carried out to find out whether the combination of 'age' and the other variables gave a better explanation of actual and adjusted yields. The different models are written as:

i. $$Y_e(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot SOC(s,t) + \varepsilon(s,t) \qquad [5.6a]$$

ii. $$Y(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot Vac(s,t) + \varepsilon(s,t) \qquad [5.6b]$$

iii. $$Y(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot U(s,t) + \varepsilon(s,t) \qquad [5.6c]$$

where $U(s,t)$, are the amounts of urea applied to section s in year t.

iv. $$Y(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot RP(s,t) + \varepsilon(s,t) \qquad [5.6d]$$

where $RP(s,t)$, are the amounts of rock phosphate applied to section s in year t.

v. $$Y(s,t) = \beta_0 + \beta_1 \cdot Age(s,t) + \beta_2 \cdot MOP(s,t) + \varepsilon(s,t) \qquad [5.6e]$$

where $MOP(s,t)$, are the amounts of muriate of potash applied to section s in year t.

5.2.3 CUPPA Tea Simulation Model

The CUPPA Tea (Cranfield University Plantation Productivity Analysis for Tea) simulation model (Matthews and Stephens, 1998b) simulates the growth and yield of tea by taking into consideration the effects of solar radiation, atmospheric humidity, temperature, day length, and soil water availability on crop growth and development. The model operates on a daily time step and includes routines describing shoot growth and development, dry matter production and partitioning and the crop water balance (Mathews and Stephens, 1998b,c). It simulates the growth and development of shoots on a daily basis thereby representing the behaviour of the whole crop. The rate of shoot growth and development is calculated as a function of temperature, day length, humidity and crop water status. The amount of water taken up by the crop is calculated as a function of the potential evaporative demand by the canopy, the amount of soil water and the root distribution in the soil profile. The potential evaporative demand is determined by the crop leaf area, level of sunlight, temperature, humidity, and wind speed. The model also calculates the water stress factor as the ratio of actual water uptake to the potential water demand to modify shoot development and extension rates and also dry matter production. This model is designed to extrapolate the results of field experiments to wider ranges of similar environments, and has the ability to evaluate the effects of different management decisions on yield and its distribution over a range of years.

To calibrate the model, weather, soil and yield data from TRA were used. The model was run by changing the input parameters such as temperature, shoot numbers, and day length according to Indian conditions (Table 5.1). As no data were available on shoot growth and development for cultivars grown in India the genotype parameters for clone 6/8 (a widely grown Kenyan cultivar also validated by Panda et al., 2003 in Northeast Indian conditions) were used as an alternative. Yield was simulated for Indian conditions by modifying the weather parameters. Most of the growth parameters of TRA clones or seedling varieties are not known and hence calculations had to rely on the clone 6/8 characters. A previous study carried out by Panda et al., (2003) using the CUPPA Tea model in Terai and Tezpur region of Assam for modelling the influence of irrigation on tea yields also considered the clone 6/8 characters. For our study, the model was calibrated under Indian conditions to compare the simulated yields with seedling, clonal, and mixed (seedling + clones) tea at the estate level.

Day length influences growth and dormancy in tea bushes. According to Panda et al. (2003), the day length in Northeast India varies from 10.3 hours in December to 13.7 hours in June. When day length is below 11.15 hours for six weeks, tea bushes become dormant as stated by TRA. Hence, in Northeast India (25 – 27° N latitude), tea bushes remain dormant during the winter season for approximately three months due to the combined effects of short days and low temperature. As Northeast India is situated much further away from the equator than the tea-growing zone in Tanzania where the model was developed (6° S latitude), the critical lower day length was set at 11.5 hours to match with the conditions in Assam. The minimum temperature required for shoot extension was set at 13^{0}C (De Costa et al., 2007), while the optimum temperature in CUPPA Tea set to 24^{0}C. Leaf temperatures in Northeast India are often 5 – 10^{0}C above air temperature (Hadfield, 1976). Thus the critical temperature used in CUPPA Tea is equivalent to a leaf temperature of around 30 – 35^{0}C, identified as the optimum temperature for photosynthesis (Hadfield, 1976; Panda et al., 2003). Maximum temperature for shoot development was set at 35^{0}C, and the extension base temperature at 12^{0}C based on the Indian conditions. The total number of actively growing shoots per unit area (1 m^2) has been assigned to 700 based on the section size. The weather files have been created using daily temperature, wind, rainfall, evaporation, mean vapour pressure and sunshine hours. Using data of TRA, the evaporation was set at 9.5 mm. Soil pH, SOC and bulk density data were taken from the 2007 experiment. The original model can simulate yields at different plucking intervals from 7 to 21 days. For TRA, 7 days plucking intervals were assigned to the model, since this is the standard plucking interval in Northeast India.

The model was set up to run from 1 January onwards. Early January is the time of 'skiffing' in which the top layer of foliage is removed during the winter season as part of the pruning practices (Panda et al., 2003). In TRA, the first flush of plucking occurs in the middle of March followed by the second flush at the end of April. The model was also calibrated to the standard plucking of two leaves and a bud. As root depth was not recorded, maximum root depth was assumed to be 100 cm, corresponding to the approximate depth of the water table during the monsoon (Panda et al., 2003). The model was run under "without irrigation" conditions, and assuming no limitations due to nutrients, pests or diseases. As the model currently does not allow handling such limitations, the simulations mimick water limited yields that are cultivar-specific.

Simulated yields were compared with observed yields for the 3 years and correlations were established. Yields were categorized into three groups:

(i) sections with seedling tea, (ii) sections with clonal tea, and the (iii) sections with mixed (seedling + clonal) tea.

The sensitivity of the CUPPA Tea Model output to changes in the input parameters was investigated by running the model with the assigned input parameters held constant at default values, except for the one under consideration. We subjected the model to 1 – 5% variation in the standard values. The model sensitivity was measured by the ratio β of the percentage change in the predicted yields to the percentage change in the input parameter.

5.3 Results

5.3.1 Descriptive Statistics

Table 5.2 shows average tea yields, cultivars and age and vacancy percentage of the individual sections. As the mentioned factors differs largely between sections, the yield range turned out to be substantial, i.e., 1368 – 3412 kg ha^{-1}. Table 5.3 shows that mean monthly tea yield ranges between 229 – 278 kg ha^{-1}. The survey carried out by Dutta et al. (2010), covering the tea growing areas of Northeast India shows a mean tea yield ranging between 1500 – 2500 kg ha^{-1} over a period of 5-10 years.

Section No.	*Area (ha)*	*Cultivars*	*Types*	*Age (Years)*	*Vacancy %*	*Yield (kg ha^{-1})*
CM - 3	10	Betijan/Kharijan/ TV-1/TV-10	Mixed	76	42	1733
CM - 4	13	Betijan/Kharijan	Seedling	77	40	1673
CM - 5	10	Betijan/Kharijan	Seedling	76	40	1494
CM - 13	5	Betijan/Kharijan	Seedling	53	53	1368
CM - 15	8	TV-1, T3E3, S3A3	Clones	43	13	3219
CM - 16	16	TV-1, T3E3, S3A4	Clones	40	12	3412
TK - 2	16	Betijan/Kharijan + Clones	Mixed	83	53	2108
TK - 3	10	Betijan/Kharijan + Clones	Mixed	83	40	1972
TK - 4	7	Betijan/Kharijan	Seedling	80	63	2153
TK - 8	10	Betijan	Seedling	86	37	1987
TK - 11	12	TV-1, T3E3, S3A4	Clones	38	12	2951

Table 5.2: Average sectional yields, varieties, age and vacancy percentage for Tocklai tea estate for the period 2007 - 2009.

Tocklai Tea Estate	*Section Level*			
	Min	*Max*	*Mean*	*Std. Dev.*
2007	21	448	229	143
2008	28	601	278	184
2009	52	537	272	48
All	21	601	260	157

Table 5.3: Descriptive statistics of monthly tea yield at the section level (kg ha^{-1}) from 2007 – 2009.

5.3.2 Correlation Analysis

Correlation analysis for actual yields showed dependencies between yield and age, vacancy percentage, SOC, and fertilizer applications (Table 5.4a). The same was true when vacancy percentage was reduced to zero (Table 5.4b). Real and vacancy-adjusted tea yield correlated strongly and negatively with age, but positively with N, P and K fertilizers.

	Yield (kg ha^{-1})	*Age (Years)*	*Vacancy %*	*pH*	*OC (%)*	*Urea (kg)*	*R. Phos (kg)*	*MOP (kg)*
Yield (kg/ha)	1	-0.76**	-0.91**	0.47	0.66*	0.74**	0.68*	0.79**
Age (Years)	-0.76**	1	0.74**	-0.43	-0.71*	-0.35	-0.36	-0.42
Vacancy %	-0.91**	0.74**	1	-0.42	-0.65*	-0.61*	-0.58	-0.64*
pH	0.467	-0.43	-0.42	1	0.48	0.3	0.28	0.34
OC (%)	0.662*	-0.71*	-0.65*	0.48	1	0.03	-0.06	0.13
Urea (kg)	0.737**	-0.35	-0.61*	0.3	0.03	1	0.98**	0.98**
R. Phos (kg)	0.682*	-0.36	-0.58	0.28	-0.06	0.98**	1	0.97**
MOP (kg)	0.792**	-0.42	-0.64*	0.34	0.13	0.98**	0.97**	1

Table 5.4a: Correlation coefficients of actual yield and different explanatory variables Legend: *: significance at p = 0.05, **: significance at p = 0.01, ***: significance at p = 0.001

	Yield (kg ha^{-1})	*Age (Years)*	*pH*	*OC (%)*	*Urea (kg)*	*Rock Phos (kg)*	*MOP (kg)*
Yield (kg/ha)	1	-0.68*	0.45	0.59	0.79**	0.73*	0.84**
Age (Years)	-0.68*	1	-0.43	-0.71*	-0.35	-0.36	-0.42
pH	0.45	-0.43	1	0.48	0.3	0.28	0.34
OC (%)	0.59	-0.71*	0.48	1	0.03	-0.06	0.13
Urea (kg)	0.79**	-0.35	0.3	0.03	1	0.98**	0.98**
Rock Phos (kg)	0.73*	-0.36	0.28	-0.06	0.98**	1	0.97**
MOP (kg)	0.84**	-0.42	0.34	0.13	0.98**	0.97**	1

Table 5.4b: Correlation coefficients of adjusted yield and different explanatory variables (Legend as in table 5.4a)

5.3.3 Linear Regression Analysis

Applying Eq. [5.1], significant positive linear effects could be observed at the estate level between actual and vacancy-adjusted monthly yields and monthly rainfall, for 2007 and 2009 (Table 5.5a and 5.5c). The R^2 is relatively low, ranging between 0.15 – 0.47 in Table 5.5a and 0.19 – 0.51

in Table 5.5c. Applying the same equation to explain yield in month x + 1 by rainfall in month x gave a marked improvement for actual yield in 2009 (R^2 = 0.66), and in all three years for the vacancy-adjusted yields (R^2 0.47 – 0.69) (Table 5.5b and 5.5d).

The section-wise regression analysis (Eq. [5.2]) for actual and adjusted yields with age as the explanatory variable revealed a significant, negative and linear effect on tea yield (Table 5.6a and 5.6b). Application of Eq. [5.3] showed, not surprisingly, that vacancy percentage also has a significant negative and linear effect on tea yield (Table 5.6a). Soil pH for the estate ranged between 4.3 and 5.3. The section-wise regression analysis (Eq. [5.4a]) did not show any significant effect on tea yield, illustrating that the observed pH range is not limiting tea growth. The SOC percentages for the estate ranged between 0.5 and 1.2%. Applying Eq. [5.4b] shows a significant positive effect of SOC on tea yield (Table 5.6a) with R^2 = 0.44.

The fertilizer applications for the estate ranged from 53 – 104 kg ha^{-1} of urea, 23 – 58 kg ha^{-1} of rock phosphate and 40 – 86 kg ha^{-1} of MOP. Applying (Eq. [5.5]) shows that urea, rock phosphate and MOP all have a significant positive effect on both actual and adjusted yields (Table 5.6a and 5.6b). The R^2 for actual and adjusted yields due to urea application were 0.54 and 0.62 respectively. For rock phosphate and MOP, these values were 0.47 – 0.53 and 0.63 – 0.71 respectively. The R^2 observed for vacancy-adjusted yields is much higher than those for actual yields (Table 5.6a and 5.6b).

Year	*N*	R^2	*Intercept, β_0*	*Rainfall, β_1*
2007	10	0.473	577	2.76*
2008	10	0.146	716	1.97
2009	10	0.471	653	3.47*

Table 5.5a: Linear relations between tea yield and rainfall in 10 months of harvesting at the estate level (2007 – 2009).

Year	*N*	R^2	*Intercept, β_0*	*Rainfall, β_1*
2007	9	0.428	664	2.50
2008	9	0.410	528	3.32
2009	9	0.661	645	3.80**

Table 5.5b: Linear relations between the monthly rainfall (x) and the actual tea yield of the following month (x + 1) during 9 months of harvesting at the estate level (2007 – 2009).

Year	N	R^2	Intercept, β_0	Rainfall, β_1
2007	10	0.481	806	3.79*
2008	10	0.187	872	2.81
2009	10	0.507	953	5.05*

Table 5.5c: Linear relations between adjusted yield and monthly rainfall at the estate level from 2007 – 2009.

Year	N	R^2	Intercept, β_0	Rainfall, β_1
2007	9	0.470	885	3.61*
2008	9	0.578	571	4.87*
2009	9	0.693	953	5.49**

Table 5.5d: Linear relations between the monthly rainfall (x) and the adjusted tea yield of the following month ($x + 1$) during the 9 months of harvesting at the estate level from 2007 – 2009.

Model	R^2	Intercept	Age	Vacancy	pH	SOC	Urea	R. Phos.	MOP
Yield & Age	0.576	3482	-36**						
Yield & Vacancy	0.818	2778		-47***					
Yield & pH	0.219	-4403			1129				
Yield & OC	0.438	-854				2214*			
Yield & Urea	0.543	-646					1.84**		
Yield & R. Phos.	0.465	-437						3.02*	
Yield & MOP	0.628	-665							2.42**

Table 5.6a: Linear relations between actual yield and different explanatory variables at the section level from 2007 – 2009.

Model	R^2	Intercept	Age	pH	SOC	Urea	R. Phos.	MOP
Yield & Age	0.463	3601	-32*					
Yield & pH	0.199	-3631		1055				
Yield & OC	0.353	-206			1945			
Yield & Urea	0.618	-305				1.92**		
Yield & R. Phos.	0.533	-91					3.17**	
Yield & MOP	0.707	-314						2.52***

Table 5.6b: Linear relations between adjusted yield and different explanatory variables at the section level from 2007 – 2009.

5.3.4 Multiple Regression Analysis

Equations 5.6a – 5.6d were applied to test the effects of the best possible combinations between age and vacancy percentage, SOC and fertilizer applications (Table 5.7a and 5.7b). The tables show that age and fertilizer application are both significant in explaining yield differences (Table 5.7a). Neutralizing the effects of vacancies is not adding any explanation (Table 5.7b). The analysis revealed that the younger the tea plants were, the more effective the fertilizer application was.

Model	*R²*	*Intercept*	*Age*	*SOC*	*Vacancy*	*Urea*	*R. Phos.*	*MOP*
Yield & Age – OC	0.607	2194	-28	837				
Yield & Age- Vacancy	0.835	3126	-9		-39**			
Yield & Age- Urea	0.828	1642	-27**			1.33**		
Yield & Age – R. Phos	0.771	1914	-28**				2.09*	
Yield & Age – MOP	0.848	1462	-25**					1.76**

Table 5.7a: Multiple regression of tea yield with age and other explanatory variables

Model	*R²*	*Intercept*	*Age*	*SOC*	*Urea*	*R Phos.*	*MOP*
Yield & Age – OC	0.489	2461	-24	741			
Yield & Age - Urea	0.805	1505	-22*		1.52**		
Yield & Age – R. Phos	0.736	1785	-23*			2.42*	
Yield & Age – MOP	0.837	1284	-19*				2.02**

Table 5.7b: Multiple regression of adjusted tea yield with age and other explanatory variables

5.3.5 Calibration of CUPPA Tea Model

The yield distribution of made tea predicted by CUPPA Tea agreed closely with the observed made tea yields under rainfed conditions (Figure 5.2a – 5.2i). CUPPA Tea could predict the month of occurrence of the first flush (March) and the second flush (April) correctly, but the predicted yields show larger peaks than the observed yields during these two months. Predicted yields during July to September were higher than the observed yields in seedling tea (Figure 5.2a – 5.2c). In clonal tea, observed yields showed higher peaks during July to September for the year 2008 – 2009 (Figure 5.2d – 5.2f). For the mixed tea, predicted and observed yields corresponded closely (Figure 5.2g – 5.2i). Throughout the simulations, maximum tea yield was obtained during the month of August. Figures 5.2a – 5.2i show that the correlation between predicted and observed yields during 2007, 2008 and 2009 were 0.72, 0.98, and 0.95 for seedling tea, 0.90, 0.97 and 0.93 for clonal tea and 0.87, 0.98, and 0.94 for mixed tea respectively.

Further, regression analysis of predicted yields against observed yields shows strong linear relationships with the R^2 values for seedling, clonal, and mixed tea yield at 0.71, 0.82 and 0.81 respectively (Figures 5.3a – 5.3c). The slope of the regression lines was 1.34 for seedling tea, 0.81 for clonal tea and 1.06 for mixed tea, showing that the model tends to over-predict for seedling tea, under-predict for clonal tea, and (surprisingly) predicts better for mixed tea. A combined scatterplot for all predicted and observed yields also gave a good fit by forcing the line through the origin ($y = x$), at a R^2 of 0.51 (Figure 5.4).

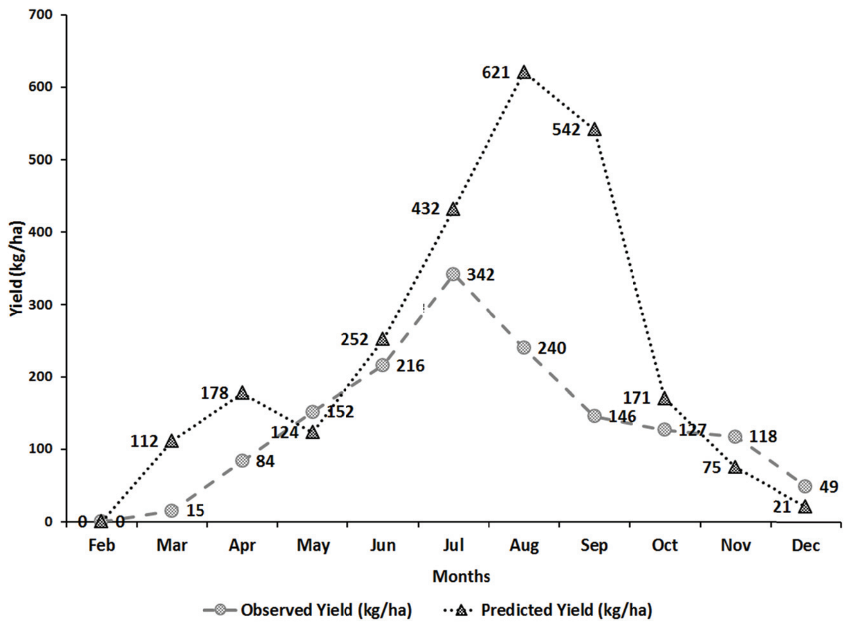

Figure 5.2a: Observed and predicted yields of seedling tea for 2007 (Correlation = 0.72).

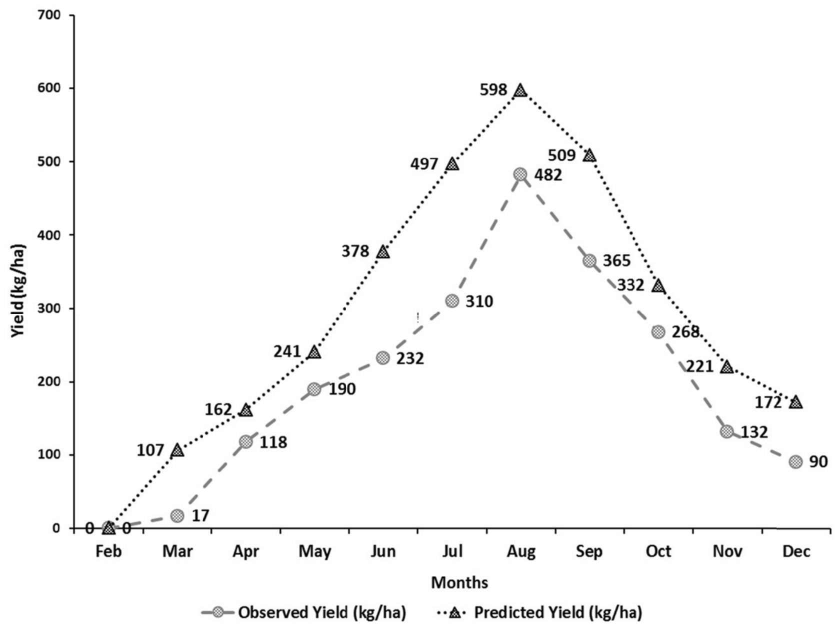

Figure 5.2b: Observed and predicted yields of seedling tea for 2008 (Correlation = 0.98).

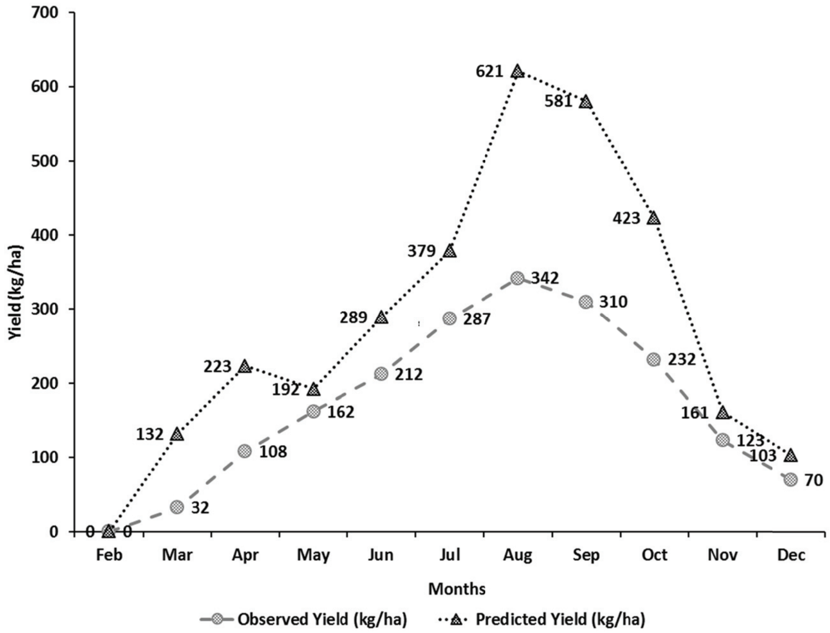

Figure 5.2c: Observed and predicted yields of seedling tea for 2009 (Correlation = 0.95).

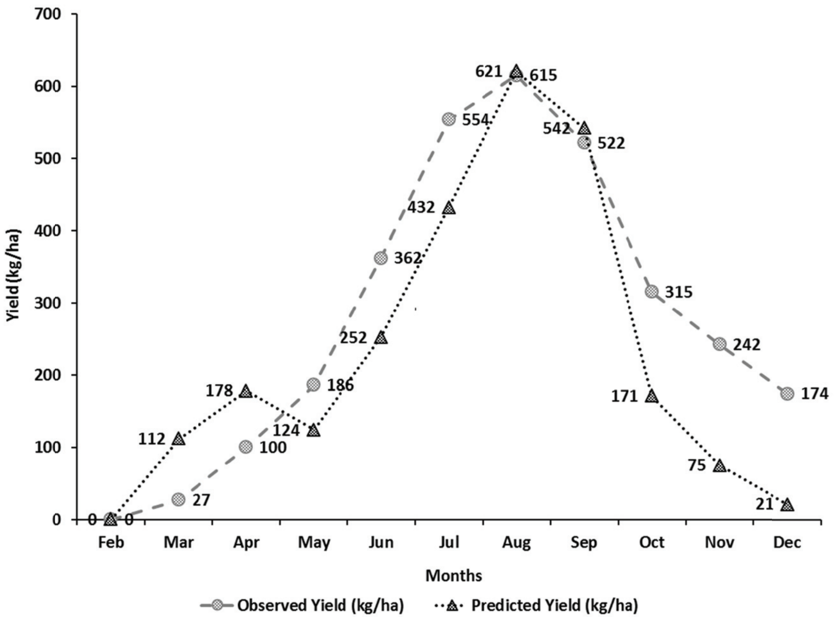

Figure 5.2d: Observed and predicted yields of clonal tea for 2007 (Correlation = 0.90).

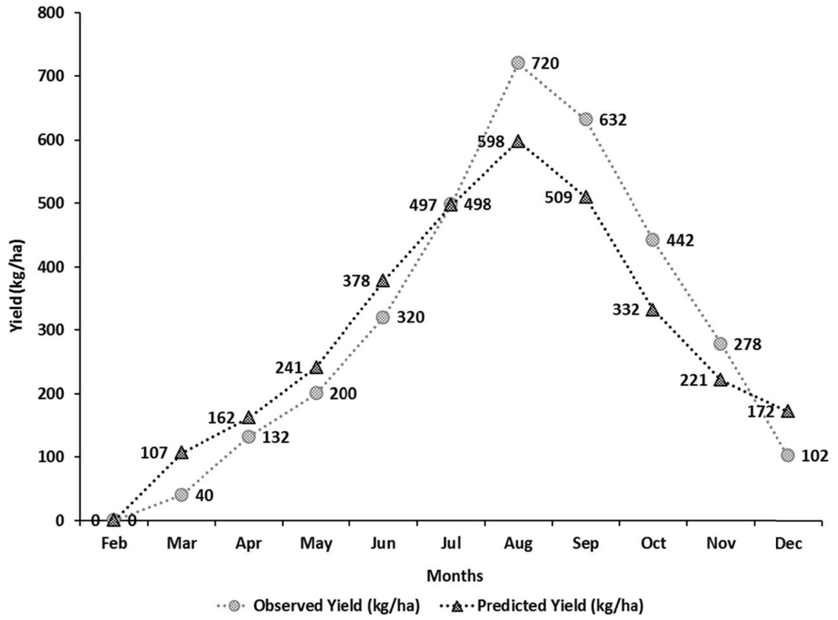

Figure 5.2e: Observed and predicted yields of clonal tea for 2008 (Correlation = 0.97).

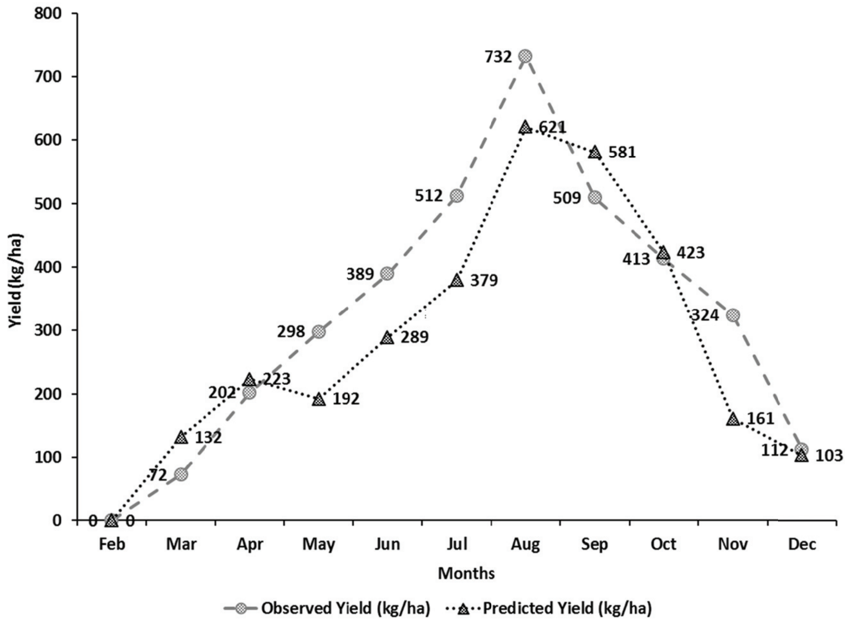

Figure 5.2f: Observed and predicted yields of clonal tea for 2009 (Correlation = 0.93).

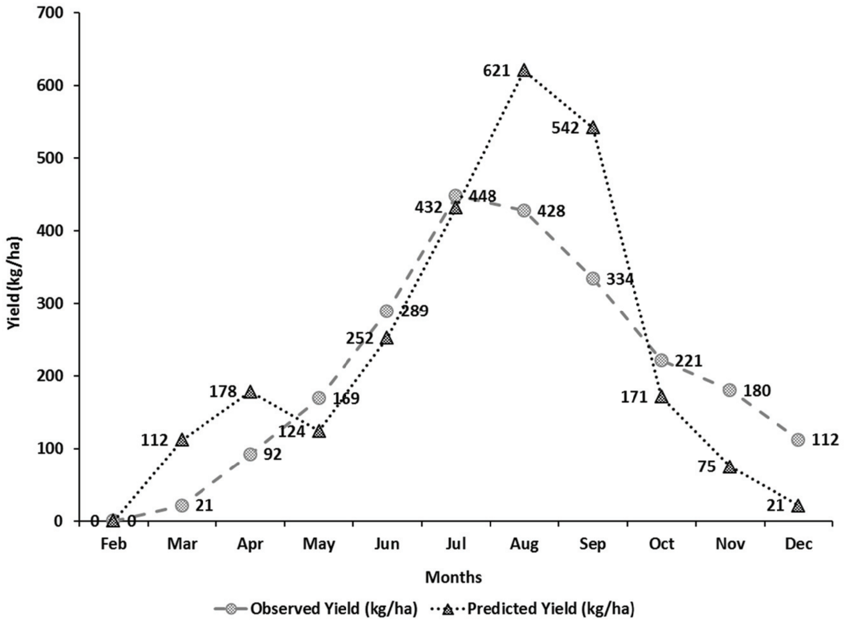

Figure 5.2g: Observed and predicted yields of mixed (clones + seedling) tea for 2007 (Correlation = 0.87).

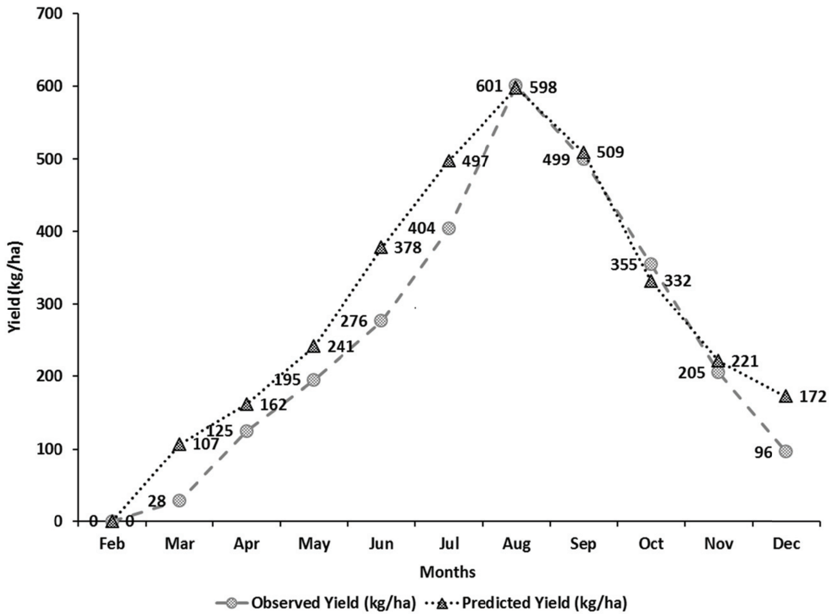

Figure 5.2h: Observed and predicted yields of mixed (clones + seedling) tea for 2008 (Correlation = 0.98).

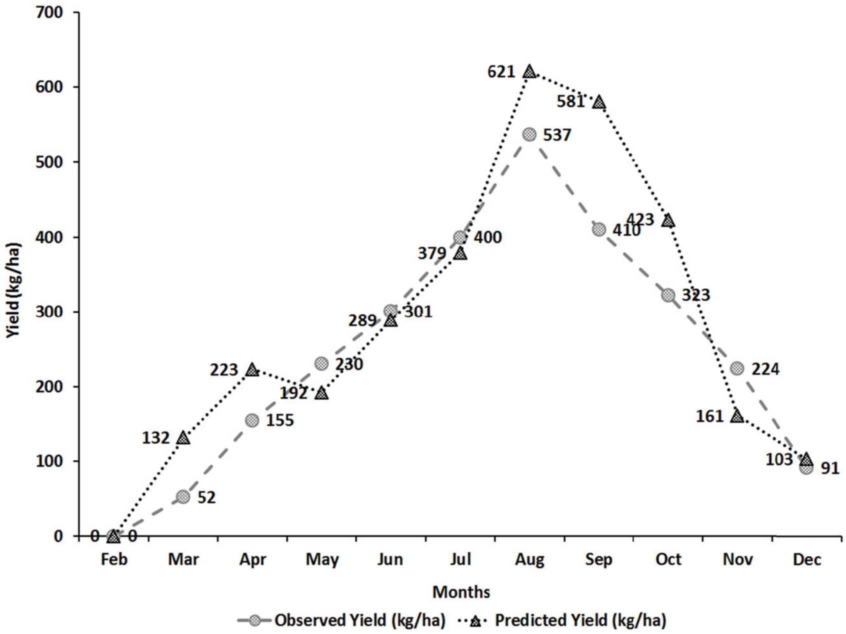

Figure 5.2i: Observed and predicted yields of mixed (clones + seedling) tea for 2009 (Correlation = 0.94).

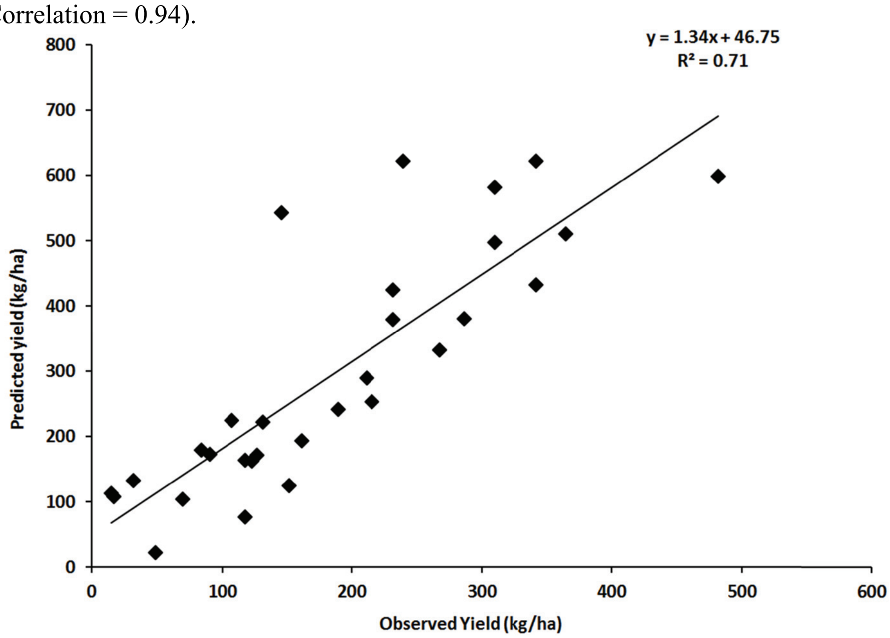

Figure 5.3a: Scatterplot showing observed and predicted yields of seedling tea (R^2 = 0.71)

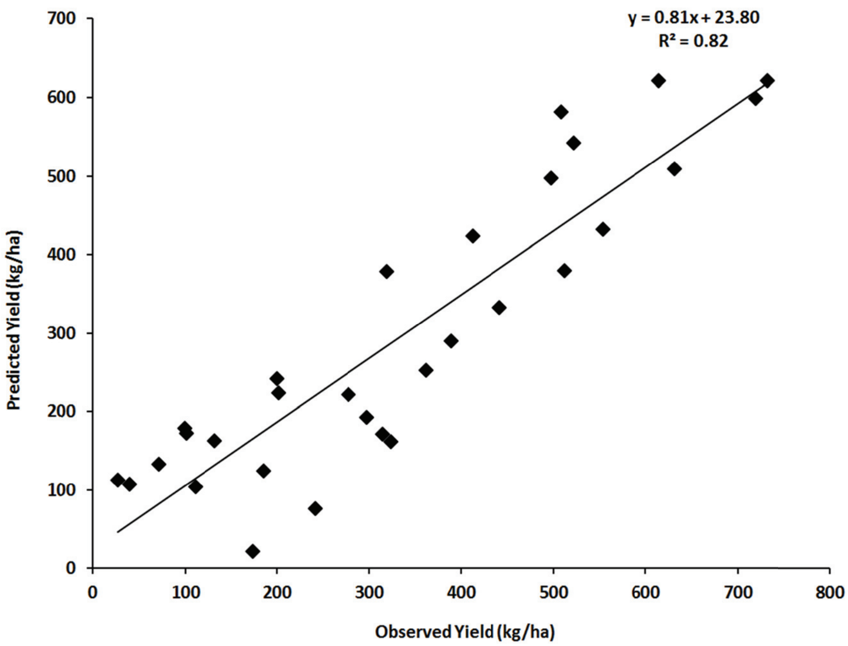

Figure 5.3b: Scatterplot showing observed and predicted yields of clonal tea (R^2 = 0.82)

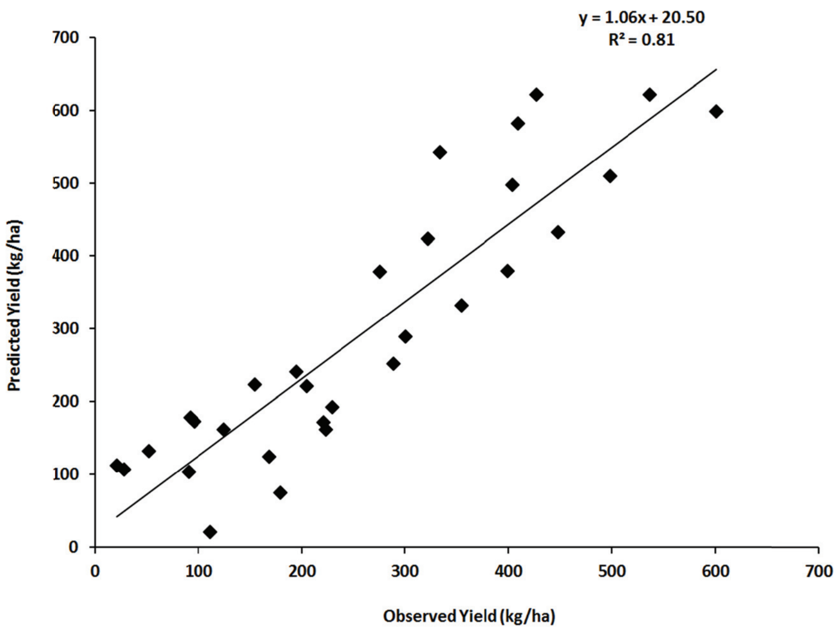

Figure 5.3c: Scatterplot showing the observed and predicted yields of mixed (clones + seedling) tea (R^2 = 0.81)

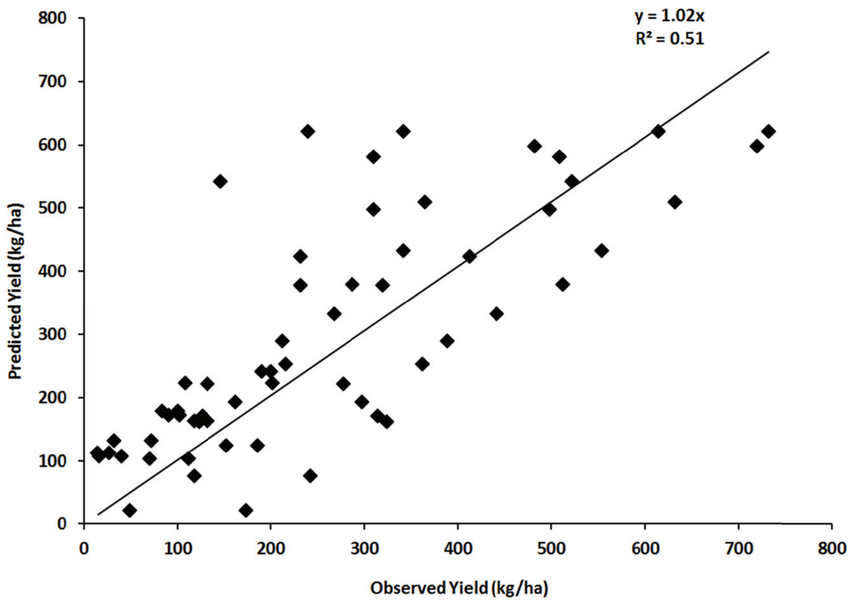

Figure 5.4: Scatterplot showing observed and predicted yields of clonal and seedling tea ($R^2 = 0.51$)

5.3.6 Sensitivity Analysis of CUPPA Tea Model

Applying the sensitivity analysis to all the parameters of the model showed that changes in photoperiod and temperature result in substantial yield changes (Table 5.8). Both parameters have $\hat{\beta}$-value > 1 unlike any other parameter. The most sensitive parameter is the critical photoperiod (φ_{crit}) below which there is no shoot development and extension ($\hat{\beta}$ = - 2.23) followed by the changes in optimum temperature (T_{opt}) for shoot development and extension ($\hat{\beta}$ = - 1.35). The sensitivity analysis performed by Matthews and Stephens (1998a) showed that the model is highly sensitive to the lowest photoperiod at which there is no bud dormancy (φ_h), but this was found to be less so under Indian conditions ($\hat{\beta}$ = - 0.91). The other input parameters did not show much effect on yield when modified isolation.

5.4 Discussion

Researcher-managed conditions in tea research are more restrictive than those in annual crops. The experiment at TRA was carried out at 11 existing plantation sections, covered by plants of different age and bush density. Moreover, a mixture of seedling, clonal and mixed (seedling + clones) tea existed, and fertilizer applications are decided on by the management. The average monthly tea yield at TRA for the three years was 260 kg ha^{-1}, but with a range of 21 to 601 kg ha^{-1}.

Although the estate uses different cultivars, their detailed information could not be used in the analysis due to the non-availability of precise cultivar and growth data. As the sections within the estate are frequently facing replanting on a gap filling basis, the present study was not based on a controlled researcher managed environment. Also data on changes in plant density as a result of replanting and the effect of shade trees per section were not known. Information on pest and diseases and different pruning regimes were not available either. Therefore, combining statistical analysis and crop modelling can be helpful tools to get insight in the factors that affect tea productivity. Although we do not have models that include related variables but we carried out separate analysis for each variable. From the analysis it was seen that one variable that is the age of plantations always corresponds to the decrease in other variables that is yield decreases with increasing age while the fertilizer applications and soil pH and soil organic carbon shows a positive effect. From the current study, it was observed that the R^2 values were higher than those bringing together agronomic data for several plantations in the area (Dutta et al., 2010), hence improving the explanatory value. Also, it was shown that "adjusted yield" approach added explanation to tea yield differences.

Linear analysis carried out on monthly rainfall data showed a clear positive effect on yield, but particularly during the month x+1, following the rainfall month x. Kamau (2008) also stated that seasonal rainfall differences within years have a marked effect on tea yields. Annual yield distribution is largely influenced by seasonal fluctuations in weather variables such as rainfall, temperature and humidity, and by soil water deficits (Matthews and Stephens, 1998b). These authors stated that large yield peaks often occur following a cool or dry season, with subsequent oscillations which may continue throughout the remainder of the season causing uneven yield distributions. This is then followed by logistical problems in both field and factory in terms of planning labour requirement, supplying adequate transport and providing factory capacity to process the harvested shoots during peak periods.

Francis et al. (2002) used different methods to study the phenotypic stability of 20 tea genotypes and stated that as age increases, yield generally decreases but the yield fluctuations between the genotypes they used were substantial. Dutta et al. (2010) also demonstrated that older plantations have lower yields. The stagnation and the decline in productivity of older tea plantations have largely been associated with the ageing tea bushes (Kamau, 2008).

Throughout the analysis, it was observed that the response of tea to pH is virtually absent, which makes sense given the pH range, in which tea thrives well. Soil pH is influenced by many soil chemical parameters though and may change depending on the external inputs used (Kamau, 2008). The tea plant itself is known to acidify the soil because of excess cation to anion uptake, leading the plant roots to excrete H+ ions (Morita et al., 1998). Application of acidifying $(NH_4)_2SO_4$ based fertilizers may have also contributed to the high soil acidity in older tea plantations (Owino-Gerroh, 1991; Dogo et al., 1994; Ruan et al., 2006).

SOC content had a significant relation with yield, which makes sense given the fact that the SOC range was between 0.5 and 1.2%. Dutta et al. (2010), reviewing data from several estates in North East India, found that significance of the relation between SOC and tea yield existed up to the point where SOC exceeded 2%. This seems like a useful threshold for making management decisions.

The age and fertilizer effects were amongst the clearest but require a sharper genotype focus when comparing the results with those of Kamau (2008) in Kenya. He found that clonal tea responds better to N irrespective of age while old seedling tea does not. He further stated that N management should be on the basis of yield ability of tea bushes as defined by genotype-density combinations and age classes. This relates closely to our multiple regression findings reported in Tables 5.7, and the findings in chapter 2. On age and fertilizer, Owuor and Odhiambo (1994) stated that the response of tea bushes to N increases until the age of 30 years followed by a gradual decline. Younger plantations should receive 150 kg N ha^{-1} yr^{-1} while for aged plantations, fertilizer applications depend on the yielding ability of the tea bushes. This can help develop more relevant fertilizer recommendations for Indian tea based on different tea age groups. The effects of rock phosphate and MOP were also clear. Even more clarity on the efficient management of Indian tea systems would come from a more large-scale comparison of the combined effect of SOC levels and fertilizer use efficiency.

The entire analysis was done using monthly actual and adjusted yields to observe the differences within the sections by applying statistical approaches. This helped in modeling the factors limiting tea production in the CUPPA Tea model. The partial mismatch between measured and calculated tea yields may have different reasons. Fluctuations in tea yield during the year is a well-documented phenomenon in many environments, with both short-term variation within a growing season (Fordham, 1970) and variation between seasons of the year (Barua, 1969; Squire, 1979). However Matthews and Stephens (1998a) stated that causes of seasonal variations in tea yield are not well understood. Temperature (Stephens and Carr, 1990) and photoperiod (Barua, 1969) have been implicated in the decline of shoot growth in the cool season. Moreover, variations in temperature alone are sufficient to explain the occurrence of production peaks through their influence on shoot growth rates (Squire, 1979; Stephens and Carr, 1990), but it is not clear whether the synchronization of shoot growth postulated by Fordham (1970) and Cannell et al. (1990) is necessary for such peaks to be produced and whether synchronization can be caused by seasonal variations in temperature alone.

The biggest test for this model is its performance in entirely different climatic and soil conditions from which it was developed and its sensitivity to run with limited amount of data. The model was developed and calibrated for clonal tea grown in the highlands of East Africa. It was applied in a completely different environment in Northeast India without modification to any of the crop parameters except that the daily weather data was fed into the model. Low resolution input data inevitably limits the potential accuracy of the model output. The model was calibrated in the absence of Indian cultivar information and had to rely on the existing genotypic parameters by simply providing the TRA's daily weather data and modifying the temperature data in the general input parameter file according to Assam conditions. This led to the assumption that the simulated yields obtained from the model should be compared with yields of seedling, clonal and mixed (seedling + clones) tea since the current genotype information could not be used for a specific Indian cultivar. While running the model, initial assumptions on the shoot population, structure and soil water content were also made. However, in the absence of information on the management practices, it was felt that making further changes to the input parameters was not warranted although the results gave a better fit.

With the limited amount of available data and given the uncertainties in the starting conditions, a relatively good correspondence between observed and predicted yields could be noticed and the model could predict the first and the second flush correctly. This gives an indication of the robustness of the assumptions underlying the model. Although the model could predict yields under Indian conditions, it could not specify the simulated yield results to a particular clone or seedling tea. Instead, we compared the results between seedling, clonal and mixed tea. In order to simulate yield of a particular cultivar, more precise information needs to be collected and the general input parameter files of the model need to be calibrated according to the Indian conditions which would then allow to compare more accurately the simulated yields to a single cultivar grown in different areas. The results presented here suggest that the CUPPA-Tea model can be used with some confidence on contrasting soil types, genotypes and also on daily, weekly and monthly weather data.
The model does not have a fertilizer application module, and assumes “adequate” plant nutrition. The same holds for the incidence of pests and diseases. But still the simulated yields are in close correspondence with the observed yields suggesting applied fertilizer rates and crop husbandry are not limiting. None the less, inclusion of the fertilizer module in the future under Indian conditions may give a better prediction compared to the one currently done. Further simulations should also involve both irrigated and non-irrigated tea estates.

For the sensitivity analysis, we followed a simple approach in which one parameter was considered at a time and subjecting it to a change of ± 1 – 5% followed by observing their linear dependence. Strong linear dependence was observed. Although there are several other methods such as Monte Carlo filtering, sampling based sensitivity, variance based methods, those methods are more time consuming and complicated. The results of the sensitivity analysis further show that many of the input parameters do not influence the resulting yield much. This may be due to the absence of some data for the Indian conditions. A limitation of the model at present is its inability to predict the shoot population density, which must be supplied as an input and remains constant throughout the simulation. Soil nitrogen status appears to have a large influence on shoot population density. Stephens and Carr (1994), for example, suggest that improved nitrogen nutrition from soil can result in a reduction in apical dominance and a consequent increase in the number of actively growing shoots. Clonal differences in shoot population density are also known to account for large differences in annual yields (Stephens and Carr, 1990), although there is often a negative correlation between shoot population density and mean shoot weight (Cannell et al., 1990). Further work is necessary to quantify these effects for inclusion in the model. The next stage could be the integration of a nitrogen nutrition module into the CUPPA Tea model. This will allow investigation of the interactions between the two important inputs, fertilizer and water, and should allow the formulation of rational plans for optimization and input substitution for any combination of input costs and tea prices.

It is recognized that tea planters have to make strategic and tactical management decisions for improving profitability of their tea business. It is not only important for such decisions to be economically and ecologically sound, but it should also be acceptable to all stakeholders. In such a scenario, the CUPPA Tea model (Matthews and Stephens, 1998b,c) may support decision making on how to maximize tea yields. However, such models do not have an in-built economic component. During the course of the study, it was also observed that ageing tea plantations can only remain economically viable if uprooting and replanting programmes are followed. Improvement in agronomic practices and proper scheduling of fertilizer applications may result in reducing yield gaps. Regular surveys of soil quality and productivity indicators in representative tea growing areas can support management practices and can reduce the need for inputs such as fertilizers. Use of high yielding cultivars is another way of reducing the yield gaps. Differences between seedling tea yield, clonal tea yield and potential yield are also the indicators for increasing yields through improvements in genotypes and management.

Future recommendations should include studies on soil and plant factors at the field and bush level. It should also involve studies on the dynamics of productivity and resource use at the plantation level. Experiments on specific Indian cultivars need to be carried out to understand the parameters that affect its growth and yield and these parameters should be incorporated into the CUPPA Tea to parameterize the model to the Indian conditions.

5.5 Conclusions

This study concluded that major differences in tea yield is due to variation in management practices and uncontrolled environmental conditions. Tea yield at the section level is mostly affected by age of the plantations and fertilizer applications. Yield decreases with increase in age while application of urea, rock phosphate and muriate of potash gives positive effects. The study also shows that statistical modelling could extract relevant information from the available data.

We further conclude that the CUPPA Tea Model can be calibrated in Indian conditions and the simulated yield results obtained are in close correspondence with the observed yields. The model can be used on contrasting soil types, genotypes and also on daily, weekly and monthly weather data. Therefore, to be further calibrated and validated for Northeast Indian conditions, more required input parameters needs to be collected in a series of plantations.

Table 5.1: Input parameters of the original CUPPA Tea Model, and modifications made for the Tocklai Tea Estate.

*TRA.INP is the general input parameter file of the CUPPA Tea Model

Input Parameters Used	*TRA.INP*	*Modifications in TRA.INP*
Population Density	Default	
Row Spacing	Default	
Pluck Interval	Modified	7 days in NE India
Pluck Upper Limit	Modified	2+1 Bud
Pluck Lower Limit	Default	
Shear Height	Default	
Break Back	Default	
Pluck to Leaf	Default	
Minimum Pluck Length	Default	
Maximum Pluck Length	Default	
Irrigations	None	No irrigation data considered
Pluckings	Default	
Irrigation Threshold	Default	
Leaf Weight	Default	
Green Stem weight	Default	
Stem Wood Weight	Default	
Reserves Weight	Default	
Fine Root Weight	Default	
Thick Root Weight	Default	

(Continuation of Table 5.1)

Input Parameters Used	*TRA.INP*	*Modifications in TRA.INP*
Genotype Name	Modified	Changed to Seedling/Clone
Radiation Use Efficiency	Default	
Extinction Coefficient	Default	
Dry Matter Temperature Respo	Default	
Development Base Temperatur	Modified	Increased from 8°C to 13°C
Development Optimum Temper	Default	
Development Maximum Tempe	Modified	Reduced from 40°C to 35°C
Extension Base Temperature	Modified	Increased from 10°C to 12°C
Critical Shoot Day Length	Default	
Shoot DL Sensitivity	Default	
Critical SD	Default	
SD Sensitivity	Default	
Critical Delta Day Length	Default	
Critical Upper Day Length	Modified	Assigned 12.5 hrs instead of 12.15 hrs
Critical Lower Day Length	Modified	Assigned 11.5 hrs instead of 11.25 hrs
Mean Last Leaf	Default	
Weight Stage Slope	Default	
Maximum Leaf Age	Default	
Root Depth Growth Rate	Default	
Specific Root Length	Default	
Soil Data File	Default	
Soil Description	Default	
Soil Albedo	Default	
Soil Evap Stage1 Max	Modified	Increased from 7.5 to 9.5
Drainage Constant	Default	
Run Off Parameter	Default	
Soil Depth	Default	
Humus Mineralization Factor	Default	
Root Factor	Default	
Root Depth	Default	
Shoot Number	Modified	Increased from 500 to 700
NH4	Default	

(Continuation of Table 5.1)

Input Parameters Used	*TRA.INP*	*Modifications in TRA.INP*
Sat WC	Default	
Bulk Density	Primary data	TRA soil BD data used
Organic Carbon	Primary data	TRA soil OC data used
pH	Primary data	TRA soil pH data used
Simulation Start Date	Modified	Mar-07
Simulation End Date	Modified	Dec-09
Class Number (Shoots)	Modified	Changed from 500 to 700
Dry Matter Routines	Default	
Water Routines	Default	
Nitrogen Routines	Default	
Irrigation Mode	Modified	Mode was switched off
Harvest Interval Mode	Modified	Mode was switched on
Start Year From	Default	
Weather Directory	Modified	**Assigned as TRA87, TRA88 & TRA89
Weather Station	Default	
Weather Station Description	Primary data	TRA daily weather data used
NO3	Default	
Genotype File	Default	

**TRA87, 88, and 89 represent the weather data of 2007, 2008 and 2009 respectively

Parameter	Description	$\hat{\beta}$ value *Tanzanian Condition*	$\hat{\beta}$ value *Indian Condition*
φ_h	Lowest photoperiod at which there is no bud dormancy (h)	-2.64	-0.91
φ_{crit}	Critical photoperiod below which there is no effect on shoot development and extension rates (h)	-2.16	-2.23
T_{opt}	Optimum temperatures for shoot development and extension (°C)	-1.65	-1.35
ρ	Slope of the regression between dry weight and leaf number of harvested shoots	1	1
N_b	Number of shoots in the basal population	1	1
T_{bd}	Base temperature for shoot development	-0.42	-0.23
T_{bl}	Base temperature for shoot extension	0	0
a_{S1}	Stage 1 phenochron requirement per leaf	0.27	0.21
a_{S2}	Stage 2 phenochron requirement per leaf	0.36	0.28
b_{S1}	Stage 1 shoot extension rate constant	0.02	0.01
b_{S2}	Stage 2 shoot extension rate constant	-0.14	-0.06
α	Mean last leaf of the total shoot population	-0.14	-0.04
T_{high}	Maximum temperature for shoot development and extension	-0.1	-0.07
φ_m	Highest photoperiod at which bud dormancy is 100%	0.06	0.05
SCV	Coefficient of variation of shoot growth parameters	0.03	0.03
λ	Slope of the relative response of shoot development or extension rates to photoperiod	-0.03	-0.01
$d\varphi/dt_{crit}$	Critical rate of change of photoperiod above which bud dormancy does not occur	0.01	0.01
Y	Slope of the relative response of shoot length extension rate to saturation deficit	0	0
SD_{crit}	Critical saturation deficit value below which there is no effect on shoot extension rate	0	0

Table 5.8: Sensitivity ($\hat{\beta}$) of predicted annual yields to input parameters of the model (Matthews, R.B. and Stephens, W., 1998b).

'$\hat{\beta}$' is the ratio of the percentage change in the annual yields to the percentage change in the specified parameter, with all other parameters held constant at standard values. Parameters are ranked according to the absolute value of $\hat{\beta}$'

6

Conclusions, Reflections and Further Recommendations

This chapter provides the conclusions, reflections and further recommendations on the research that was being carried out.

This thesis addresses the perceived problem of declining productivity in the Indian tea sector. A large set of data has been made available from seven estates in North East India. Statistical methods are applied to quantify relationships between tea yield and genotype (G), environmental (E) and management (M) variables, both for a set of secondary data, as well as from a three year field trial at Tocklai Tea Research Institute. Also, remote sensing is used to understand the underlying spatial patterns within the sections of the estates, tea quality is monitored, and a model is calibrated that calculates tea yield from the G, E and M variables. The research resulted in the following overall conclusions for the different research objectives.

6.1 Conclusions

Objective 1: *To analyze tea yields as a function of genotype, environment and management (G×E×M) factors, using secondary data from seven tea estates in Northeast India, covering a period of up to 10 years.*

The study was carried out on a data set from seven estates during 10 years. Rainfall and soil chemical properties did not cause major variations among tea yields, but age explained yield differences to a large extent: tea yield decreases with increasing age. Combined with N fertilizer, the explanation on yield was even better showing that younger tea plants have a stronger response to fertilizer than older plants. Effects of pruning are inconclusive. Pruning analysis was inconclusive due to the recovery time needed for freshly pruned plants. On the relatively short time period for this study, pruning did not show any benefit but on a longer term, however, it may have a more positive effect on tea yield. Spatial dependence could be observed at the section level while including N fertilizer as an independent variable. The study further concludes that at the estate level, major differences in tea yield occurred due to variation in management practices and uncontrolled environmental factors. Tea yield at the section level is mostly affected by age and N application.

Objective 2: *To monitor tea plantations at different spatial scales using remote sensing and extracting spatial patterns of vegetation and bare soils during tea replantation and understanding the causes of such patterns from multi-temporal data.*

This study focuses on identifying patterns within the sections during the different stages of replantation and rejuvenation. Different levels of information were obtained using wavelets. Wavelets applied on different images at various resolutions were able to reveal underlying patterns within individual sections. The study concludes that remote sensing images and relevant ground truth contribute to assess, analyze, monitor and model the characteristics of tea bush growth. Wavelets provide an important tool for identifying and describing crop features. Daubechies (db4) and symlet (sym8) wavelets give better results to monitor patterns during the different stages of replantation as compared to Haar wavelets. The sym8 wavelet is symmetrical and reveals smooth details whereas the db4 wavelets are asymmetrical and isolate fine details and signal discontinuities. Decreasing the level, the differences between db4 and sym8 increase as the wavelets become more flattened and their shape become more pronounced.

The study further concludes that the selected patterns within the fields are weakly correlated with slope, flow accumulation and compound topographic index (CTI). A strong quantitative linear relationship between the extracted patterns and topographic parameters however could not be established. The study finally shows that the influence of the various hydrological processes related to vegetation, accuracy of DEM, drainage information and soil properties like pH, organic carbon could be properly evaluated using cross correlations. To obtain more consistent patterns, further attempts should involve monitoring a single section from the time of uprooting until planting of new tea seedlings.

Objective 3: *To assess tea quality based on quality data, near infrared (NIR) spectroscopy and remotely sensed (NDVI) data for recognition of tea leaf chemistry differences and exploring these methods to develop an approach for quality monitoring.*

The factors influencing tea quality are complex. It is therefore important to establish effective linkages between remote sensing retrieval models and agronomic models. The integration of remote sensing and GIS is an important part of digital agriculture, and its successful application specially in monitoring tea quality will expand the application of remote sensing and GIS for tea plantations. The present study explores the possibility of using remote sensing as a tool for evaluating the green leaf and black tea quality and deriving relationships between them.

This study concludes that relationships exist between remote sensing, spectroscopy and tea quality parameters, thus indicating that NDVI and NIR spectroscopy could be used for quality monitoring. It was also concluded that during the active growth stage (April – October), maximum biomass is obtained which would help in monitoring the concentration of foliar biochemical parameters of tea using NDVI. Quantifying the effects of tea quality parameters, NDVI and NIR spectroscopy show that liquor brightness as a quality criterion is affected by the catechins, theaflavins and caffeine content. In particular, higher levels of epigallocatechingallate (EGCG) and epicatechin (EC) and lower levels of caffeine contents reduce liquor brightness. Also higher levels of EGCG and ECG result in increased caffeine content in green leaf. Further, application of remote sensing is site specific which means that for monitoring tea quality, a section should be free from shade tree effects to avoid interference of reflectances between tea canopy and shade trees. Availability of high resolution remote sensing data such as Geo Eye (0.41 m), SPOT (2.50 m) and LISS IV (5.8m) for the same date of leaf collection is important to ensure effective monitoring of tea quality parameters. Attempts to study at individual plant level should be made. A higher frequency of observations would result in more effective monitoring of tea quality.

Objective 4: *To measure and model tea productivity and to simulate yield by seasonal data using the CUPPA Tea model.*

This study aimed to explain variation of monthly tea yields at the section level. Actual yields and yields adjusted for vacancies in the field were compared by applying different statistical models. The data set was also used to calibrate the CUPPA Tea model that was originally developed under Tanzanian conditions. Yield decreases with an increasing age at the section level. A monthly rainfall analysis shows that rainfall has a significant positive effect on tea yield. Yield variations are also caused by vacancy: increased vacancies decrease yield. Fertilizer applications also influence tea yield as a positive yield response to NPK fertilizer exists. Also, young plants respond better to fertilizer applications than older plants. The CUPPA Tea model plays an important role in predicting seasonal yields at the estate level. Simulation modelling indicates that the influence of seasonal variations in temperature and photoperiod on shoot growth rates results in the occurrence of yield peaks during the tea growing season. Absence of primary data on shoot growth and development hampered a full-fledged calibration. For that, and subsequent validation, further experiments need to be carried out on individual tea clones or seedlings. The close correspondence between observed and predicted yields suggests that the model is capable of predicting monthly yields at the individual estate level and hence could be used with some confidence under Northeast Indian conditions.

6.2 Reflections

This study focused on tea plantations in Northeast India. Different factors such as age, soil pH, soil organic carbon, rainfall, fertilizer applications and pruning cycles affecting tea yields were quantified, and the causes for yield stagnation and decline were determined. The CUPPA Tea model could be calibrated to fit Northeast-Indian conditions. The study also shows that remote sensing is an efficient tool for monitoring replantation and tea quality. Remote sensing could identify patterns from different stages of replantation, whereas the derived patterns show relationships between slope, flow accumulation and the compound topographic index (CTI). The study further shows that the influence of hydrological processes related to vegetation, DEM, drainage information and soil properties can be evaluated using cross correlations. Moreover, vegetation indices such as Normalized Difference Vegetation Index (NDVI) reveal the relationships between different quality parameters of green leaf and black tea. It shows that NDVI do have potential for monitoring tea quality at the condition of maximum biomass thereby giving an indication of setting up an approach for future monitoring of tea plantations. In this sense, remote sensing has the potentials to contribute to reviving the tea sector.

Seven estates have been considered for this study based on data availability. Data from each of these estates were provided by the estate managers. The monthly and yearly data were collected from the estate records. We do not have control over the data however. Therefore, the accuracy of the data could not be ascertained. The CUPPA Tea model could not be validated due to a lack of independent data sets. It shows that the future simulations require a sharp genotype focus as well as a proper parameterization of the model to adapt itself to the Indian conditions. Information on individual clonal cultivars needs to be collected in the future and simulations should be done on the basis of these cultivars. For such a simulation to take place, field experiments need to be set up to collect other potentially important parameters. In the present study, the simulation was done on the basis of the available data and the parameters already existing in the model. The limited number of estates did not allow us to carry out the spatial analysis extensively for different regions and hence the spatial variations between the different estates could not be ascertained. At the section level, however, that was carried out in one estate where spatial dependence clearly exists between the different sections. This shows the possibility that with more estates under different environmental and management conditions in different regions a clearer and more complete picture may be obtained of the spatial variability. This can be further sharpened towards the sections within the estates. Such an analysis has not yet been carried out. Further, changes in plant density as a result of replanting, information on pest and diseases and the number of shade trees per section were also not available.

The present study did not take into consideration any specific cultivars. The analyzed estates use different cultivars such as seedling, clonal and mixed plants at the section level. The analysis was based on the overall cultivars present within the estates. Results obtained for specific clonal, seedling, or mixed plants may respond differently to different environmental and soil conditions. Different tea growing regions have different environmental and soil conditions. Therefore, results may vary when applied to those regions. Application of remote sensing to extract information from tea bushes lying below shade trees may also have an impact on our findings.

The tea plantation can be considered as an agricultural system that consists of many components: tea plants, other plants like shade trees, weeds, the soil, the hydrology, insects and diseases that feed on the plants, insects and animals that feed on the pests, and the weather. As is shown by the present study, the components of a tea ecosystem are interlinked. Relations between the components can be identified and modeled with mathematical and statistical models. As every part of the ecosystem has a function that affects other parts it is important to consider the tea ecosystem as a whole.

Currently, the amount of available quantitative and quantifiable information is increasing rapidly in space and in time. Yields are recorded at the section level, leaves are analyzed in terms of their quality, remote sensing images provide quantitative satellite information, soil and groundwater compositions are measured and weather information is continuously available at the estates. Information is available at various scales: throughout the country, at individual plantations, at individual sections, at the plant level, and even at the DNA level. As the study shows, integrating these different sources of information requires either the use of (spatial) statistics or a well-established quantitative model.

This is resulting into a more quantitative information system. To further develop aspects of precision agriculture a quantitative GIS on integrated plantation management may be set up, e.g. a tea plantation management system (tPMS). Such a system should contain all spatial information on landuse/landcover, soil fertility, health of tea bushes, fertilizers, pesticides and weedicides, irrigation data, pruning and pest and disease information of a tea estate. Such a system would facilitate analysis and planning and could lead to reduce the environmental effects from excessive use of fertilizers, pesticides and weedicides.

Availability of quantitative information can have an effect on management as well as it may be used as a decision support system (DSS) to support proper planning and correct decision making. Under the current situations, only fertilizer and pruning data were available at the section level for individual estates. Availability of detailed management data like fertilizer applications, different pruning regimes, pesticides and weedicides applications, irrigation information on monthly and yearly basis would give more precise information by quantifying the effects of different factors on tea yield and production. Information on different cultivars would give a better insight into the behaviour of individual cultivars to different management practices. Future studies should involve location specific yield trials to understand the pruning effects and nutrient balance of individual tea plants at cultivar level.

One interesting possible addition would be the inclusion of hydrological information. Estimating the rate of recharge is essential in developing the ground water resource of tea plantations. Therefore, a soil water balance model for tea could be useful, where recharge will be estimated using a volume balance for the water entering and leaving the root zone after considering the change in soil moisture storage. This model would estimate recharge, interception of rainfall by vegetation, preferential flow and changes in soil moisture storage. Runoff, interception and preferential flow are essential components of a soil water balance and therefore needs to be considered using the water balance equation which would give a better insight into the effects of ground water on tea plantations and its relation to yield. Therefore, to obtain realistic estimates of recharge, more precise information on the processes of runoffs, interception and preferential flow would be needed. This study already observed that future research should involve more extensive soil sampling at the individual section level to better understand the effects of soil parameters like pH, soil organic carbon, texture and bulk density on different tea cultivars and their influence on tea yield and production which was lacking in the present study where analysis had to be carried out using limited soil data for few number of estates. The role of remote sensing in monitoring pests and disease detection at the early stage of crop growth is another important issue. Detecting the gradual spread of pests and diseases and monitoring their temporal pattern would help managers to get first-hand knowledge about their field situation while modelling the dynamics of pest populations and quantifying their effects on tea yield and production would help planters to take measures at the appropriate time. Though the present study tried to model the influence of weather parameters on tea yield using the CUPPA Tea model, future studies should take into account specific cultivars and their response to different weather conditions which was absent in this study. Yield simulations should therefore be done for different estates located in different tea growing regions of India and their yield should be compared. So, the concept of cultivar specific CUPPA Tea simulation for different estates is an important area for future research.

The present study shows that remote sensing and statistical models could play an important role in detecting, monitoring and quantifying the problems faced by the tea plantations. Such methods and tools would provide a base for future monitoring of tea plantations not only in terms of yield and quality but would also help planters to plan and execute their work in a more decisive manner.

This study offers ample scope for future research. The current approach may be applied to different tea growing countries to see the effects of different environmental and management factors on tea production. A full experiment to simulate the CUPPA Tea model in different tea growing environments may be explored. Estate level data are important to study the spatial variability within estates in different regions. Therefore, future research should focus on large sample sizes from several estates and derive and use existing spatial dependences at the estate and the section level. Research may further focus on exploring the phenology of tea plants and its behavior to different environmental and management conditions based on designed experiments. This would help in better understanding of the cultivar response to looming climate change and its impact on tea production and quality.

6.3 Reviving the tea sector

Decline in tea production may undermine the economic viability of the tea industry in India. Understanding the causes, impacts and opportunities is of utmost importance. Dissemination of knowledge on the functioning of the tea ecosystems in participation with all stakeholders (managers, farmers, researchers, extension, policy makers) should, therefore, get high priority. Space technology may come in handy for monitoring plantations. Strategic decisions about uprooting and replanting tea plantations should be given careful considerations at the section, estate and tea factory levels. To harvest an everlasting benefit, the tea industry will have to take up uprooting and replanting at a substantial scale while looking into the real scientific cause of establishment problem immediately after uprooting to reduce/remove the gestation period. To monitor effectively and in real time, the use of space technology which may include remote sensing and a satellite communication and monitoring system is inevitable and the planters should be given adequate knowledge to handle such technologies efficiently.

Regular surveys of soil quality and productivity indicators in tea growing areas can support management practices and can either make fertilizer use more efficient, or reduce the need for fertilizer applications. Maintenance of soil fertility is mandatory to obtain desirable tea yields. To achieve high yields and quality, exact parameters on soil physics, soil biology and soil chemistry in relation to two years of rehabilitation/crop rotation period has to be undertaken. For this, it is necessary to know the various inputs to soil affecting the fertility and availability of organic carbon, potash and sulphur so that effective soil management techniques could be put into action. Calculating and monitoring nutrient balances may also help in applying the right mixes of fertilizers and manure. Pest and diseases further affect yield and quality of tea, but have not been studied in this thesis.

As tea is an important beverage, from both a management and a commercial point of view, exploring the role of remote sensing and GIS and other key parameters in the GIS environment would help managers to identify the affected areas within their estates and to take remedial measures. Integrating remotely sensed data with secondary data can provide a deep insight into the cultural practice being implied to the tea ecosystem. Stresses associated with moisture deficiencies, insects, fungal and weed infestations, can be detected early enough to provide an opportunity to the planters for undertaking mitigation measures. It would help planters to identify areas within the field which are experiencing difficulties, so that the correct type and amount of fertilizers, pesticides or herbicides can be applied. The planter will not only improve the productivity from his land, but will also reduce his farm input costs. By establishing relations between tea quality parameters and remote sensing and linking it to tea production would help planters take effective measures to improve upon quality and productivity. All the above mentioned issues would go a long way in revival of the tea sector in Northeast India.

6.4 Recommendations

The above leads to the following recommendations for future investments in the tea sector:

1. Identification of tea bush degradation symptoms and criteria to be used as a diagnostic tool for decision making on uprooting and replanting. The causes for degradation in seedling tea bushes and of newly planted clonal tea bushes are still unclear and as a result remedial measures are still unknown. Identifying such degradation would encourage tea expansion and replanting by using high yielding cultivars, tolerant to harsh environmental and biotic conditions.
2. Increased attention to multiple abiotic stresses (drought, cold, unbalanced nutrition) under less favorable soil and weather conditions. This would help in better understanding of the factors that are responsible for affecting tea production.
3. Modeling the population dynamics of tea pest affecting the plantations and their influence on yield decline. Pests may be a major yield limiting factor. A better modeling would enable scientists to better understand the effects of pest infestation on the phenology of the tea plant and its effect on tea production.

4. Monitoring gradual spread of tea pests and diseases within sections and their effects on the crop phenology may provide a further insight into the factors affecting tea production.
5. Modeling the gradual spread of pest and diseases at the section level within an estate. Such a study has been carried out already on four estates; a large scale study in different tea growing regions would help to better understand the spreading mechanism and its causes for yield stagnation.
6. Research on nutrient balances to measure productivity and sustainability. Such a study would enable us to understand the amount of nutrient taken up by tea plants and the amount of nutrient lost from soil due to different environmental factors. Nutrient balances should then be related to soil nutrient stocks and to environmental, economic and production targets.
7. Isolation, screening and identification of possible tea-specific soil borne pathogens that could be responsible for the degradation. This would help in developing better remedial measures to be undertaken to control such pathogens from affecting tea plants and degrading soil fertility.
8. Application of microwave remote sensing which has the ability to penetrate beyond clouds and canopy cover to monitor tea plantations. This would enable scientists to extract information from tea canopies and soils lying below the shade trees.
9. Testing more cultivars on their response to G×E×M and their effects on tea yield may be attempted by gathering more detailed information like identification of factors limiting improvements in the productivity of existing tea and likely distribution of yield throughout the year.
10. Further study should involve calibrating and validating CUPPA Tea model for Indian cultivars based on new primary data sets that also cover input parameters that are not determined on a routine basis. Experiments on specific Indian cultivars need to be carried out to understand the parameters that affect its growth and yield and these parameters should be incorporated into the CUPPA Tea to parameterize the model in Indian conditions.
11. Advance statistical methods and multispectral and hyperspectral remote sensing sensors may come in handy for further assessing of tea quality. Creating correlation models for retrieving bio-chemical content in stems and leaves and modeling its influence on quality is an important aspect. Attempts to study at individual plant level

should be made using high resolution remote sensing data, Geo Eye (0.41 m) and SPOT (2.50 m). More frequent observations would result in effective monitoring of tea quality from time to time. Trials should also involve resolution merging techniques to monitor quality. Further attempts should include different clones and their quality parameters analyzed at different time periods to see their effects.

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Biography

Rishiraj Dutta was born on 4th August, 1980 in Jorhat district of Assam, India. In 1996, he completed his high school from his hometown Jorhat and went on to complete his higher secondary from Chennai, India during 1996 – 1998. In 1999, he joined Assam Agricultural University and completed his graduations in agriculture in 2003. He then joined as an Officer Trainee at the Indian Institute of Remote Sensing (IIRS), Indian Space Research Organization, Dehradun, India in 2004 for his post graduate studies and obtained his master's degree in Geoinformatics in 2006 under the joint MSc. programme of ITC, The Netherlands and IIRS, Dehradun.

In 2006, he worked as a GIS Consultant at the International Water Management Institute (CGIAR), Colombo, Sri Lanka and worked on the FAO sponsored Global Irrigated Area Mapping (GIAM) project as an Indian Partner before joining for his PhD at ITC, The Netherlands in 2007 to pursue his doctoral studies from the Department of Earth Observation Science, Faculty of Geoinformation Science and Earth Observation, University of Twente, The Netherlands. His topic of research is "Spatio-temporal analysis of tea productivity and quality in Northeast India." His PhD is a joint research programme between Faculty ITC, University of Twente and Tea Research Association, Assam, India under the research theme "Stochastic methods for image mining and data quality (DAQUAL)."

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