Mapping cryptic invaders and invasibility of tropical forest ecosystems: *Chromolaena odorata* in Nepal

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Mapping cryptic invaders and invasibility of tropical forest ecosystems: *Chromolaena odorata* in Nepal

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Dedicated to my Guru,

Dr. Jan De Leeuw
Abstract

For centuries, people continuously increased the rate of biological invasions and there is no sign of slowing down. From the depth of the Ocean to the crest of Himalayas, they are occupying pristine and semi-natural ecosystems at an alarming rate, threatening human, animal, plant as well as ecosystem health. Efforts to avoid or eradicate them are not achievable except for very few cases. Currently, therefore, their management aims at controlling invaders and mitigating their impact rather than eradication. Limitation of resources forces land managers to carefully plan and prioritize interventions only in areas most severely affected by invaders. Hence, information on the actual and potential distribution of invaders is considered crucial for their management.

It has long been recognized that remote sensing (RS) and geographical information systems (GIS) could contribute to help solving this problem. Remote sensing has so far been applied predominantly to invasive species that dominate the canopy of the ecosystem. The large majority of invasive species do however not show up in the canopy and thus remain difficult to detect by remote sensing in a direct and straightforward manner. Techniques for mapping such cryptic invaders have not been developed so far. In this thesis we explored methods to map the distribution of Chromolaena odorata (L.) RM King & H Robinson, one of the world’s worst invasive species. This cryptic heliophyte originating from central America invaded the understorey of many tropical forest ecosystems throughout the world. C. odorata is a cryptic invader hidden under the forest canopy in the Terai of Nepal. It occurs predominately in opened up forest, with increased light intensity. The approach to map its distribution was to develop first remote sensing techniques to map forest canopy density and light intensity reaching the understorey and next relate these radiation maps to various aspects of the life history of C. odorata.

To set the scene we reviewed in chapter 2 existing methods to map the distribution of invasive species. Next, we explored the quality of four alternative methods to predict forest canopy density (Chapter 3). This comparative study revealed that an artificial neural network best explained canopy density in terms of variance explained and bias. A Landsat ETM+ image processed through a neural network predicted 81% of light intensity reaching the understorey. The resulting radiation map was the environmental data layer that was subsequently used to map the distribution of C. odorata. This study revealed that in the Nepalese Terai C. odorata failed to produce seed below a light intensity of 6.5 mJ m\(^{-2}\) day\(^{-1}\), and that light intensity determined 93% of the variation in \(\log_{10}\) seed production per plant
(Chapter 4). This enabled us to map its distribution in Nepal based on under-canopy light intensities.

*C. odorata* invades new areas by generative reproduction (wind dispersal of pappus-bearing achenes). Once established, clonal propagation through underground corms enhances further expansion of populations. We have discovered (Chapter 5) that the age of corms can be determined using corm rings in cross sections. While individual corms survive for only five years, we obtained evidence that multi-corm genets, which must have been much older, had developed in forests with opened canopy. We furthermore demonstrated that light intensity positively related to the rate of clonal growth. The light dependence of the expansion rate of plants is apparently a key attribute explaining the invasion success of this species. Any disturbances in forest canopy density leading to increased light intensities would ultimately trigger its clonal growth.

The canopy in tropical forest ecosystems in Nepal is severely degraded offering light conditions suitable for *C. odorata*. The degradation of the forest canopy was attributed to a series of interrelated causes including human dimensions and government policies (Chapter 6). Herbarium records revealed that *C. odorata* invaded southern Nepal shortly after the initiation of malaria control. We furthermore demonstrated that this was followed in Chitwan district by an influx of migrants, land use changes and degradation of the forests. It was therefore argued that the species invaded because of canopy degradation, which was caused by change in land use and demography and triggered by malaria control. This process of malaria control followed by migration increased human population growth rates that we described for Chitwan district occurred in tropical regions all over Nepal. Hence, we suggest that it must have contributed to the rapid spread of *C. odorata* in the lowland Terai forest belt.

Field observations revealed that *C. odorata* did not invade the tropical forests in the west of Nepal below 83°45’ east longitude. We were unable to explain this distribution pattern with simple climatic indicators. However, a bioclimatic indicator, the length of the growing season predicted the absence from west Nepal remarkably well. This suggests that *C. odorata* requires a minimum length of the growing period to accumulate sufficient resources to establish and persist. We thus conclude that an agro-ecological modeling approach yielded a better prediction than the commonly used bioclimatic approach (Chapter 7).
Since, deforestation and forest degradation are a point of concern for management of both biological invaders and native biota, there is a need to more closely monitor biological conservation areas because of the potentially irreversible impacts of deforestation and forest degradation. In chapter 8 we assess the rate of deforestation and the current degree of forest degradation in the Terai of Nepal. Forest canopy density class was predicted with 82% overall accuracy. Data analysis revealed that the forested area reduced from 21774 km² in 1958 to 12649 km² in 2000 corresponding to an annual rate of decline of 1.38%. Our analysis further revealed that 70% of the forested area outside conservation areas had canopies with density below 60%, thus confirming widespread degradation. More surprisingly, 50% percent of the forested area inside protected areas had such opened canopies. This indicates that canopy degradation is also very common inside protected areas. These areas play a special role in the conservation of internationally threatened forest communities, for instance Nepalese tropical rain forests. Our analysis revealed that canopy opening prevailed as well in these communities. We argue that from a biodiversity point of view conservation effort should focus on the preservation and restoration of these forest types. The forest degradation maps presented in this chapter could serve as a start to prioritize such interventions.

In this thesis, we demonstrated how the impressive developments in computational performance, the rapid growth of remote sensing and GIS technologies for spatial data acquisition and analysis could be used beyond their traditional application in mapping canopy-dominant invasive species. We have shown how a few of these cost-effective mapping techniques can reliably be up scaled to the national level to map the distribution of even those invasive species that do not dominate the canopy of forest ecosystems.

This thesis emphasizes the importance of site-specific microclimatic variation and empirical observations of the species’ ecology, while applying remote sensing techniques in invasion studies. This could significantly reduce the uncertainties and the degree of “erroneous prediction”. Maps displaying seed-producing sites could be used to significantly reduce the costs of controlling C. odorata infestation by providing information on the spatial segregation of source and sink populations. These will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems. Such an approach may prove particularly valuable when implementing control measures under circumstances of limited capital and labour. This thesis also showed the necessity to understand the connection between the human historical, socio-economic, and cultural context with the environmental
conditions and the ecology of the invader. It facilitates conceptualising the situation and hopefully it also helps in translating research results into appropriate policy measures.
Abstract in Dutch (Samenvatting)

Al eeuwenlang dragen menselijke activiteiten bij aan de verspreiding van soorten. In sommige gevallen levert dit geen probleem op. Maar, de enorme toename van biologische invasies is een steeds grotere zorg voor natuurbehoud en -beheer. Van de diepste oceanen tot de top van de Himalaya verstoren invasieve soorten natuurlijke en door de mens gebruikte ecosystems. Dit vormt een bedreiging voor ons milieu; zowel voor de van oorsprong aanwezige planten en dieren als voor de gezondheid van het hele ecosystems. De snelheid waarmee dit gebeurt, neemt alsmaar toe en er is geen enkel teken van vermindering van het probleem. Pogingen om biologische invasies te voorkomen of terug te dringen zijn slechts in enkele zeldzame gevallen succesvol geweest. Daarom concentreren natuurbeheerders zich nu voornamelijk op het onder controle houden van de schade van zulke soorten in plaats van het totaal terugdringen van de soort. Beheerders en managers hebben meestal te kampen met beperkte financiële middelen en beschikbare arbeidskracht. Daardoor moet men interventies zorgvuldig plannen zodat men een zo groot mogelijk rendement kan behalen. Het is duidelijk dat daarbij informatie over de werkelijke en de potentiële verspreiding van een invasieve soort van cruciaal belang is.

Het is inmiddels bekend dat het gebruik van geografische informatie systemen (GIS) en verschillende aardobservatie technieken, ofwel remote sensing (RS), een goede bijdrage kunnen leveren aan het in kaart brengen van de verspreiding van al dan niet invasieve soorten. Tot nu toe is remote sensing voornamelijk gebruikt om soorten te karteren die dominant voorkomen in de bovenste laag van de vegetatie van het ecosystems. De grote meerderheid van alle invasieve soorten maakt echter geen deel uit van deze bovenste laag en blijft dus moeilijk rechtstreeks te detecteren met behulp van remote sensing technieken. Methoden om zulke wat moeilijker waarnembare en meer verborgen soorten in kaart te brengen zijn nog niet beschikbaar. In dit proefschrift worden methoden onderzocht om de verspreiding van een van de meest problematische invasieve soorten ter wereld, *Chromolaena odorata* (L.) RM King & H Robinson, in kaart te brengen.

Deze van oorsprong centraal Amerikaanse soort, waarvan men weet dat hij afhankelijk is van voldoende licht, komt tegenwoordig voor in de ondergroei van bossen in de gehele tropische zone van onze aardbol. *Chromolaena odorata* is in Nepal binnengedrongen in de bossen in het laaggelegen deel van het land, genaamd de Terai. De soort wordt voornamelijk gevonden op plaatsen waar het bos wat meer open is en waar voldoende licht door de boomkronen heen valt en de
ondergroei bereikt. In deze studie is geprobeerd eerst een methode te ontwikkelen om de dichtheid van het bladerdek van de bomen in kaart te brengen. Vervolgens werd dit vertaald naar de hoeveelheid licht die beschikbaar was voor de ondergroei. Tenslotte hebben we deze resultaten gerelateerd aan de verspreiding en verschillende eigenschappen van C. odorata.

De eerste stap in dit onderzoek was het creëren van een overzicht van alle bestaande methoden voor het in kaart brengen van de verspreiding van invasieve soorten. Dit is beschreven in hoofdstuk 2. Daarna werden vier verschillende methoden om de dichtheid van het bladerdek van de boomlaag te bepalen met elkaar vergeleken. Deze studie, beschreven in hoofdstuk 3, laat zien dat een neuraal netwerk het best presteerde in het meten van de dichtheid van het bladerdek. Een Landsat ETM+ satellietbeeld dat gebruikt werd in neuraal netwerk voorspelde met een nauwkeurigheid van 81% de lichtintensiteit die beschikbaar was voor de ondergroei in het bos. Deze lichtintensiteitkaart werd vervolgens als belangrijkste milieuvariabele gebruikt om de verspreiding van C. odorata te voorspellen. Hoofdstuk 4 van dit proefschrift laat zien dat in de Nepalese Terai, C. odorata geen zaad produceert als de lichtintensiteit lager is dan gemiddeld 6.5 mJ m⁻² per dag. Verder blijkt lichtintensiteit 93% van de variatie te verklaren in de log₁₀ getransformeerde zaadproductie per plant. Hierdoor is het dus mogelijk de verspreiding van deze soort in kaart te brengen op basis van lichtintensiteit die onder het bladerdek van het bos beschikbaar is.

Chromolaena.odorata dringt nieuwe gebieden binnen met behulp van generatieve voortplanting via zaad en windverspreiding. Zodra planten gevestigd zijn kan voortplanting en uitbreiding van populaties ook plaatsvinden via klonale groei en voortplanting via stengelknollen. We hebben ontdekt (hoofdstuk 5) dat de ouderdom van stengelknollen kan worden bepaald door een doorsnede te maken en jaarringen in de knol te tellen. Een individuele stengelknol blijkt maximaal 5 jaar oud te kunnen worden. Er werd echter ook gevonden dat in meer open bosvegetatie door aanmaak van steeds nieuwe stengelknollen, klompjes van die knollen een leeftijd bereikten die veel hoger lag. Tevens werd aangetoond dat lichtintensiteit positief gecorreleerd was met de mate van klonale groei. De afhankelijkheid van licht is blijkbaar de meest belangrijke eigenschap die het invasieve succes van deze soort bepaalt. Indien verstoring van de boomlaag in het bos leidt tot verhoging van de lichtintensiteit dan zal dit uiteindelijk Chromolaena odorata kunnen aanzetten tot klonale groei.
De kroonlaag van vrijwel alle tropische bosecosystemen in Nepal is zwaar gedegenererd en biedt lichtcondities in de ondergroei die geschikt zijn voor *Chromolaena odorata*. Deze achteruitgang kan worden toegeschreven aan een serie van aan elkaar gerelateerde menselijke activiteiten, beleid en management (hoofdstuk 6). Uit herbariumgegevens blijkt dat *C. odorata* via het zuiden in Nepal binnendrong kort na de eerste pogingen malaria te verdrijven uit het laagland. We hebben ook laten zien dat dit in het district Chitwan resulteerde in een toestroom van migranten, veranderingen van landgebruik en bosdegradatie. Daarom betoogt dit onderzoek dat *C. odorata* binnendrong als resultante van bosdegradatie veroorzaakt door veranderingen in landgebruik en demografie en uiteindelijk geïnitieerd werd door maatregelen ter controle van malaria. Dit proces werd uitgebreid beschreven voor het Chitwan district maar vond in feite plaats in alle laagland gebieden binnen Nepal. Daarom wordt gesuggereerd dat dit de oorzaak is van de snelle verspreiding van *Chromolaena odorata* over een zeer groot deel van de gehele laagland zone van Nepal.

Uit veldwaarnemingen bleek echter dat *Chromolaena odorata* zich niet verspreidde in het westen van Nepal, ten westen van de lijn met breedtegraad 83°45’ oosterlengte. Het bleek onmogelijk dit verspreidingspatroon te verklaren met behulp van eenvoudige klimaatfactoren. Maar de factor “lengte van het groeiseizoen” bleek in dit geval een buitengewoon goede indicator voor de verspreiding van Chromolaena. Het lijkt erop dat deze soort een bepaalde minimumlengte van de groeiperiode nodig heeft om voldoende reserves te ontwikkelen om zich blijvend te kunnen vestigen. Daarom concluderen we dat bij het in kaart brengen van *Chromolaena odorata* in het laagland van Nepal, de toepassing een agro-ecologisch model een betere benadering is dan de meer gebruikelijke bioklimaatmodellen (hoofdstuk 7).

Ontbossing en bosdegradatie zijn punten van zorg voor zowel het behoud van oorspronkelijke biota als voor het in de hand houden van invasieve soorten. Daarom is een goed monitoring programma nodig vanwege de mogelijk onomkeerbare gevolgen van ontbossing en bosdegradatie. In hoofdstuk 8 wordt ingegaan op de snelheid van ontbossing en de huidige stand van zaken betreffende bosdegradatie in het Nepalese laagland. De dichtheid van het bladerdek van de bossen werd vastgesteld en geclassificeerd met een nauwkeurigheid van 82%. Analyses lieten zien dat het bosgebied verkleind werd van 21774 km² in 1958 tot 12649 km² in 2000. Dit komt overeen met een gemiddelde jaarlijkse afname van 1.38% van het bosoppervlak. Verder bleek dat 70% van de bossen buiten de beschermde gebieden een dichtheid van het bladerdek hadden wat lager lag dan
60%, wat op verregaande degradatie duidt. Nog verrassender was dat 50% van de bossen binnen beschermde gebieden ook een dergelijke open structuur bleken te hebben wat ook ernstige bosdegradatie binnen protectiegebieden betekent. Deze gebieden spelen een belangrijke rol in de bescherming van internationaal bedreigde bosgemeenschappen zoals bijvoorbeeld de Nepalese tropische regenwouden. Verminderen van de dichtheid van kroonlaag bleek ook in deze bossen een algemeen voorkomend verschijnsel. Vanuit het oogpunt van bescherming van biodiversiteit is dus bescherming en herstel van juist deze bostypen erg belangrijk. Kaarten die bosdegradatie weergeven, zoals beschreven in dit hoofdstuk, kunnen een goed beginpunt zijn voor het stellen van prioriteiten bij dit soort interventies.

Uit deze thesis blijkt hoe de enorme uitbreiding in rekencapaciteit, de snelle ontwikkeling van remote sensing en GIS technieken voor het verzamelen en verwerken van ruimtelijke gegevens gebruikt kan worden buiten de traditionele toepassingen. Voorheen bleef de kartering van invasieve soorten vaak beperkt tot rechtstreekse waarneming van soorten die deel uit maakten van de toplaag van de bosvegetatie. Nu kunnen we ook indirect minder goed zichtbare soorten in kaart brengen. Daarnaast hebben we laten zien dat een aantal kostefficiënte karteringstechnieken met goede betrouwbaarheid van lokaal naar nationaal niveau kunnen worden vertaald.

Deze thesis benadrukt het belang van standplaats specifieke variaties in microklimaat en veldwaarnemingen van eigenschappen van een soort binnen de toepassing van GIS en remote sensing modellen. Zorgvuldige toepassing hiervan bij het in kaart brengen van invasieve soorten kan onzekerheden in uitkomsten verminderen en het risico op verkeerde voorspellingen terugdringen. Voor *Chromolaena odorata* kan het gebruik van kaarten die de zaadproducerende “source-populaties” ruimtelijk scheiden van de niet reproductieve “sink-populaties” een aanzienlijke vermindering in kosten opleveren voor het in de hand houden van deze soort. Hiermee kunnen namelijk veel beter prioriteiten gesteld worden voor wat betreft in welke gebieden interventiemaatregelen genomen moeten worden. Dit is in alle gevallen van belang maar zeker in omstandigheden waar kapitaal en arbeidskracht slechts zeer beperkt beschikbaar is. Tenslotte blijkt uit deze thesis dat het noodzakelijk is een goed begrip te hebben van de historische, sociaal-economische en culturele context in samenhang met de milieuomstandigheden en de eigenschappen van de invasieve soort. Dit maakt het mogelijk de situatie goed te doorzien en hopelijk de onderzoeksresultaten te vertalen in doeltreffende beleidsmaatregelen.
Abstract in Nepali (सारांश)

शतांत्र देखि मानव धरा तिन्द्र पारुएको मिथिका प्राणीको अवक्रमणको गति कम हुने सकेक देखि ऐको हो। प्राणका मात्रासम्म गहिराई देखि हिमालयाका उचाई सम्म आफ्नो प्राकृतिक वासस्थान बाट विभिन्न प्राकृतिक जीवपरिवृत्ती तनत्रमा हुँदा दरमा फैलिएको बिचुरो प्राणीले मानव, जनता, वनस्पति तथा जीवपरिवृत्ती पहुँचीको वस्तुचनालाई चुनिन्त मिथिला कृति चाहिँ। यी प्राणीहरूले पैरलाइबर रहेको नयन नयन गति र निमुड पने जनको अर्थ न्युन प्राणी समुदायका मानक सफल देखि हुँदैन। त्यसैले हालसाँग निमित्त पाँचेन भन्दा व्यवस्थापन गर तिनहरुको अवक्रमण प्राप न्युन गति निभाउँ र र्ङुङ्खो प्राकृतिक प्रवालक आधार हरू गति वाच्य व्यक्ती इरिएको हुँदैन। त्यसैले मिथिका प्राणीहरूको व्यवाह वस्तुचनालाई र वासस्थानको जानकारी हुने अर्थ आवश्यक हुन्।

लामा समयदेखि हुन सवेदन तथा भू-सुस्तना प्राणीहरू यस क्रममा योग्य निष्कर्ष पुनरुत्थान सके प्रामाणण भएको हुँ। तापिन्द्र हुँदा सवेदन प्राणीको प्राकृतिक पर्वर्त्तको माध्यमले तहमा बास गर्न जगतीहरूमा भलाई लागि गर्न सकिएको हुँ। मिथिका प्राणीहरूको तथाकथा अर्थ ठुलो संचालण मिथिका प्राणीहरूको प्राकृतिक पर्वर्त्तको माध्यमले तहमा बास गर्न धेरौँ देखि हुँदा सवेदन प्राणीहरूको प्राकृतिक प्रवाल गर्न सकिएको हुँ। अतः यसता लुकेक बनने प्राणीहरूको माध्यम प्राकृतिक विकास भएको छ। त्यसैले प्राकृतिक जीवपरिवृत्ती पहुँचीको लुकेक बनने यसता मिथिका प्राणीहरूको माध्यममा मैले नया प्राकृतिक सुस्चाहाको छ। यस प्राकृतिक प्रशासक (Chromolaena odorata) व्यवस्थानको वाच्यक तथा वस्तुवाच्य माध्यममा प्रवाल गर्न। यो नस्तास्ति संसारका १०० सबै भन्दा खरा मिथिका व्यवस्थानको अर्थमा पवित्र। यो सारका उपाध्याय देशहरूले बन जगल भिन्न प्रकारको हुँ। यस अध्ययनमा सबै प्राकृतिक बन जगल को मध्यमले तह तथा बन जगल को तल्लो को सम्म पुनरु गर्ने प्रक्षाल जागी प्रसाधनका विविधहरूको विविधान गर्न। तत्व प्रचारिक प्रकाश माध्यमका नक्सलहरू संग नमनराखिक प्राकृतिक विविध प्रक्षालहरूको सम्भव स्थापित गरिएको हुँ।

आरम्भ खण्ड २ मा मिथिका वनस्पति माध्यम विविधहरूको सिहारेकोत्तर गरिएको छ। तत्त्व प्रचार पनि घनत्व माध्यमका बार देखि प्राकृतिक विविधहरूको स्थापङ्को अविचार गरिएको हुँ (खण्ड ३)। प्रकाश माध्यमको तसै प्रकाशीय अध्ययनमा समुठ तनको बन जगल प्राकृतिक बाट बन घनत्व घनत्व लाई तपाईले ८१ प्रकृतिलाई सप्तपाठाका साथ माध्यम गर्न सकिएको परिमाण देखिएको हुँ। यस प्राकृतिक अर्थ गतन विद्वानको प्राकृतिक बनले वीट सन्तति प्रति गर्न तथा न्युन भ्रमण परिक्रमा दिने देखिएको हुँ।

यस प्राकृतिक प्रकाशमा ८१ प्रति प्रति बन प्राकृतिक जीवपरिवृत्ती पहुँचीको तल्लो को सम्म पुनरु प्रकाश लाई नयन सकिए देखिएको। यस्तैले प्रकाशित प्रकाशमा ६५ माइको जुन प्रति बन प्रकाश दिन न्युन प्रकाश पनि नपालको तराइका स्थानहरूमा विह उपाध्यय गर्न सकिएको हुँ। बीच हुँदा निर्देशिका ६९ प्रति प्राकृतिक सप्तपाठाका वीट प्रकाश माध्यम बाट गर्न सकिएको हुँ। तल्लो तहमा पुनर्दै प्रकाश माध्यमको हामिलिका नेपालमा वनमाध्यमका व्यवस्थापण माध्यम गर्न समय प्रदान गर्नुको लागि (खण्ड ४)।
बन्नमारले तया प्रसारत विउँहुवाँट नयाँ स्थानहरू मिल्ने गर्दछ। एक पटक स्थापित विरामको
जमिन मूल रहेको गानोले बारा पल्न आफ्नो संख्या बढी गरिन्छ। यो परिणामै सँगो जीवने गानो
गराले तुल्यावाहन र खेल्दा रहेको छ। युवानांसँगो "गानो जीवने गर्ने र खेल्दा रहेको छ। यो
परिणाम प्रारम्भको अहम भूमिका रहेको छ। यो लौचनको यसको मिथिहास प्रकारहरूको सफलता को मूल घर
भएको देखिन्छ। बन
पारिणामलाई कृपाले देखिन्छ हुँदा, बन्नमारले हे-जबू जीतोपन्नको बढावा दिने गर्न। एको गानो
पार्श्व वर्ण समय मात्र जीवित रहन सक्छ, तापिन वहुगामायुक विरुचा खुला बन्दुव्र मूल दीघ–
जीव हुन सक्छ।

नेपालको उष्ण बन बातावरणको माध्यमले तहमा निर्देश रूपमा देखि हुनेछ र बन्नमारले
गानोले निर्देश भित्रहाँ माध्यमले प्रक्षेपित भएको छ। यो जनसङ्ख्या तथा सरकारी
स्वीकार लागाउँको जोरले अवलोक–सवोध संग गायिकाको छ। (खेल्दा ६)। बन
परिणाम नूतना
विश्वासण ने पारिवारको तराई क्षेत्रमा आफ्नो उन्मुक्त सँगी बन्नमारले भित्रहाँ संगो देखिन्छ।
ौँ उन्मुक्त पर्यावरण भित्रको तराई तिर पुसाइ में कम तिय भए। यसले भू-भाल तरा
भू-उन्मुक्त पर्यावरण तारी क्षेत्र तथा जोग पाऊको माध्यमले उल्लेख बढी भई बन परिवर्ती
प्रतिरोधको माध्यमले तहमा धर्मको विवाह तथा अन्य भाषाको कवरण
निम्नगरको बन विवाह तथा अवलोक चर्चणे अन्य रैयाने वितरको वाहनका रोकी बन्नमारको बढी
तथा वैकल्यको लागि सुहाउँदै बातावरण मूलमा गन्ने टेका पुकारमा यो भए। रैयाने भित्र
वितरण नियमामा जीर्णको भए तपाईले यो यिक्रेयान्त ने पारिवारको तराई क्षेत्रको प्रतिनिधित्व देखिन्छ।

हाल नेपालमा बन्नमाला हैरान्त नवरा परिणाममा फैलिएको पाइँदै। साधारण
बातावरणको सुचकर हुँदा वस प्रजातिको फैलावट प्रदायन सहकर्ता पाइने बनसाइत हुक्को
आवश्यक मूलमा समय (Length of growing season) जस्ता कृषी-बातावरण सुचकर हुँदा
परिणामले यस वितरको अनुप्राप्तित प्रदायनुँ। स्थायित परिणामले जोगमक्को
प्रक्राश तथा मात्र दंगको निजीको निर्देशण बनामको बासस्थान तथा देखि हुने मने राष्ट्रीय सरकार
बनसाइत हुक्को आवश्यक मूलमा समय तथा ताप्तमकिले बनामको बासस्थान मिलाउँ पल्ने
पाइँदैको छ। विरुचा बढीको लागि यादि भएको मूलमा समय परिवर्त्तन नेपालमा पुसाइ भएको माध्यम
उल्लेख रूपमा देखि कम हुँ। जसको गन्ने बन्नमारले हुक्क, फल तथा फल जमा पाने गन्ने
भोजन भट्टे मात्र मूलमा नून हुँदै देखिन्छ। यसैले यो भने सकिन्छ कि कृषी-बातावरणको नूतना
विधिबन्नमाले कृषी-नूतना अनुप्राप्तिको माध्यम छ भरप्राय सकिन्छ। अति: कृषी-
बातावरणको सुचकर हुँदा बनामको माध्यम छ। उपयोगी सिक्क भएको छ। (खेल्दा ६)।

नेपालमा सरकार द्वारा विनियमित बनामको अवस्था द्वारा देखिन्छ। तथापि मौली
निम्नलिखित नेपालमा यस विधिको नेपालीको छ। भने प्रसार आफ्नो गाडी।
मिथिहास तथा रैयाने प्राणी माध्यममा बन विवाह र क्षेत्रले महत्त्व भूमिका रखेको छ। यो प्रक्षेप
अर्ने चाहिएको विषय हो। खेल्दा ८ मा नेपालको तराईमा बन विवाह र अर्ने सरकारी
विवरण गर्नेछ। बनसाइत घरोखुली एक प्रतिनिधि सर्क्याका साथ माध्यम गन्ने सकिन्छ।
तथापि विश्वस्तिय नून ९३४ मा पैकेको २६७५३ वर्ग किलोमिटरबन क्षेत्रमा नून २०००
सममा आई पुष्प वार्षिक १३८ प्रतिशतका दर्श घटी १२६४९ वर्ग किलोमिटर बाँकी रहेको

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यह अनुसंधान बाट ५० प्रतिशत सरस्थित क्षेत्र वाहरका जंगलको छैन ६० प्रतिशत भन्ना कम रहेको देखिन्छ । यसले अन्यायिक बन विनाश र धर्म भएको पुष्टी हुन्छ । अन्यायको अर्को वरु, सरस्थित क्षेत्र भिविको बनको ५० प्रतिशत हुन समेत खुला हुन। यसले नेपालका सरस्थित क्षेत्र भिविक समेत बन छैन विनाश भैज्ञहरूको तथा उजागर छैन । यही क्षेत्रहरूले अन्तराटीय रूपमा लोपनिवृत्त बन प्रकाशरको संरक्षणमा महत्वपूर्ण भूमिका खेलने गरेको छ । यस अनुसंधान बाट यस्ता बन प्रकाशरका समेत बनद्दृढ़तको विनाश भएको देखिएको छ । एकक विविधताको टुटुटकोनले यी बनप्रकाशरको संरक्षणमा विशेष ध्यान दिनुपर्निमा मा जोड दिन चाहन्छ । यस खण्डमा प्रकाशरका वन विनाशका नकारहरूले बन संरक्षणमा अत्यन्त भूमिका खेलन सक्छ ।

यस शोध पत्रमा मैले दुर संवेदन तथा भू-सुचना प्रणालीको प्रभावकारी विकासले भू-तवायक सकलन, प्रशोधन तथा विश्लेषणका निकृष्ठ सम्बन्धनाहरू देखाएको प्रमाणित गरे । यस पहाडिद्वारा परम्परागत भू-सुचना उपयोगको भन्ना पर वनजगलको तल्लो तहमा नुकेर बने मिथुनाहरूले वनस्पति मान्य समेट गरे सकिन्छ । खिच प्रभावकारी यह विविध द्वारा बनजगलको यथावच वितरन तथा मिथुनाहरू प्रणालीको ग्रामीण स्तरस्तर महत्वपूर्ण मान्यको मैले यस अनुसंधानले बन वातावरण तथा वनमार्ग विरुध्यापनमा महत्वपूर्ण योगदान पुनरुत्थान छ । मैले आशा लिएको छ ।

यस अनुसंधानले सुधार-मौषम तथा ध्वनि ग्रामीण अवलोकनलाई प्राप्तिकरात दिन्छ । नीउ उपराम स्थान नस्लाई नीउ उपराम हुने बाहिरी नयाँ जानकारी दिइ । बनमारादि नियन्त्रण बर्चमा उल्लेख कमी त्याउन महत्त्व पुनरुत्थान छ । यसले प्रभावकारी प्रणाली वास्तविकताको तह निर्धारण गर्न मिथुनेर र मिथुनेर जीव परिवार पहूली पूर्णतिको पुनरस्थापनमा सहयोग गरे छ । खासगरी अनुप मजेंट तथा मानव समाज परिवर्तन यो नियन्त्रण उपयोग नीउ भूभूमि सारिन हुन सक्छ । अत्यन्त यस अनुसंधानले मानव इतिहासको सामाजिक, आयोकका तथा सार्थकता पहुँच र महत्व पयावरण तथा मिथुना हाँ। विविध नियन्त्रको सम्बन्धको स्थान भांत हुनुपर्निमा मा जोड दिएको छ । यस अनुसंधानले परिस्थितिको यथावच प्रणाली गर्न भन्ना यसको निर्माण उपयुक्त नीति निर्माण गर्न मा समेत सहयोग पुनरुत्थान छ । मैले विश्वास लिएको छ ।
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P.S.: Please address all future communications to me at my ITC e-mail address: joshi@itc.nl or National Herbarium, Godavari, Kathmandu, Nepal.
CHAPTER ONE

Mapping cryptic invaders and invasibility of tropical forest ecosystems
1. Mapping cryptic invaders and invisibility of tropical forest ecosystems: *Chromolaena odorata* in Nepal

1.1 Consequences of biological invasions

Invasive species have intrigued ecologists for long (Elton 1958). In recent years, the establishment and spread of such species in areas where they do not occur naturally, are receiving increasing importance from scientists, policymakers and the public. Numerous studies demonstrated the dramatic effect of invaders on recipient ecosystems (Mack *et al.* 2000). Introduced species are among the greatest threats to native biological diversity and the functioning of natural ecosystems. Bio-invasion has been homogenizing the world’s flora and fauna (Hobbs 2000a), altering bio-geo-chemical cycles (Polley *et al.* 1994) and is recognized as a primary cause of global biodiversity loss (Czech and Krausman 1997, Wilcove and Chen 1998) and species extinction (di Castri 1989).

1.2 Invasive species and biological invasion

What are “invaders”? The verb “to invade” meaning “to enter in a hostile manner” has existed for about 500 years (Oxford English Dictionary 1989). “Invasion” originally referred specifically to human warfare, the “action of invading a country or territory as an enemy”. Its meaning then expanded to include “a harmful incursion of any kind”. In law and philosophy, the meaning includes “encroachment upon the property, rights, privacy, etc of anyone”. The current meaning combines the concept of entering a foreign territory and having some short of harmful impact.

What does the terms invaders and invasion stand for when used in an ecological context? Elton, “the father of invasion ecology” did not seem it necessary to define these terms in his classical book on invasion (Elton 1958). Since then, a number of definitions of invaders and invasion have been proposed. Kolar and Lodge (2001) defined invasive species as “a non-indigenous species that spreads from the point of introduction and becomes abundant”. According to di Castri (1990) “A biological invader is a species of plant, animal or micro-organism which, most usually transported inadvertently or intentionally by man, colonizes and spreads into new territories some distance from its home territory”. Definitions for the common term ‘invasive’ include non-indigenous species that have colonized natural areas (Burke
and Grime 1996) as well as widespread species that have negative effects on the recipient ecosystem (Davis and Thompson 2000, Mack et al. 2000). Richardson et al. (2000) proposed a biogeographical approach that described invasions as a process in which non-indigenous species progress through ‘established’, ‘naturalised’, and ‘invasive’ stages. Based on similar approach, Colautti and MacIsaac (2004) proposed an invasion stage based neutral terminology under which, a non-indigenous species passes through localized and numerically rare to widespread and dominant stage.

Several terms have been used more or less synonymously to address invasive species including aliens, naturalized species, non-indigenous, invaders, pests, colonizers, weeds, immigrants, exotics, neophytes, transformers and introduced species (Jarvis 1979, Heywood 1989, Dukes and Mooney 1999, Lonsdale 1999b, Williamson 1999, Berdichevsky et al. 2000, Brabec and Pysek 2000, Colautti and Maclsaac 2004) or even more colourful terms, for instance bioterrorists (Meyerson and Reaser 2003). These terms however have different meanings (Binggeli 1996, Alpert et al. 2000, Richardson et al. 2000). The mixing of closely related terms that do not articulate exactly the same concept may confuse ecological debate (Thompson et al. 1995, Richardson et al. 2000, Daehler 2001, Davis and Thompson 2001, Rejmánek et al. 2002, Colautti and Maclsaac 2004). Surprisingly almost all authors used the word “invasive” to define “invasive species” (or “invasives”) without a common definition.

The definitions given above differ in the ones, that include an element of harm and those who do not (Pyšek 1995, Daehler 2001). Richardson et al. (2000) remarked that there is a gradient of invasive species without any impact on their environment towards species with an increasing intensity of impact. He used the term “transformer species” proposed by Wells et al. (1986) for those invasive species, which “change the character, condition, form or nature of a natural ecosystem over a substantial area”. In the context of this thesis, we considered the definition that includes “spatial spread” and “harmful impact” of the elements associated with the concept of an “invasion” is more useful than one that does not.

### 1.3 Species invasiveness

The term invasiveness is used to describe species with inherent traits making them successful invaders. In other words invasiveness is traits that enable a species to invade a new habitat (Alpert et al. 2000). As Vitousek et al. (1995) clarified invasiveness is the establishment of self-sustaining plant populations that are
expanding within a natural plant community with which they had not previously been associated”.

Most introduced species do not find a tolerable environment nor an available ecological niche, hence do not survive (Lodge 1993). It is estimated that 10% of exotic species get established while only 1% become invasive (Groves 1991). So, only a fraction of all introduced species become invasive. What makes an introduced species a successful invader? Almost all successful invaders are opportunist species characterized by a ruderal strategy (Grime 1979). It has been claimed that invasion success depends on inherent species’ traits such as genotype, mechanism of seed dispersal, germination requirements, reproductive capability and their competitive ability (Baker 1965, Rejmanek and Richardson 1996, Molofsky et al. 1999).

1.4 Invasibility of ecosystems

Others maintain that exotic species become successful invaders because of the invasibility of the recipient ecosystem to invasion. Invasibility has been defined as a measure of an ecosystems’ susceptibility to colonization by exotic species (modified from (Ewel 1986, Smallwood 1994)). When considering an invasive species from the angle of the invasibility of the recipient ecosystem one focuses on factors and site properties that make the ecosystem prone to invasion rather than traits of the species. Davis et al. (2000) formulated a number of testable predictions for plant invasibility, for example, that environments will be more susceptible to invasion during a period immediately following an abrupt increase in the rate of supply or a decline in the rate of uptake of a limiting resource. A better understanding of factors determining invasibility may offer a way to predict the spatial extent, rates and directions of spread of invaders.

1.5 Information requirements for invasive species management

Initially invasive species management aimed at eradication. Experience has learned however, that this is not achievable except for very few cases. Currently, therefore invasive species management aims at control of invaders and mitigation of their impact rather than eradication. Limitation of resources forces invasive species managers to carefully plan and prioritize interventions. Ideally, priority should be given to interventions, which optimize benefits in terms of damage reduction and durability and cost effectiveness. This could typically be realized in areas more severely affected by invaders. Information on the actual and potential distribution of
invaders is considered crucial for their management (Reichard and Hamilton 1997, Rejmánek 2000). As Edward O. Wilson (Wilson 1997) has noted, "Extinction by habitat destruction is like death in an automobile accident: easy to see and assess. Extinction by the invasion of exotic species is like death by disease: gradual, insidious, requiring scientific methods to diagnose." Maps predicting the severity of the impact and damage could thus be used to localize areas requiring interventions most urgently. To this end, the development of advanced remote sensing and GIS technologies offers remarkable possibilities.

1.5.1 Remote sensing and Geographical Information System

Since Elton's time, ecologists have struggled to account for the distribution and spread of alien species. Remote sensing and GIS have successfully been applied to map the actual and potential distribution of invasive plant and animal species (McCormick 1999, Haltuch et al. 2000, Stow et al. 2000). Remote sensing applications appear to be restricted to detection of invasive species dominating the upper layer of the invaded community (McCormick 1999, Coulter et al. 2000, Haltuch et al. 2000). We however observed (Chapter 2) that 67% of the world's 100 worst invasive species (ISSG 2004) do not dominate the ecosystem canopy, and hence can not be detected directly through remote sensing. Most of these cryptic invaders are small and go unnoticed or are hidden from remote sensing devices for instance when growing in the understorey of forest (Pysek and Prach 1995, Gerlach 1996, Chittibabu and Parthasarathy 2000). Indeed detection of forest understorey species using remote sensing has hardly been attempted (Jakubauskas and Price 1997).

Applying remote sensing to mapping cryptic invasive species is not straightforward since the captured spectral information will not be directly attributable to these species. Species spectra models can thus not be inverted to predict their distribution. Remote sensing thus has little to offer to cryptic invaders successful mapping because of their invasiveness. It could however offer far little explored possibilities in those cases where the invasibility of the recipient ecosystem determined the invaders' success.

Such case might occur in degraded forests invaded by exotic species, which are adapted to increased light intensities associated with the opening of the forest canopy. Potentially, a combination of remote sensing, GIS and ecological knowledge could be used for mapping the distribution of understorey invasive species based on remotely sensed information on the degree of degradation of the forest
overstorey. So far, such techniques have to our knowledge not been used to predict the distribution of invasive species.

### 1.5.2 Scientific challenge and objectives

We consider it scientifically challenging and desirable from a societal point of view to develop accurate and adequate means of mapping and modeling the distribution of cryptic invasive species over larger areas. The research proposed here aims at the development of remote sensing and geographical information techniques relevant for management of such cryptic invasive species.

The objectives of this thesis are:

- To review published approaches to mapping of invasive species, the application of remote sensing and GIS techniques in there, define the limitations of these approaches and identify possibilities for innovation of mapping and modeling invasive species distribution.
- To investigate the possibility of predicting from satellite remote sensing the forest canopy and light intensity penetrating through the canopy as indicators of the invasibility of forest ecosystems.
- To develop a technique to model spatial distribution of a cryptic forest understorey species *Chromolaena odorata* (L.) RM King & H Robinson in Nepal and its population ecology and to predict its reproductive success.
- To develop a model to predict the vegetative expansion of *C. odorata* based on knowledge of the influence of light intensity on the dynamics of its vegetative reproduction.
- To investigate the chain of causes that made lowland forest ecosystems in Nepal susceptible to invasion.
- To upscale local pattern to regional processes of ecosystems invasibility to localize areas or ecosystems most critically require interventions to control such invasive species.
- To make an integrated assessment of the complexity of deforestation and forest degradation for biological conservation in the tropical regions of Nepal.
1.6 Materials and method

1.6.1 The species: *Chromolaena odorata* (L.) R. M. King & H. Robinson and its biology

*C. odorata* (family Asteraceae, sub-family Lactucoideae tribe Eupatoriae; commonly known as Syam weed) is a Central American shrub that has become highly aggressive invasive throughout many tropical countries (McFadyen and Skarratt 1996). *C. odorata* was originally classified as *Eupatorium odoratum* L. (Syst. 10 (2):1905) but subsequent revision by King and Robinson (1970) resulted in the species being assigned to the genus *Chromolaena* DC (The name of the plant is based on Greek and refers to the bracts: *chroma* = colour and *chlaena* = cloak or blanket, also Latin *laena* = cloak). *C. odorata* is characterized by white, reddish or bluish flowers lacking ray florets. The species is distinguished by the three prominent veins in the leaves; rather consistent pattern of many rows of phyllaries (bracts) that are progressively longer and give a markedly cylindrical appearance to the head; straw-coloured, narrow-linear, angled bristly achenes having short white stiff cilia on the angles; and by the pungent odour emitted by the crushed leaves.

The worldwide range of expansion and the large economic and ecological impact of this species has been widely addressed (Epp 1987, De Rouw 1991, Gautier 1992b, Akpagana et al. 1993, McFadyen and Skarratt 1996, McWilliam 2000, Leslie and Spotila 2001). It has been therefore listed among the one hundred of the world’s worst invasive species (ISSG 2004). *C. odorata* is a clonally growing multi-stemmed erect, diffuse, scrambling heliohytic shrub grows up to 2m or higher; often forming dense thickets. Every clone consists of a root system with a corm (a modified stem to store food reserve under ground) supporting a number of shoots. *C. odorata* has a ruderal strategy and occurs in a wide range of environments including road verges, neglected agricultural fields and as an understorey species in forest. As a heliophyte (Gautier 1992a), it requires sufficient light to grow and produce seeds (Erasmus 1985, Witkowski and Wilson 2001).
1.7 Study area

1.7.1 Local scale

In order to represent the range of ecological conditions in Nepal, at local scale, a north-south cross section of central Nepal has been selected for this study. The area is located between 84° 15’– 85° 15’E longitude and 27° 00’ – 27° 45’N latitude. This section is an eye view of vertical and horizontal (to some extent) biogeography of Nepal where east and west floristic region meets. It has an undulating extremely diverse hilly terrain with an altitude of below 100 to 2500m above mean sea level. It includes some parts of inner valleys of relatively flat plains, most parts of the east west running the Churia hills (first foot hills of massive Himalayan mountain chain) and some part of the Mahabharat (inner mountain range), representing most of the Nepalese ecosystems.

Figure 1-1. Map of the world (top); ETM+ mosaic image (band 7, 4, 2) of Nepal, the study area at national scale (middle) and ETM+ image (band 7, 4, 2) of part of the Chitwan district, the box showing the location of the study area at local scale (below).
1.7.2 National scale

Nepal (latitudes of 26º 22' N and 30º 27' N and longitudes of 80º 04' E and 88º 12') covers an area of 147,181 sq. km, with a length of about 885 km, and an average width of 193 km (Figure 1-1). Although it covers a small geographic area, it represents 118 ecosystems and is one of the world’s richest pockets in species diversity. Two-third of the area is occupied by hills and mountains that rises from the Terai, the northernmost part of Indo-Gangetic plain at about 59 m in the south to the crest of the Himalaya reaching upto 8848 m altitude in the north. The presence of extreme ranges of altitude has created a striking vertical zonation in climate, soil or land use within a small geographical area that makes it a paradise for many invasive plants including *C. odorata*.

1.8 Outline of the Thesis

This thesis represents a collection of research papers partly accepted or published in peer reviewed journals and international conference proceedings.

**Chapter 1** provides a general introduction on invasion and invasive species and the application of GIS and remote sensing techniques in mapping and modeling the distribution of invasive species. It outlines shortcomings of current attempts in mapping invasive species. Next it states the research problems and objectives introduces the invasive shrub *C. odorata* and the study area.

**Chapter 2** reviews the application of remote sensing and GIS in mapping actual and predicting potential distribution of invasive species. Distinction is made into four categories of invasive species based on whether they appear in and dominate the ecosystem canopy or not. The argument was that the possibility to apply remote sensing to map invaders differs between these categories. This review summarizes remote sensing techniques applied and outlines the potential of new remote sensing techniques. It also demonstrates that remote sensing has so far been applied predominantly to canopy dominant species. This contrasts with our findings revealing that the large majority of the world’s worst invasive species do not dominate the canopy. The mapping of these invaders received little attention so far. The chapter also reviews techniques used to map the risk of invasion for areas not invaded so far.

As we intended to map the distribution and biometry of *C. odorata* from the degree of openness of forest ecosystems, we first investigate the possibility of predicting
forest canopy density from satellite imagery over large areas. In recent years a number of alternative methods have been proposed to predict forest canopy density from remotely sensed data. However, it remains difficult to decide which method to use, since their relative performance has never been evaluated. In Chapter 3, the performance of 1) an artificial neural network, 2) a multiple linear regression, 3) the forest canopy density mapper and 4) a maximum likelihood classification method was compared for prediction of forest canopy density using a Landsat ETM+ image. Comparison of confusion matrices revealed that the regression model performed significantly worse than the three other methods. As a continuous variable, about 89% of the variance of the observed canopy density was explained by the artificial neural network, which outperformed the other three methods in this respect. Moreover, the artificial neural network gave an unbiased prediction, while other methods systematically under or over predicted forest canopy density.

Remote sensing has so far been applied predominantly to canopy dominant species. The mapping of forest understorey invaders has received little attention so far. In Chapter 4, possibilities of not only mapping the presence and absence but also seed productivity of such invader were revealed by applying canopy density mapping classifier in combination with GIS expert knowledge, biophysical factors and field data. The relation between light intensity, forest canopy density and other environmental variables and the cover and seed production of C. odorata was established and these models were inverted to predict its seed productivity. Light intensity determined 93% of the variation in log₁₀ seed production per plant. C. odorata failed to produce seed below a light intensity of 6.5 mJ m⁻² day⁻¹. Further analysis revealed that C. odorata was absent above this light intensity in case of a high biomass of other shrub and herb species, a situation occurring in the absence of grazing. We therefore suggest that other species control C. odorata through competitive exclusion in the absence of grazing, whereas grazing breaks the dominance of these other species thus creating the conditions for C. odorata to rise to dominance. Predicted C. odorata cover and seed production per plant were combined into a map displaying an index of the seed production per unit area. Such map displaying seed producing sites could be used to significantly reduce the costs of controlling C. odorata infestation.

Plant invaders establish through dispersal of propagules, typically in the form of seeds. Once established, they may further increase their local dominance by vegetative regeneration. Vegetative regeneration in the short-lived perennial C. odorata is clonal. The corm stores food reserve under full light conditions and increases in size over time. In Chapter 5, we investigated how vegetative spread of
C. odorata was determined by light intensity. We first described the presence of year rings in the corms of C. odorata. These “corm rings” allowed us to estimate the age of individual plants. We next sampled a large number of plants under a range of light conditions. We demonstrated that the increase of corms biomass over time was controlled by light intensity. Corm biomass increased with plant age in open and medium open forest, but not in closed forest. We next demonstrate that the size of the plants as expressed by the number of shoots depended on the biomass of the corm system. Hence there appears to be a positive feedback under high light conditions more resources are allocated to corms, allowing next season to enlarge the photosynthetic apparatus, which subsequently allows allocation of more resources to the corms. Light intensity apparently controls this feedback and the possibility of C. odorata to develop vegetatively. We finally predict from forest canopy density areas where C. odorata populations are expected to expand vegetatively.

“What made this exotic species a successful invader?” is a fundamental question in managing invasive species. Was it the intrinsic ability of species to invade or the susceptibility of the ecosystem to invasion? Chapter 6 addresses these questions for the invasion of C. odorata in the Nepalese Terai. In Nepal, malaria control increased human population growth rates to levels exceeding 10% per year in the 1960’s. This resulted in land use change and scarcity of grazing lands outside forests. The increasing demand for grazing and wood resources resulted in an opening up of the forest canopy. It is deduced that the pressure to exploit the forests for grazing increased over time as a result of land use change and increased human population density. Our results indicate that the neotropical shrub C. odorata maintains invasive populations at canopy densities below 60%, which prevail in forests with opened canopies. Hence, C. odorata invaded because canopy opening made the environment suitable for it. Herbarium record revealed that C. odorata invaded southern Nepal shortly after the initiation of malaria control and degradation of the forests. We therefore argue that the degradation and opening of the canopy of the low land Nepalese forests facilitated and accelerated C. odorata invasion which was caused by change in land use and demography triggered by malaria control.

Chapter 7 we presented the expert, empirical expert and principal component analysis based model to predict presence and absence of C. odorata in Nepal. Selection of explanatory variables was largely based on our understanding of species autecology and empirical observation. High resolution interpolated climate surfaces derived from the SRTM and a combination of altitude, precipitation and
length of growing season for *C. odorata* allowed us to predict its distribution with 80% accuracy. While the principal component analysis could predict its distribution with 86% accuracy. Furthermore, very high resolution interpolated surfaces data are more robust in delineating climatic variability within which *C. odorata* could thrive. Furthermore, coarse scale for species prediction is not appropriate for country similar to Nepal where topographic and climatic variation is high because course scale can not deal with all response shape.

**Chapter 8** assess the spatial extent and severity of deforestation and forest degradation processes in the Terai district of Nepal using field survey records, existing vegetation maps, and remote sensing data to determine the different degrees of deforestation and forest degradation. Our results showed that 66% of the total forest area in Terai region had canopy cover below 60% thus confirming widespread degradation. More surprisingly fifty percent of the forested area inside protected areas had similar open canopies. This study demonstrates the effectiveness of remote sensing in retrieving and analyzing of such data, in particular for detection, extrapolation, and interpretation, area calculation, upscaling and monitoring to make geo-referenced information easily accessible to non-GIS users. This study provides useful information for improving planning strategies for sustainable forest management. The forest degradation maps presented in this article could serve as a start to prioritize such interventions.

Finally, **Chapter 9** synthesizes the findings and conclusions of previous chapters and discusses the research approach applied in mapping, modeling and managing cryptic invasive species. It summarizes what we have learned and proposes a plan for dealing with invasibility of tropical ecosystems in Nepal. It outlines a road leading managers and restoration ecologists towards the restored biotic world we desire and deserve.
CHAPTER TWO

Remote sensing and GIS applications for mapping and spatial modeling of invasive species

This Chapter is Based on:
2 Review: Remote sensing and GIS applications for mapping and spatial modeling of invasive species

Abstract

Biological invasions form a major threat to the sustainable provision of ecosystem products and services, both in man-made and natural ecosystems. Increasingly, efforts are made to avoid invasions or eradicate or control established invaders. It has long been recognized that remote sensing (RS) and geographical information system (GIS) could contribute to this, for instance through mapping actual invader distribution or areas at risk of invasion. Potentially GIS could also be used as a synthesising tool for management of interventions aiming at invasive species control. This chapter reviews the application of remote sensing and GIS in mapping the actual and predicting the potential distribution of invasive species. Distinction is made into four categories of invasive species based on whether they appear in and dominate the ecosystem canopy or not. We argue that the possibility to apply RS to map invaders differs between these categories. Our review summarizes RS techniques applied in here and outlines the potential of new RS techniques. It also demonstrates that RS has so far been applied predominantly to canopy dominant species. This contrasts with ecological databases revealing that the large majority of invasive species do not dominate the canopy. The mapping of these invaders received little attention so far. In this chapter, we reviewed various possibilities to map non-canopy invader species. The chapter also reviews techniques used to map the risk of invasion for areas not invaded so far.

Key words: Review, Remote sensing, GIS, Invasive species, Classification, Mapping techniques, Scale, Sensors, Challenges

2.1 Biological invaders

Invasive species are a current focus of interest of ecologists, biological conservationists and natural resources managers due to their rapid spread, threat to biodiversity and damage to ecosystems. Invasions may alter hydrology, nutrient accumulation and cycling, and carbon sequestration on grasslands (Polley et al. 1997). The global extent and rapid increase in invasive species is homogenising the world’s flora and fauna (Mooney and Hobbs 2000) and is recognized as a primary cause of global biodiversity loss (Czech and Krausman 1997, Wilcove and Chen 1998). Bio-invasion may be considered as a significant component on global change and one of the major causes of species extinction (Drake et al. 1989).
This chapter attempts to provide a review of several studies that assess the utility of remote sensing (RS), or remote sensing coupled with geographical information system (GIS), in mapping and modeling the distribution of invasive species. The term invasive species is also more or less synonymously referred to as aliens, barriers, naturalized species, invaders, pests, colonisers, weeds, immigrants, exotics, neophytes, introduced species or transformers (Heywood 1989, Richardson et al. 2000). These terms come from studies having different view points on the problem but in the context of this paper they should be considered as similar.

2.2 Application of RS and GIS techniques in mapping biological invasions

Remote sensing technology has received considerable interest in the field of biological invasion in the recent years. It is a tool offering well-documented advantages including a synoptic view, multi-spectral and multi-temporal coverage data since 1960s (Pearson et al. 1976, Lillesand and Kiefer 1994). It is now widely applied on collecting and processing data. It has proved to be a practical approach to study complex geographic terrain types and diverse inaccessible ecosystems. It provides a wide range of sensor systems including aerial photographs, airborne multi-spectral scanners, satellite imagery, low and high spatial and spectral resolution and ground based spectrometer measurements.

Remote sensing technology has many attributes that would be beneficial to detecting, mapping and monitoring invaders. Spatial heterogeneity complicates the study of seasonal and long-term trends of biological invasion. Remote sensing, however, with its broad view has the potential to deliver the relevant information. Satellite imagery is available for most of the world since 1972 (Lillesand and Kiefer 1994). The multi-date nature of satellite imagery permits monitoring dynamic features of landscape and thus provides a means to detect major land cover changes and quantify the rates of change.

Integrated GIS and remote sensing have already successfully been applied to map the distribution of several plant and animal species, their ecosystems, landscapes, bio-climatic conditions and factors facilitating invasions (McCormick 1999, Rowlinson et al. 1999, Haltuch et al. 2000, Los et al. 2002). An increasing number of publications (Figure 2-1) is dealing with the application of remote sensing and GIS in the data collection and analysis of invasive animal and plant species, their abundance, distribution, mapping, modeling and factors influencing their distribution.
Figure 2-1. Publications on application of remote sensing and GIS techniques in mapping invasive species.

Mapping the type and extent of bio-invasions, the impact of invasions or potential risks of invasions requires accurate assessment and modeling of species distributions. So far no synoptic literature review has been published in the field of mapping invasive species. To sketch the possibilities, limitations and challenges of remote sensing techniques in mitigation of invasive species, this paper provides an overview of the application of remote sensing and GIS technologies in mapping biological invasions. We addressed the following questions.

- What mapping techniques have been used to map and predict the potential distribution of invasive species?

- What sensors and what image processing and classification techniques have been used to map the actual distribution of invasive species?

- For what species groups (canopy versus non-canopy members, plant versus animal species) has successful mapping been reported? Is there any evidence that the reported successful applications tend to be biased towards any particular species groups?

- To what extent has sensitivity to scale and the reliability of the mapping product been addressed?
• Which available mapping techniques so far not applied to invaders could be used to improve the mapping of invasive species?

We searched for articles on biological invasions using several electronic databases (AgECONCD, GEObASE and SOILCD), covering international agricultural, economical and rural development literature, Journals, monographs, conferences, books and annual reports. We also searched other sources such as scientific abstracts, worldwide web, CD ROMs and libraries within and outside the Netherlands. Several experts were contacted who provided additional references.

2.3 Mapping actual and potential distribution: from global to local scale

At national or continental level, maps of invasive species distribution are mainly interpolations from recorded observations compiled and stored in herbaria, zoological collections and research institutes. Maps are often generated by manually drawing polygons (boundaries) around areas where the species is known to occur or alternatively using some automated interpolation procedures. For example the distribution map of Chromolaena odorata, one of the world’s worst invaders is displayed in Figure 2-2. The map displays the distribution as a continuous surface. This suggests that the species occurs throughout the area represented by the map polygons. In reality, species are not homogeneously distributed across their distribution range. Instead they prevail in certain environments while they are absent from others. Maps showing discontinuous patches would more realistically represent such a distribution pattern. However, at small scale (typically <1 to a million) we prefer to use interpolations, while realizing that they are generalizations, displaying the broad geographic range within which the species is known to occur.
Figure 2-2. The world distribution of *Chromolaena odorata*: area under infestation (Black) and native range (Grey). Map based on global invasive species database (ISSG 2004).

The need to display the discontinuity and patchiness in distribution patterns emerges while moving towards larger scales. Here, it would be impractical to derive maps through interpolation, because it would require sampling every patch, a costly operation particularly when larger areas are to be mapped.

2.4 Remote sensing techniques

Digital camera photography and videography are recently introduced as cheap, easily available and flexible alternatives to standard photography, particularly when the data are to be transferred onto a computer system. There are systems available that cover the near infrared (NIR) and infrared (IR) as well. Multispectral scanners register reflectance in a number of spectral bands throughout the visible, near- to far-infrared portions of the electromagnetic spectrum. Broad-band scanners have few spectral bands of one hundred or more nm wide. Hyperspectral scanners have more (tens up to several hundreds) but narrower (from tens to a few nm wide) spectral bands. Broad-band scanners have been successfully applied to discriminate between broad land cover types such as forest versus bare soil and built up area. The higher spectral resolution of hyperspectral scanners allows discrimination of more subtle differences such as those between individual species (Figure 2-3).
2.5 Classification of invasive species

The data captured by remote sensing devices will be most directly related to the properties of that canopy. We introduced a classification of species based on their remotely sensed canopy reflectance response (Figure 2-4). It is the canopy of an ecosystem (be it vegetation or fauna) that reflects the electro-magnetic radiation that is captured by remote sensing devices.
Figure 2-4. Application of remote sensing in detecting individual invasive species (may be an animal or plant) as represented in white colour object. Class I: Canopy dominant species (A), class II: Mixed canopy dominant species (B), class III: Pseudo-canopy dominant species (C) and class IV: Understorey species (D).

Class I includes species dominating the canopy and forming homogeneous single species stands. Class II includes species that are members of a multi species canopy and directly reflects electro-magnetic radiation. Class III includes species not reflecting, but influencing the reflective properties of canopy members belonging in class II and I. Class IV finally includes all species that neither dominate canopy nor influence the reflective properties of other species in class I and II.

2.5.1 Canopy dominant species

Several invasive species dominate the canopy of the earth surface forming homogeneous single species stands that extend over larger areas. Included are a large number of tree species such as Melaleuca quinquenervia. Canopy dominance among invaders is not restricted to tree species, it also occurs in grasses (e.g. Arundo donax, Spartina anglica), floating water hyacinth (Eichhornia crassipes) and submerged aquatic vegetation (Caulerpa taxifolia, Undaria pinnatifida, Oscillatoria sp.) and among colonial animals such as zebra mussels (Dreissena polymorpha).

From aerial photography and videography to multispectral and multitemporal scanners have been used for identifying and mapping invasive species (Venugopal
For instance, detection of invasive *Prosopis glandulosa* var. *torreyana* using TM images (Harding and Bate 1991), *Gutierrezia sarothrae* with NOAA-10 low resolution spectral image (Peters et al. 1992), *Kalmia angustifolia* (Franklin 1994) and *Arundo donax* using high spatial resolution (~4m) AVIRIS data (Ustin et al. 2002), *Cynodon dactylon* with aerial video and colour-IR photographs (Everitt and Nixon 1985), *Populus tremuloides* clones using hand-held video (Stohlgren et al. 2000) are some of the examples of mapping canopy dominating species.

Some of the reported invasive species dominate submerged aquatic ecosystems. For those ecosystems, remote sensing methods described so far, are limited, because little light is reflected back by submerged organisms. Budd et al. (2001) used Advanced Very High Resolution Radiometer (AVHRR) remote sensing reflectance imagery and found a significant relationship between reflectance before and after *Dreissena polymorpha* invasion. Hill et al. (1998) modelled the propagation of the green alga *Caulerpa taxifolia* and predicted the local pattern of expansion, increase of biomass and covered surfaces, and invasive behaviour. Gross et al. (1988) estimated biomass of the *Spartina alterniflora* using a hand-held fixed band radiometer configured to collect data in Landsat TM. Welch et al. (1988) related 13 invasive macrophytes distributions (including *Hydrilla verticillata*, *Potamogeton* sp., and *Lemna perpusilla*) to environmental factors influencing aquatic plant growth using bathymetry and herbicide applications maps and statistical data on nutrients, dissolved oxygen, biological oxygen demand, and turbidity into a PC-based GIS. A significant change was found in the ratio of emergents to subemergents as well as the total area of aquatic macrophytes.

### 2.5.2 Mixed canopy dominant species

Plant characteristics such as life form, leaves, flowers etc determine reflectance. If a species is dominant enough in the canopy and characteristics can be distinguished from other species, than it is possible to detect such individual species based on spectral reflectance. The ability of high spectral and spatial resolution sensors to discriminate between invasive and native species depends on intra-specific variability in spectral reflectance. Everitt & Nixon (1985) demonstrated that a family of spectra can represent a particular species, and invasive species are easily separated using low altitude aerial photographs or field spectographs. For example, Menges et al. (1985) found colour IR (CIR) aerial photography to be useful for detecting *Sarcostemma cyanoides*; *Parthenium hysterophorus*; *Sorghum halepense*; *Sisymbrium irio* and *Amaranthus palmeri* in different crops. Young et al.
(1976) detected growth timing of *Chrysothamnus viscidiflorus* using colour photography. Feyaerts & van Gool (2001) proposed an online system that distinguishes crop from weeds based on multispectral reflectance gathered with an imaging spectrograph.

### 2.5.3 Pseudo-canopy dominant species

Numerous investigators have worked on developing techniques for using multispectral data in invasive species mapping and detection (Eav et al. 1984, Medlin et al. 2000, Vrindts et al. 2002, Zhang et al. 2002b). Analysis of hyperspectral data has produced encouraging results in the discrimination of healthy and infected canopy dominant species. For example, Fouche (1995) identified rootrot-infested cashew nut trees, *Phytophthora cinnamomi* infestation in avocado orchards and infected citrus trees. They could be differentiated from their healthy neighbours, using low-altitude aerial colour infrared (CIR) imagery. Gebhardt (1986) used IR measurements of crop canopy temperature to detect differences in water supply and nematode infestation. Smirnov & Kotova (1994) monitored the infection by *Heterobasidion annosum* in areas with pollution levels exceeding 15 Ci/km2 after the Chernobyl nuclear disaster in Russia. Kharuk et al. (2001) analysed large-scale outbreak of the *Dendrolimus sibiricus* in the forests using NOAA/AVHRR imagery and found that the imagery could be used for detecting dying and dead trees. Using principal component and cluster analyses Zhang et al. (2002b) observed that the sensitive spectral wavelengths and reflectance values could discriminate *Phytophthora infestants* infection on tomatoes.


### 2.5.4 Understorey species

Few researchers have pointed out the possibilities of application of remote sensing in studying forest understorey invaders. Plant species such as *Chromolaena odorata*, *Ulex europaeus*, *Clidemia hirta*, *Lantana camara*, *Mimosa pigra*, *Psidium cattleianum*, *Rubus ellipticus*, *Schinus terebinthifolius* and most of the invasive animal species are examples of this category. Most of the invasive animals, lower flora, herbs, shrubs and fauna are found to be understorey vegetation, making
detection using direct remote sensing techniques almost impossible. Nevertheless, a combination of remote sensing techniques, GIS and expert knowledge still offer potential to detect understorey invasion through development of models and risk maps. May et al. (2000) quantified remotely sensed airborne data into physical and ecological variables, obtaining an improved spatial and temporal representation of the dynamics of native and exotic plant communities. Hence, such information could potentially be used in mapping non-canopy dominant invasive species as well as predicting the probability of actual and potential sites and areas where environmental conditions are susceptible to infestation.

2.6 Monitoring and prediction of invasion risk

Predicting the probability of biological invasion and probable invaders has been a long-standing goal of ecologists. A major challenge of invasion biology lies in the development of pre and post predictive models and understanding of the invasion processes. Introduced species vary in their invasive behaviour in different regions (Krueger et al. 1998). Prediction is more difficult than finding an explanation. Predicting the ecological behaviour of a species in a new environment may be effectively difficult, therefore attempts at predicting invasions have generally been unsatisfactory (Williamson 1999). Furthermore, estimating animal species numbers, population size and related features is rather difficult in comparison to plants. However, Kolar & Lodge (2001) indicated clear relationships between the characteristics of releases and the species involved, and the successful establishment and spread of invaders. Allen & Kupfer (2000) developed a modified change vector analysis (CVA) using normalized multi-date data from Landsat TM and examined Adelges piceae infestation. Luther et al. (1997) pointed out the importance of logistic regression techniques to develop models for predicting forest susceptibility and vulnerability and to assess the accuracy of forecasts. Using an integrated multimedia approach in the vegetation database for invasive species provides a unique way to represent geographic features and associated information on interrelationships between flora, fauna, and human activities (Hu 1999). Predictions of malaria risk mapping (Kleinschmidt et al. 2000) and microbiological risk assessment for drinking water (Gale 2001) are some examples of risk mapping and prediction that have been done in the field of biological invasions.

Applications of these promising quantitative approaches in an Integrated GIS environment may allow us to predict patterns of invading species more successfully. Although remote sensing and GIS technology provides particularly valuable insight into the effectiveness of an ongoing invasive species control programme, the cost of
monitoring should be within the affordable range as pointed by Benton & Newnam (1976).

2.7 Issues of scale and accuracy

Scale is one of the central issues in invasion ecology. All observations depend upon the spatial scale, size of the study area investigated and resolution of the remote sensor. Habitat evaluation of a species is influenced strongly by spatial scale (Cogan 2002). The variations in the landscape patterns are scale-dependent (Rescia et al. 1997). Unfortunately there is no “correct” scale; it depends on survey purpose (Trani 2002). Hence, in most of the cases, landscape scale is used as an appropriate scale for modeling.

McCormick (1999) reported 91% accuracy in mapping Melaleuca quinquenervia and pointed out the superiority of large scale of colour infrared aerial photographs for identifying, mapping and effective management of exotic species. Carson et al. (1995) found that the Landsat TM and SPOT data with ground resolution of 30 and 20 meters respectively, are not considered useful for mapping at species level, unless the stand of an invasive species is large enough. Multi-date imagery therefore appears to improve mapping and modeling the infestation pattern of canopy dominant species (Mast et al. 1997, Hessburg et al. 2000). Bren (Bren 1992) examined the invasion of Eucalyptus camaldulensis into an extensive, natural grassland in a high flood frequency site using 45 years time series aerial photographs (taken in 1945, 1957, 1970, and 1985) extrapolated model showed the almost complete extinction of extensive grass plains. Hessburg et al. (2000) used aerial photo (from 1932 to 93) of interior northwest forests, USA and found emergent non-native herb lands. Mast et al. (1997) provided a quantitative description of the Pinus ponderosa tree invasion process at a landscape scale using historical aerial photography, image processing and GIS approaches. Welch et al. (1988) applied GIS to analyse aerial photo for monitoring the growth and distribution of 13 aquatic emergent, submerged and free-floating species. They produced vegetation maps using large scale (1:8000-1:12000) color infrared aerial photographs of different years (1972, ‘76, ‘83, ‘84, ‘85).

Current developments in sensor technology have the potential to enable improved accuracy in the mapping of vegetation and its productivity. Rowlinson et al. (1999) indicated that using manual techniques to identify infested riparian vegetation from 1:10,000 scale black and white aerial photographs yielded the most accurate and cost-effective results. The least accurate data sources for this purpose were aerial
videography and Landsat thematic mapper (TM) satellite imagery. High spatial (less or equal to 1m) but low spectral resolution remote sensing data appeared to be useful in mapping invasive Chinese tallow trees with an accuracy of greater than 95 percent (Ramsey et al. 2002). Medlin et al. (2000) detected infestations of Senna obtusifolia, Ipomoea lacunosa, and Solanum carolinense with at least 75% accuracy using multi-spectral digital images. Vrindts et al. (2002) distinguished seven weed species with a more than 97% correct classification using a limited number of wavelength band ratios. Everitt et al. (2001b) noted that Juniperus pinchotii had lower visible and higher near-infrared (NIR) reflectance than associated species and mixtures of species allowing a mapping accuracy of 100 percent. Lass et al. (2000) tested accuracy of detection of a homogenous population of Centaurea solstitialis at different spatial resolution. Their result showed a low commission and omission errors with 0.5m spatial resolution than 4.0m. Very-high spatial resolution (0.5 m) colour infrared (CIR) digital image data from colour-infrared digital camera imagery showed potential for discriminating Acacia species from native fynbos vegetation, other alien vegetation and bare ground (Stow et al. 2000). In cases where different spatial resolutions resulted in equal detection accuracy, the larger spatial resolution was selected due to lower costs of acquiring and processing the data.

All these studies noted the importance of image resolution, spectral characteristics, superiority of lower scaled aerial photographs and images. It also shows clearly that for accurate mapping of invasive species it is important to consider the phenological stage in aiming of taking the aerial photographs or images. Although high spectral and spatial resolution provide the ability to classify canopy dominant species, precise classification of a species is still difficult. Several such studies of the spectral properties of invasive species have been derived, mostly from low altitude aerial photography or field spectrographs. However, the information reaching the remote observer will be minimum.

Other factors for instance, atmospheric noise, humidity, shadow, contribution from soil may add to the confusion and the chance of discrimination of separate species low. Furthermore, variation in orientation of leaves, age of a leaf, variation in leaf area index, different slopes of the locations where the individuals are found could make the spectral signature of a species difficult to define. It is not however practically feasible to determine the ideal wavelengths for discrimination when large numbers of invasive species are present. Furthermore, if the presence of number of invasive species per pixel increases, the difficulty in identifying the individual components that contribute to the mixed spectrum also increases. These problems
will be further aggravated if species variability in spectral signatures is high. For large scale direct remotely sensed monitoring of several invasive species, the possibility of correctly identifying all individuals through direct mapping thus appears doubtful.

### 2.8 Summary and conclusions

In this article, we attempted to evaluate the potential of remote sensing and GIS techniques for the critical task of invasion mapping. Although the use of RS and GIS techniques for mapping invasive species and invaded ecosystems is increasing rapidly, the literature on means and methods for invasive species mapping remains scattered and often contradictory. Most of the IUCN’s worst invasive species fall under our class IV species, in which straightforward application of remote sensing is almost impossible. Recent remote sensing and GIS applications on detecting invasive species were mainly dealing with species belonging to class I (Figure 2-5).

![Figure 2-5. Mapped and not mapped 100 world’s worst invasive species included in the list of International Union for Conservation of Nature and Natural Resources. Class I: Canopy dominant species, II: Mixed canopy dominant species, III: Pseudo-canopy dominant species and IV: Ecosystem understorey species.](image)

For instance, most of the understorey species that have been declared as the world’s worst invaders by the ecologists have not caught the attention of remote sensing experts. In the same way species such as *Melaleuca quinquenervia* or *Tamarix ramosissima*, which dominate entire ecosystems forming a monotypic dense canopy, do not necessarily need the use of high spectral resolution imagery and vice versa. It is not clear whether RS and GIS techniques will prove equally
strong for mapping mobile invasive species such as *Acridotheres tristis* (Bird), *Aedes albopictus* (mosquito) or *Boiga irregularis* (snake). This needs further testing in the near future.

The status of many exotic species with respects to their invasiveness is not well documented. Therefore, the ability of remote sensing and GIS techniques to monitor changes in different ecosystems may be crucial if the effect and the cause of rarity are to be assessed. Cases of actual applications are still not much more than the traditional investigations. Rapidly shifting interest in remote sensing and GIS of bio-invasion mapping has resulted in the development of a diverse range of mapping techniques. However, the technology needs further development in terms of real world applications in the mapping of invasive species. Moreover, mapping, modeling and predicting biological invasion will still be a major challenge for ecologists because the biological processes involved are very complex. This complexity makes it difficult to retrieve or delineate invasions that occur in diverse ecosystems. As Specter and Gayle (1990) pointed out the proliferation of new technologies does not guarantee their application to real world problems.

Although restricted to few taxa, studies revealed the potential of remote sensing and GIS application in mapping and modeling invasive species. There are possibilities of generating in-depth information in detecting, mapping and analyzing the impact of invasion on an area or entire ecosystem and species level properties. To enhance the result of invasion mapping, there is a clear need of combined use of remote sensing, GIS and expert knowledge. Management dealing with invasive species requires accurate mapping and modeling techniques at relative low costs. Development of those will be a valuable step towards conservation of native biodiversity.

### 2.9 Future research

The increasing number of sensors and classification algorithm have provided spatial ecologists with tremendous opportunities to advance the application of RS and GIS techniques in mapping and modeling the distribution of invasive species. However, application of remote sensing is strongly limited when dealing with world’s worst forest understorey plant species. Direct detection of such species using remote sensing tool are hardly explained (Jakubauskas and Price 1997).

Understanding of distribution pattern of understorey species may only be possible when interrelation between ecological complexities of forest overstorey and
understorey species could be established. Consequently, mapping forest canopy openings could be a potential factor to predict the distribution of forest understorey heliophytic invaders. Although, the literature review revealed a wide variety of proposed methods (Boyd et al. 2002), there is little indication which method would be superior in performance in comparison to others, because very few of the reported methods have been validated for their accuracy, and so far no comparative studies have been undertaken. We argue that high accuracy in forest canopy classification may holds particular promise since growth of forest understorey heliophytic invasive species depends on light intensity reaching to the forest floor, which is regulated by the canopy itself.
CHAPTER THREE

Remotely sensed estimation of forest canopy density: a comparison of the performance of four methods

This Chapter is based on:
Remote sensed estimation of forest canopy density: a comparison of the performance of four methods

Abstract

In recent years, a number of alternative methods have been proposed to predict forest canopy density from remotely sensed data. To date however, it remains difficult to decide which method to use, since their relative performance has never been evaluated. In this study, the performance of 1) an artificial neural network, 2) a multiple linear regression, 3) the forest canopy density mapper and 4) a maximum likelihood classification method was compared for prediction of forest canopy density using a Landsat ETM+ image. Comparison of confusion matrices revealed that the regression model performed significantly worse than the three other methods. These results were based on a z-test for comparison of weighted Kappa statistics, which is an appropriate statistic for analysis of ranked categories. About 89% of the variance of the observed canopy density was explained by the artificial neural networks, which outperformed the other three methods in this respect. Moreover, the artificial neural networks gave an unbiased prediction, while other methods systematically under or over predicted forest canopy density. The choice of biased method could have a high impact on canopy density inventories.

Key words: Forest canopy density, Classification, Remote sensing, Neural networks, Weighted Kappa, Bias prediction.

3.1 Mapping forest canopy density

The distribution and rate of decline of tropical forests has successfully been assessed using remote sensing images (Myers 1980, Prince 1987, Ringrose and Matheson 1987, Ford and Casey 1988, Iverson et al. 1989, Sussman et al. 1996). About 13.5 million hectares of tropical forest is cleared annually for agriculture, pastures, timber products and infrastructure development (FAO 2001, Geist and Lambin 2002). These figures only consider complete clearing and do not include forest degradation, a more gradual process, which (Tanner et al. 1996) considered relevant to account for as well.

The world-wide extent of forest degradation is unknown. Forest degradation is characterized by a reduction in forest quality and biomass by an opening up of the canopy. This is particularly so in the tropics, where local population exploit forest resources.
Forest canopy density expressing the stocking status constitutes the single major stand physiognomic characteristics of the forest. The degree of forest canopy density is expressed in percentages. Remotely sensed estimates of forest density have been used to indicate the degradation status of forest (Tiwari et al. 1986, Prince 1987, Ringrose and Matheson 1987, Ford and Casey 1988). There are a variety of empirical approaches that can be used to map forest canopy: 1) object based classification (Dorren et al. 2003), 2) artificial neural network (Boyd et al. 2002), 3) linear regression (Iverson et al. 1989, Zhu and Evans 1994, DeFries et al. 1997, Levesque and King 2003), 4) decision tree classification (Souza Jr. et al. 2003), and 5) forest canopy density mapper (Rikimaru 1996, Rikimaru and Miyatake 1997). Hence, the literature review reveals a wide variety of proposed methods. So far, there is little indication which method would be superior in performance in comparison to others, because very few of the reported methods have been validated for their accuracy, and so far, no comparative studies have been undertaken.

Typically, error matrices have been used to assess the performance of methods to estimate canopy density (Congalton and Green 1999, Oetter et al. 2000, Souza Jr. et al. 2003, Peddle et al. 2004). Error matrices are appropriate to reveal the performance of classifications resulting in categories. In the case of canopy density, predictions have been made in the form of ranked categories (Rikimaru and Miyatake 1997, Saatchi et al. 1997, Scarth and Phinn 2000). Forest canopy density, however, is a continuous variable by nature. Hence, it would be more appropriate to predict forest canopy density in a continuous variable, rather than categories, which allows to assess the performance of predictions in terms of random and systematic error components.

The main objective of this study is to compare the performance of different methods, namely 1) artificial neural networks (ANN), 2) multiple linear regression technique (MLR), 3) a semi-expert deductive approach i.e. forest canopy density mapper (FCD) and 4) maximum likelihood classification (MLC) to predict forest canopy density in percent as a continuous variable.
3.2 Material and methods

3.2.1 Study area

The field study was conducted in Feb.-Mar. 2003 and Sept.-Oct. 2003 in a forest corridor (Figure 3-1) linking the Himalayan middle mountains to the Royal Chitwan national park in Chitwan district, Nepal (27° 31´ to 27° 44´ N and 84° 24´ to 84° 31´ E). The forests consists of almost pure stands of Shorea robusta Gaertn. interspersed by riverine Acacia catechu (L.f.) Willd., Dahlbergia sissoo Roxb. and Trewia nudiflora Linn. mixed forests and grasslands in shallow depressions and along riverbanks. The area was chosen for this particular study because the high population density surrounding the forest resulted in strong gradients of degradation and forest canopy density from the forest edge to the interior.
3.2.2 Field and image data

A Landsat ETM+ image of October 24, 2001 was geo-referenced with subpixel accuracy of 17m. The thermal band was resampled to 30 m pixel size to normalise the spatial scale differences between the optical and the thermal band. The spectral radiance of each seven bands (band 1 to 7 of the ETM+ imagery) was calculated and than converted to reflectance which was finally used as an input for further analysis (NASA 2005).

Field data were collected from 372 sites selected by uniform random sampling using a land cover map of the area. Estimation of canopy density was based on two methods: 1) Densitometer estimation and 2) hemispherical photographs. At every site, densiometer estimation of canopy was recorded and hemispherical photographs were taken at the centre of a 30 x 30m plot.

![Hemispherical photograph of forest canopy taken with fisheye lens attached to a Nikon digital camera.](image)

Figure 3-2. Hemispherical photograph of forest canopy taken with fisheye lens attached to a Nikon digital camera.  

Hemispherical canopy photography (Figure 3-2) is one indirect optical technique that has been widely used in studies of canopy structure and forest light transmission. Photographs taken skyward from the forest floor at the height of 1.2
m with a 180° hemispherical (fisheye) lens produce circular images that record the size, shape, and location of gaps in the forest canopy. These data are subsequently combined to produce estimates of growing-season light transmission, as well as other measures more directly related to canopy structure, such as openness, leaf area, and sunfleck frequency (Chazdon and Field 1987, Rich 1990). An index of sky openness corresponding to sky directly visible from the leaf (i.e. from the camera position) was computed from each photograph using Gap Light Analyzer (GLA) software version 2 (Frazer et al. 1999) and related to the canopy openness.

A view angle of 114° for canopy density calculation was considered. This corresponded to a 900m² canopy area for an average tree height of 22.5m. From this larger sample a sample of 50% of the sites (n=186) was randomly selected to develop method to predict canopy density (see 3.2.3). The remaining subset of n=186 sites was used to validate the predictions of these methods (see 3.2.4).

3.2.3 Forest canopy density prediction

3.2.3.1 Artificial neural networks (ANN)

Artificial neural networks (hereafter neural networks) are neurologically inspired statistical mechanisms also employed in classification of forest cover using various sensors (Barrow et al. 1993, Boyd et al. 2002). Here, a three-layer feedforward error-backpropagation artificial neural network implemented in Interactive Data Language (IDL) was used (Skidmore et al. 1997) in order to predict forest canopy density as a continuous variable. The algorithm minimises the root mean square error between the observed and the predicted values. We followed (Atkinson and Tatnall 1997) to search for system parameters to increase the accuracy of the method and avoid overtraining of the neural network.

The neural networks with the sub sample of 186 sites with canopy density and the seven ETM+ bands was trained and the best combination of optimum learning rate and momentum to minimize the root mean square error (RSME) was empirically established. The best results were obtained with a learning rate of 0.7, a momentum of 0.7 and four hidden nodes. The RSME stabilized after approximately 7000 epochs. Finally, 20 iterations of 7000 epochs were performed and the best one was selected based on root mean square error.
3.2.3.2 Multiple linear regression techniques (MLR)

Multiple linear regression techniques (hereafter multiple regression) have been used to model the relation between spectral response and closed canopy conifer forest cover (Ripple 1994). In this study, we developed a multiple linear regression model, which best described the relation between canopy density and the seven ETM+ spectral bands. The regression eq. using \( n = 186 \) observations is:

\[
Y = 3.32 + 0.021 * B_1 - 0.002 * B_2 + 0.003 * B_3 \\
+ 0.024 * B_4 - 0.023 * B_5 + 0.021 * B_6 - 0.029 * B_7
\]

Equation 3-1

\[ R^2 = 0.62, \, F_{7,178} = 41.44, \, p<0.01, \] where \( Y = \) Predicted forest canopy density and \( B_1 \) to \( B_7 \) is the reflectance value of band 1 to band 7 of Landsat ETM+ image.

3.2.3.3 Forest canopy density mapper (FCD)

Rikimaru (1996) introduced an alternative deductive approach i.e. forest canopy density mapper (hereafter density mapper) to map forest canopy density using four indices (vegetation, bare soil, shadow and surface temperature) derived from Landsat TM imagery. Based on these four variables, nine canopy density classes namely 0, 1-10, 11-20,….., 71-80+ were obtained.

This model involves bio-spectral phenomenon modeling and analysis utilizing data derived from four indices namely: Advance Vegetation Index (AVI), Bare Soil Index (BI), Shadow Index (SI), and Thermal Index (TI). Using these four indices, the canopy density for each pixel was calculated in percentage. Advanced vegetation index AVI reacts sensitively for the vegetation quantity compared with NDVI. Shadow index increases as the forest density increases. Thermal index increase as the vegetation quantity decreases and bare soil index increases as the bare soil exposure degrees of ground increase. After normalization of the Landsat ETM+ bands (except band 6) these indices has been calculated using equation:

\[
\text{if } B_4 - B_3 < 0, \, AVI = 0 \quad \text{.......(Case a)} \\
\text{if } B_4 - B_3 > 0, \, AVI = \left(\left(B_4 + 1\right) \times \left(256 - B_3\right) \times \left(B_4 - B_3\right)^{1/3}\right) \quad \text{.......(Case b)}
\]

Equation 3-2

\[
BI = \frac{(B_5 + B_3) - (B_4 - B_1)}{(B_5 + B_3) + (B_4 + B_1)} \times 100 + 100
\]

Equation 3-3
\[
SI = (256 - B_1) \times (256 - B_2) \times (256 - B_3)
\]

Equation 3-4

where: B is the spectral band of ETM+ image.

The DN value of thermal band (band 6) of ETM+ image was converted to units of absolute radiance using 32 bit floating point calculations (NASA 2005). The temperature calibration of the thermal infrared band (band 6) into the value of ground temperature has been done using equation:

\[
T = \frac{K_2}{\ln \left( \frac{K_1}{L \lambda} + 1 \right)}
\]

Equation 3-5

where: T = Effective at-satellite temperature in Kelvin; K1 = 666.09 watts/(meter squared * ster * μm) K2 = 1282.71 Kelvin; L = Spectral radiance in watts/(meter squared * ster * μm).

As an intermediate step, VI and BI were synthesized into Vegetation Density (VD) value using principal component analysis and VI and SI into Scaled Shadow Index (SSI) by linear transformation of SI. In areas where the SSI value is zero, this corresponds with forests that have the lowest shadow value (i.e. 0%). In areas where the SSI value is 100, this corresponds with forests that have the highest possible shadow value (i.e. 100%). Details in Rikimaru, 1996). Finally, VD and SSI were synthesized into a forest canopy density value as:

\[
FCD = (VD \times SSI/O)^{1/2} - 1
\]

Equation 3-6

The method requires intervention by an operator to establish threshold values. The accuracy obtained in three SE Asian countries averaged 92% (Rikimaru and Miyatake 1997). For this study, FCD- mapper software ver. 2 (Rikimaru and Miyatake 1997) and ILWIS 3.2 (ILWIS 2005) were used.

3.2.3.4 Maximum likelihood classification (MLC)

As a parametric classifier, maximum likelihood classification method (here after maximum likelihood) calculates the probability that a given pixel belongs to a specific class and assigns the pixel to the class having the highest probability (Richards 1999). The training set of 186 pixels into ten canopy classes namely 0, 1-10, 11-20, ..., 71-80+ was classified. The Interactive Data Language (IDL 6.0) and ENVI 4.0 (ENVI 2003) was used for image classification.
### 3.2.4 Comparison of classifier performance

ANN and MLR predicted forest canopy density as a continuous variable, whereas FCD and MLC methods predicted canopy density as a categorical variable. Therefore, to compare the performance of all four classifiers using Kappa statistics, we grouped ANN and MLR classification results into ten canopy classes same as FCD and MLC. Normally in remote sensing the performance of image classification methods is analysed using error matrices and Kappa statistics (Congalton and Green 1999). In this case, with ranked rather than nominal categories in the table, the weighted Kappa statistic (Naesset 1996) was used. Table 3-1 gives the agreement weights used for the weighted Kappa. A z-test was performed for a pairwise comparison of the methods, testing the null hypothesis $\kappa_1 = \kappa_2$, where $\kappa$ is the weighted Kappa value for the map produced by the method.

**Table 3-1. Matrix with agreement weights used for calculation of weighted Kappa**

<table>
<thead>
<tr>
<th>Observed category</th>
<th>Predicted category</th>
<th>0</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80+</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
<td>0.67</td>
<td>0.56</td>
<td>0.44</td>
<td>0.33</td>
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<td>0.11</td>
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</tr>
<tr>
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<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
<td>0.67</td>
<td>0.56</td>
<td>0.44</td>
<td>0.33</td>
<td>0.22</td>
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</tr>
<tr>
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<td>0.89</td>
<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
<td>0.67</td>
<td>0.56</td>
<td>0.44</td>
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<td>0.89</td>
<td>0.78</td>
<td>0.67</td>
<td>0.56</td>
<td>0.44</td>
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</tr>
<tr>
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<td>0.67</td>
<td>0.78</td>
<td>0.89</td>
<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
<td>0.67</td>
<td>0.56</td>
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</tr>
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<td>0.67</td>
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<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
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</tr>
<tr>
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<td>0.44</td>
<td>0.56</td>
<td>0.67</td>
<td>0.78</td>
<td>0.89</td>
<td>1.00</td>
<td>0.89</td>
<td>0.78</td>
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</tr>
<tr>
<td>70</td>
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<td>0.33</td>
<td>0.44</td>
<td>0.56</td>
<td>0.67</td>
<td>0.78</td>
<td>0.89</td>
<td>1.00</td>
<td>0.89</td>
<td></td>
</tr>
<tr>
<td>80+</td>
<td>0.11</td>
<td>0.22</td>
<td>0.33</td>
<td>0.44</td>
<td>0.56</td>
<td>0.67</td>
<td>0.78</td>
<td>0.89</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, the predicted against observed canopy density values were plotted for the four methods and their agreement tested by a simple linear regression for each. The coefficient of determination and slopes and intercepts were used to assess the performance of predictors. An unbiased predictor would be expected to have a slope ($\beta$) of 1 and intercept ($\alpha$) of zero. Hence the hypothesis: $H_0: \alpha = 0$ and $H_0: \beta = 1$ was tested. Besides, the variance of the observed canopy density explained by the predicted density was used to assess the random errors in the model.

### 3.3 Results

Table 3-2 presents the error matrix for the artificial neural network classifier. The matrix shows that 110 out of 186 observations had been correctly classified. There were few severe outliers, only 6 observations were more than two classes and 22
observations were more than one class from the diagonal. The linear regression method correctly classified 64 out of 186 observations. There were many more severe outliers, 29 observations more than two classes and 57 observations were more than one class off diagonal (Table 3-3). The forest canopy density mapper with 92 out of 186 observations correctly predicted, 13 observations more than two classes and 42 observations were more than one class off diagonal (Table 3-4). The maximum likelihood classification predicted 82 out of 186 observations correctly, 21 observations more than two classes and 51 observations were more than one class off diagonal (Table 3-5).

Table 3-2. Error matrix for observed versus predicted canopy density class by an artificial neural network

<table>
<thead>
<tr>
<th>Predicted class</th>
<th>Observed class</th>
<th>0</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80+</th>
<th>Total</th>
</tr>
</thead>
<tbody>
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Table 3-3. Error matrix for observed versus predicted canopy density class by a multiple regression model

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<th>Predicted class</th>
<th>Observed class</th>
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Table 3-4. Error matrix for observed versus predicted canopy density class by the forest canopy density mapper

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<tr>
<td>70</td>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
<td>9</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>80+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>56</td>
<td>9</td>
<td>15</td>
<td>14</td>
<td>19</td>
<td>25</td>
<td>18</td>
<td>16</td>
<td>14</td>
<td>186</td>
</tr>
</tbody>
</table>

Table 3-5. Error matrix for observed versus predicted canopy density class by a maximum likelihood classification

<table>
<thead>
<tr>
<th>Predicted class</th>
<th>Observed class</th>
<th>0</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80+</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td>45</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>50</td>
</tr>
<tr>
<td>10</td>
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<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>20</td>
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<td>6</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td>19</td>
</tr>
<tr>
<td>30</td>
<td></td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>40</td>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td></td>
<td></td>
<td>14</td>
</tr>
<tr>
<td>50</td>
<td></td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
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<td>2</td>
<td>1</td>
<td></td>
<td></td>
<td>14</td>
</tr>
<tr>
<td>60</td>
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<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>11</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td></td>
<td>29</td>
</tr>
<tr>
<td>70</td>
<td></td>
<td></td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>8</td>
<td>2</td>
<td>1</td>
<td></td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>80+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>11</td>
<td>24</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>56</td>
<td>9</td>
<td>15</td>
<td>14</td>
<td>19</td>
<td>25</td>
<td>18</td>
<td>16</td>
<td>14</td>
<td>186</td>
</tr>
</tbody>
</table>

The Kappa statistics (Table 3-6) showed that neural network resulted in an overall weighted Kappa accuracy of 63.1%, which was 6.7% larger than the nominal Kappa. The weighted Kappa accuracy was increased by 5.6% for multiple regression, 10.1% for density mapper and 11.2% for maximum likelihood.
Table 3-6. Values of the overall accuracy, weighted Kappa accuracy, weighted Kappa statistic and their variances for the four methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall accuracy</th>
<th>Weighted Kappa accuracy</th>
<th>Kappa</th>
<th>Weighted Kappa</th>
<th>Weighted sigma²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial neural networks</td>
<td>59.1</td>
<td>63.1</td>
<td>0.51</td>
<td>0.55</td>
<td>0.00159</td>
</tr>
<tr>
<td>Multiple linear regression</td>
<td>34.4</td>
<td>39.8</td>
<td>0.23</td>
<td>0.29</td>
<td>0.00178</td>
</tr>
<tr>
<td>Forest canopy density mapper</td>
<td>49.5</td>
<td>54.5</td>
<td>0.39</td>
<td>0.44</td>
<td>0.00158</td>
</tr>
<tr>
<td>Maximum likelihood classification</td>
<td>44.3</td>
<td>49.8</td>
<td>0.34</td>
<td>0.40</td>
<td>0.00159</td>
</tr>
</tbody>
</table>

Table 3-6 further showed that neural network resulted in a nominal Kappa value of 0.55 and increased by 7.8% with the weighted Kappa. The weighted Kappa was 0.29 and increased by 26% for multiple regression, 0.44 and increased by 12.8% for density mapper and 0.40 and increased by 17.6% for maximum likelihood. The variance of weighted Kappa value for multiple regression was 0.00178 which was significantly higher than the values of other three methods. The variance of weighted Kappa value for other three methods was almost similar.

The z tests comparing the performance of the four methods based on weighted Kappa and their variances (Table 3-7) showed that the calculated z value for neural network and multiple regression was 4.52 which was higher than 1.96 at $\alpha = 0.05$ conclude that maps produced by the two methods are significantly different from each other. Similarly, the map produced by the neural networks was significantly different from the map produced by maximum likelihood classification. The calculated z value for density mapper and multiple regression was 2.70 which showed a significant difference between them. We failed to detect significant differences between the maps classified by neural networks and the forest canopy density mapper. Figure 3-3 shows the forest canopy density class map produced by the four methods.

Table 3-7. Values for z tests comparing the performance of the four methods based on weighted Kappa and their variances (significant at higher than 1.96 at $\alpha = 0.05$)

<table>
<thead>
<tr>
<th>Method</th>
<th>ANN</th>
<th>MLR</th>
<th>FCD</th>
<th>MLC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>-</td>
<td>4.52</td>
<td>1.93</td>
<td>2.70</td>
</tr>
<tr>
<td>MLR</td>
<td>-</td>
<td>-</td>
<td>2.64</td>
<td>1.89</td>
</tr>
<tr>
<td>FCD</td>
<td>-</td>
<td>-</td>
<td>0.77</td>
<td>-</td>
</tr>
<tr>
<td>MLC</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Figure 3-3. Forest canopy density maps produced by the artificial neural network (ANN), multiple linear regression (MLR), the forest canopy density mapper (FCD) and maximum likelihood classification (MLC).
The ANN produces the highest overall accuracy of 63 percent when compared to other three methods. The MLR incorrectly mapped the “lower” as well as “higher” canopy classes in the middle canopy classes where as MLC incorrectly mapped most of the “lower” canopy classes (Figure 3-3). The ANN classification appears similar to the output of the FCD. In summary, both ANN and FCD were significantly different from both the MLR and MLC, whilst the ANN produces the highest mapping accuracy.

Figure 3-4 presents the performance of the four methods in scatterplots of observed versus predicted canopy density. The figure shows the fitted regression line against the expected line for an unbiased predictor with intercept ($\alpha = 0$) and slope ($\beta = 1$). Visual comparisons of these pairs of regression lines suggest bias, which was further tested using the results presented in Table 3-8. The observed slope and intercept significantly differed from one and zero for the forest canopy density mapper as well as the maximum likelihood classification. Hence, we considered these two methods as biased predictors.

![Figure 3-4](image)

Figure 3-4. Scatterplot of observed versus predicted forest canopy density for the artificial neural network (ANN), multiple linear regression (MLR), the forest canopy density (FCD) mapper and maximum likelihood classification (MLR). The dotted line corresponds to an unbiased predictor, while the solid line represents the observed linear regression relationship.
We failed to reject both null hypotheses for the artificial neural network and linear regression models. The fit of the neural network predictions against the observations was quite good, with observations equally distributed across the range of observations (Figure 3-4). This was not the case for the multiple linear regression model. Here the model overpredicted at low canopy density while it underpredicted at high canopy density. Hence, we considered this also a biased predictor. We therefore conclude that the artificial neural network method did not produce biased predictions.

Table 3-8 reveals that 89% of variance of observed canopy density was explained by the predictions in case of the neural network, 64% by the multiple regression, 79% by the density mapper and 74% by the maximum likelihood. The standard error of the estimate of 9% for the neural network was considerably lower than the other three methods.

Table 3-8. Regression statistics describing the relationship between predicted and observed canopy density for the four methods

<table>
<thead>
<tr>
<th>Method</th>
<th>R²</th>
<th>Intercept (α)</th>
<th>standard errorα</th>
<th>tα</th>
<th>Slope (β)</th>
<th>Standard errorβ</th>
<th>tβ</th>
<th>Standard error of estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial neural networks</td>
<td>0.89</td>
<td>0.017</td>
<td>0.011</td>
<td>1.545</td>
<td>1.019</td>
<td>0.026</td>
<td>0.731</td>
<td>0.092</td>
</tr>
<tr>
<td>Multiple linear regression</td>
<td>0.64</td>
<td>-0.001</td>
<td>0.022</td>
<td>-0.045</td>
<td>0.992</td>
<td>0.054</td>
<td>-0.148</td>
<td>0.168</td>
</tr>
<tr>
<td>Forest canopy density mapper</td>
<td>0.79</td>
<td>0.044</td>
<td>0.015</td>
<td>2.933</td>
<td>0.912</td>
<td>0.035</td>
<td>-2.514</td>
<td>0.131</td>
</tr>
<tr>
<td>Maximum likelihood classification</td>
<td>0.74</td>
<td>0.044</td>
<td>0.020</td>
<td>2.246</td>
<td>0.920</td>
<td>0.040</td>
<td>-2.015</td>
<td>0.144</td>
</tr>
</tbody>
</table>

The methods tested in this study perform differently and produce different classification results. However, in this case the artificial neural network method is unbiased than the other three methods, achieved the highest classification accuracy as well as it could map forest canopy density as a continuous variable. The predicted canopy density map obtained from the artificial neural network classification method is shown in Figure 3-5.
Figure 3-5. Forest canopy density map produced by the artificial neural network classification method in Chitwan region, Nepal.
3.4 Discussion

Our results indicated differences in performance between the four methods. The artificial neural network performed better than multiple linear regressions, forest canopy density mapper or the maximum likelihood classification since it explained a higher proportion of the variance and its predictions were unbiased. This confirms the experience that neural networks approaches in image classification tend to be more accurate than other statistical techniques (McClelland et al. 1989, Hepner et al. 1990a, Downey et al. 1992, Kanellopoulos et al. 1992, Atkinson and Tatnall 1997, Boyd et al. 2002, Liu et al. 2003).

Hence, the neural networks classification method was superior in performance and would appear to be a first choice for mapping forest canopy density. However, the neural networks approach has some drawbacks. Firstly, there are no hard rules about neural topology and training algorithm and it is not always possible to know how a neural network obtained a given result. Secondly, like the other empirical methods it requires relatively large dataset which increases the cost of the survey.

Although a classical multiple linear regression technique is unbiased in explaining of variance of the predicted canopy density explained by the observations, poor performance of the technique showed that canopy density may not be well explained by the multiple regression analysis using TM data, a conclusion reinforced by the findings of (Jakubauskas and Price 1997).

The maximum likelihood classification method is a well-known parametric method, which looks at the shape, size and orientation of the training samples (Tou and Gonzalez 1974). If normality assumption in feature space for each training class area is valid, then the classification has a minimum overall error probability and the method is the optimal choice (Swain 1978). However, the normality assumption of the training set is sometimes violated. Here, the method has a lower overall accuracy, significantly different from neural networks and biased prediction because forest canopy density was assumed as a continuous variable and the decision boundaries do overlap (Skidmore et al. 1988). Hence, maximum likelihood classification method could not well classify forest canopy density as a continuous variable.

Some of these problems do not hold for the other methods presented. The forest canopy density mapper for instance can be used with existing expert knowledge to select the best combination of the parameter thresholds or the combination of
indices to produce an optimal classification. It was designed to increase the information collecting capability of foresters reducing cost and saving time (Rikimaru et al. 2002). Drawbacks of the forest canopy density mapper are that the performance of the method depends on the user’s personal performance, skill and use of expert knowledge. It requires intervention by an operator to establish threshold values and make specific adjustments according to vegetation type and terrain condition (Rikimaru and Miyatake 1997). The choices made influence the class boundaries in the resulting map. This can lead to subjectivity and impact on the predicted canopy density. This method is a more subjective than the three other methods. The forest canopy density mapper is thus a somewhat less accurate method, which could be used, if the analyst is aware of risk of bias and subjectivity. We propose to use this method as a quick and less accurate method for forest canopy density estimation in discrete class in those cases where neural networks methods are not an alternative. The coefficient of determination explained in this study was lower than the 92% as reported by Rikimaru (1996). This may possibly be the extreme local variation of canopy cover in our study. The better result of his study probably reflects the regional approach, where such errors played a smaller role.

Previous approaches to map forest canopy density estimated in two (Boyd et al. 2002) or a few classes (Rikimaru and Miyatake 1997, Rikimaru et al. 2002) rather than a continuous variable. The latter approach is preferred to derive information on ecological forest conditions. In this study, we demonstrated that it is possible to predict canopy density as a continuous variable with a standard error of 9%. This error is the result of an empirical neural network method development. Part of the error in the model may have been introduced by the geometric accuracy of matching the imagery to the field observations used for training and validation. The root mean square error of image registration equalled 0.56 pixels, corresponding to ± 17 m in the field. Additionally seasonality and the time difference between the date of image acquisition and field data collection may have introduced some error. It is very apparent from the results matrices (Figure 3-4) that the most of the tested methods were less predictive at intermediate canopy densities (i.e. for observed classes 20 to 40%), it could be the effect of the understorey vegetation cover, which sometimes changed considerably over such short distances due to management practices. We assume that canopy estimation by neural networks might well be more precise than the 9% error reported in this study, when the geometric accuracy could be improved, a possibility pointed out by (Rennolls 2002, Waltham et al. 2002).
3.5 Conclusions

The methods tested in this study perform differently, and produce different classifications. However, a three-layer feedforward error-backpropagation artificial neural network is an unbiased method and performed better than the maximum likelihood classification, forest canopy density mapper or traditional multiple linear regression methods in forest canopy density prediction.

The performance of a method, as expressed in the traditional confusion matrix, is often not a superior indicator of thematic map accuracy, especially when the map is based on continuous variables (e.g. forest canopy density) as a confusion matrix may not express the biased nature of a method. Presentation of data in a scatterplot rather than a traditional error matrix could be an alternative approach to evaluation of bias and unbiased methods.

The weighted Kappa could be an appropriate statistic for analysis of ranked categories. Forest canopy density is quantified as a continuous or ranked variable and an alternative approach could be using regression diagnostics. Confusion matrices and associated statistics, which have been used in previous forest canopy density studies, revealed little difference between methods in this study. The regression techniques provided better insight into the performance of the respective methods and allowed to distinguish between systematic and random errors.

The findings of our study illustrate different classification techniques can provide ecologists and land managers with reasonable accuracy in mapping forest canopy density at local landscape scales. However, canopy density differences that have been obtained for a forest canopy with the different classification methods clearly point out that the choice of biased method could have a high impact on canopy density inventories.
CHAPTER FOUR

Mapping the cover and seed production of the cryptic forest understorey invasive shrub
Chromolaena odorata

This Chapter is based on:

and

4 Mapping the cover and seed production of the cryptic forest understorey invasive shrub *Chromolaena odorata*

Abstract

Remote sensing has successfully been applied to map the distribution of canopy dominating invasive species. Many invaders however, do not dominate the canopy, and remote sensing has so far not been applied to map such species. In this study, an indirect method was used to map the seed production of *Chromolaena odorata*, one of the world’s one hundred worst invasive species. The study was executed in lowland *Shorea robusta* forest in Nepal, where *C. odorata* invaded the understorey of degraded forest. A Landsat ETM+ image processed through a neural network predicted 89% and 81% of forest canopy density and light intensity reaching the understorey respectively. We inverted these models to predict *C. odorata* seed productivity. Light intensity determined 93% of the variation in log_{10} seed production per plant. *C. odorata* failed to produce seed below a light intensity of 6.5 mJ m^{-2} day^{-1}. Further analysis revealed that *C. odorata* was absent above this light intensity in case of a high biomass of other shrub and herb species, a situation occurring in the absence of grazing. We therefore suggest that other species control *C. odorata* through competitive exclusion in the absence of grazing, whereas grazing breaks the dominance of these other species thus creating the conditions for *C. odorata* attain canopy dominance. The presence of grazing was related to distance from the forest edge, a variable that together with light intensity allowed us to map 64% of variation in *C. odorata* cover. Predicted *C. odorata* cover and seed production per plant were combined into a map displaying the total seed production per unit area. Such map displaying seed producing sites could be used to significantly reduce the costs of controlling *C. odorata* infestation by providing information on the spatial segregation of source and sink populations, which will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems. This may prove particularly valuable when implementing control measures under circumstances of limited capital and manpower.

**Key words:** Remote sensing, GIS, *Chromolaena odorata*, seed production, light intensity, invasive species, mapping

4.1 Mapping cryptic invaders

The spread of invasive species has generated interest in mapping their present distribution. Predicting the current or future distributions of species has principally been conducted using a ‘bioclimatic envelope’ that assume that climate ultimately restricts species distributions (Ungerer et al. 1999, Kriticos and Randall 2001). In addition to actual distribution, the potential distribution is increasingly mapped, in an attempt to localize areas at risk of invasion. Rouget et al. (2004) for instance predicted the potential distribution of invasive species in southern Africa from climatic variables.

Potential distribution maps may be useful for invasion risk assessment as well as for country level baseline studies. They do not however, suffice for local management of invasive species aimed at eradication or control. For such purpose, one may wish to identify, at a larger geographical scale, areas where the invader is actually present. Presence data alone may, however not suffice. With limited resources available for invasive species management one may wish to localize areas that deserve priority. Prioritization could be based on various criteria (Moody and Mack 1988, Mack et al. 2000, Pressey and Taffs 2001, Cowling et al. 2003, Reyers 2004), and for example focus on areas where the invader dominates and outcompetes native species. Alternatively, large scale maps could be useful to prioritize areas deserving control of invaders producing seeds, which potentially could infest areas not yet invaded.

Since the first satellite images reached the scientific community, remote sensing has been recognized as a possibility to map the distribution of invasive species at local scale (Tucker 1979, Anderson et al. 1993, McCormick 1999, Ramsey et al. 2002, Zhang et al. 2002a, Underwood et al. 2003). Applications of remote sensing, however have been restricted to species dominating the canopy of ecosystems (Chapter 2). Dominant species determine the spectral signature and thus species detection using their spectral signature is straightforward. Many invasive species however, do not dominate the canopy. We observed (Chapter 2) that 67% of the one hundred world’s worst invasive species (ISSG 2004) were rare or hidden below the ecosystem canopy. Such species would be difficult to localize using their spectral signature, since they contribute partly or not at all to the radiation received by a remote sensing device. Not surprisingly, none of these 67 species has successfully been mapped.
We proposed indirect mapping approaches to map this distribution of invasive species (Chapter 2). Indirect mapping approaches predict the distribution of species using knowledge about the ecological relation between a species and its environment. At regional scales, this approach is commonly used for predicting potential distribution of a species under current and future climates (Messenger 1959, Baker et al. 2000, Warren et al. 2001, Kriticos et al. 2003, Sutherst 2003, Yonow et al. 2004). At local scales, it has been recognized that the distribution of invaders is related to variability of the environment. Land-use changes such as the replacement of natural ecosystems by agricultural systems clearly alter many ecosystems and may promote biological invasions (Hobbs 2000a). Frenot et al. (2001) and Hong et al. (2003) for instance related the current distribution of invasive species to land cover types and suggested that land use change might have contributed to their invasive success.

The above paragraph suggest consensus that land use change stimulates invasions. There is however, an ongoing debate to what extent the invasive success of exotic species depends on traits of the species or the condition of the environment (Harper 1977, Johnstone 1986). Some researchers attributed invasions to inherited traits (Elton 1958, Lodge 1993, Williamson 1996). No doubt, highly invasive species combine successful reproductive, competitive and dispersal traits. The expression of these traits however, is the result of the interaction with its environment (Pysek et al. 1998). Species highly invasive in one environment may well be incapable of maintaining viable populations under different conditions. Hence, spatial information on environmental conditions affecting an invaders reproductive and competitive trait could be used to predict its distribution.

The shrub species *Chromolaena odorata* (L.) R. M. King & Robinson, originating from Central America, has invaded tropical forests around the world (Goodall and Erasmus 1996, McWilliam 2000). It typically occurs in the forest understory in the Southern Himalayas (pers. obs.). The invasiveness of *C. odorata* is thought to depend on the combination of production of large quantities of easily dispersed achenes (Cypsela) and its capability to suppress the native vegetation through light competition (Erasmus 1985, Honu and Dang 2000). These traits however, appear to be phenotypical, since the species shows a remarkable response to light (Witkowski and Wilson 2001). It remains virtually absent from dense forest, but dominates and vigorously produces seed in forest clearings and ruderal environments with more open canopies. This information suggests that light intensity determines the competitive and reproductive traits of *C. odorata*. Hence,
light intensity in the forest could possibly be used to map the distribution and reproduction of *C. odorata*.

The aim of this study was to investigate the possibility of indirect mapping techniques to localize areas, where *C. odorata* was capable of expressing its invasive traits. For this purpose, we analyzed the ecological relationships between *C. odorata* and its environment and used the acquired understanding to map its distribution.

### 4.2 Methods and Materials

#### 4.2.1 Study Area

The study area in south central Nepal is a forest corridor linking the Himalayan middle mountains to Royal Chitwan National Park (27°31´ to 27°44´N and 84°24´ to 84°31´E). The forest is dominated by *Shorea robusta* Gaertn., a drought deciduous tree species. Grasslands occur in depressions within the forest. Densely populated irrigated croplands surround the study area.

Forests in the National Park were generally well conserved. Other forests, although protected by legislation, have been severely degraded through logging and lopping of the trees, grazing of the understorey vegetation, frequent fires and collection of non-timber forest products. The resulting local variation in canopy degradation status made the study area particularly suitable for the current research.

#### 4.2.2 Data collection

The study area was visited twice. In September and October 2003, 302 plots were visited to measure forest canopy density percentage and light intensity at 1.2 m above the ground using hemispherical photography taken with fisheye lens attached to a Nikon digital camera. Total light intensity was calculated from the digital hemispherical photographs using Gap Light Analyzer software version 2 (Frazer et al. 1999).

The study area was revisited in February - April 2004, when *C. odorata* was bearing seeds. Field data were collected from 153 randomly located plots. A plot size of 30 by 30 m was used to visually estimate *C. odorata* cover percentage (Figure 4-1A). For each plot, five reproductive plants were randomly selected, and for each plant: a) number of flowering stems per plant (st), b) number of flowering branches per
stem (br), c) number of inflorescences per flowering branch (in), d) number of capitulum per inflorescence (ca) and e) number of cypselum per capitulum (sy) were measured (Figure 4-1B).

Figure 4-1. *Chromolaena odorata* growing under *Shorea* forest in the Chitwan region of Nepal (Left) and morphology of *C. odorata* (Right).

Next, the response of the seed production of *C. odorata* to the same environmental variables was analyzed. For this, only those sites where *C. odorata* was present were selected. The seed production per plant was reflected by the size and architecture of plants. From the five above described properties, we calculated the average seed production per plant (SPP):

\[
SPP = st \times br \times in \times ca \times cy
\]  

Equation 4-1

Other species in the forest understorey may have competed with *C. odorata*. Therefore, the cover (c, %) and height (h, m) of the herb (H) and shrub (S) layer in the understorey were visually estimated and from these we calculated a biomass index (BI) of these other understorey species:
Furthermore, grazing intensity was assessed based on height (m) and cover (%) of palatable plant species and the density of dung.

Topographic maps of 1996 of the study area were digitized to obtain maps of settlements, roads, forest edge, land cover and land use.

4.2.3 Data analysis

Exploratory data analysis was used to investigate the relation between the biometry of *C. odorata* and a number of environmental factors. Curve Expert 1.3 (Hyams 2005) was used to explore sigmoid functions. A path analysis (Sokal and Rohlf 1995) was conducted to determine the degree to which single environmental factors made an independent contribution to the prediction of *C. odorata* cover. The model included the multiple-way interaction of forest canopy density, grazing intensity, light intensity, biomass of the forest understorey vegetation and distance from road/trail and forest edge. Systat 11 (Systat 2004) was used for statistical analysis.

4.2.4 Mapping

4.2.4.1 Grasslands

Waterlogged depressions with open grassland, which did not represent the true forest environment, were classified using maximum likelihood image classification method as to separate only grassland from the rest and masked from further analysis.

4.2.4.2 Light intensity and forest canopy density

An artificial neural network was found to be unbiased and more accurate classifier than the other traditional methods and could well classify physical parameters as a continuous variable (Chapter 3). Hence, a three-layer feedforward backpropagation artificial neural network (ANN) consisting of an input, a hidden and an output layer (Skidmore *et al.* 1997) was used to map light intensity using the first seven bands (band 1-7) of Landsat ETM+ image of October 24, 2001 (path 142, row 42). The image was registered with sub-pixel accuracy (±17m). Light intensity reaching the
forest understorey derived from the hemispherical photographs was used to train the artificial neural network. All 302 observations were randomly divided into two groups. One subset of 151 observations was used for training and the other 151 for testing. The backpropagation algorithm used is designed to minimize the root mean square error (RMSE) between the observed and the predicted output. The combination of learning rate and momentum optimally minimizing the root mean square error was empirically established. The best results were obtained with a learning rate of 0.9, a momentum of 0.7 and two hidden nodes. Finally 20 iterations of 7000 epochs were performed (the RMSE stabilized after approximately 7000 epochs) and the best classification based on least root mean square error was selected. Forest canopy density in percentage was also calculated using the same data set and procedure. Image classification and GIS analyses were performed with ENVI 4.1 (2003), ILWIS 3.3 (2005) and ArcGIS 9.0 (ESRI 2004).

4.3 Results

4.3.1 Environment data layers

Figure 4-2 shows the environmental data layers used for analysis in section 4.3.2 and 4.3.3 and spatial predictions in section 4.3.4.
Figure 4-2. Maps of A) distance from the forest edge (m); B) distance from roads and trails (m); C) forest canopy density (%); D) average daily light intensity (mJ m⁻² day⁻¹) reaching the forest floor. Forest canopy density and light intensity maps were generated using a Landsat ETM+ image of October 24, 2001.
Figure 4-3 reveals that the light intensity map from the neural network classifier (Figure 4-2D) explained about 81% of the variance in light intensity of an independent validation sample. The prediction of light intensity was unbiased, since the slope (b) and intercept (a) did not differ significantly from 1 and 0 respectively (a = -0.002, SEa = 0.005, ta = -0.361, b = 1.003, SEb = 0.035, tb = 0.086). Similarly, in chapter 3 we reported a high reliability of the forest canopy density map.

![Figure 4-3. Scatterplot of light intensity reaching the forest floor observed in the field, against the light intensity predicted by a neural network using a Landsat ETM+ image.](image)

### 4.3.2 Cover

The cover of *C. odorata* was positively correlated to light and grazing intensity and negatively related to all other variables (Table 4-1).

<table>
<thead>
<tr>
<th>Environmental variable</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest canopy density</td>
<td>-0.69*</td>
</tr>
<tr>
<td>Light intensity</td>
<td>0.71*</td>
</tr>
<tr>
<td>Grazing intensity</td>
<td>0.32*</td>
</tr>
<tr>
<td>Distance from road/trail</td>
<td>-0.34*</td>
</tr>
<tr>
<td>Distance from forest edge</td>
<td>-0.25*</td>
</tr>
<tr>
<td>Understorey biomass</td>
<td>-0.50*</td>
</tr>
</tbody>
</table>

Stepwise multiple regression model (Equation 4-3) included light intensity (X1) and biomass of the other forest under-storey species (X2) as significant variables explaining 64% of the variance in *C. odorata* cover (Y):
Light intensity had a positive influence, while the biomass of the other under-storey species negatively influenced \( C. odorata \) cover. Hence, only two of the variables in Table 4-1 were included in this model. The six variables displayed in Table 4-1 were, however, strongly interrelated. Some may have affected cover indirectly through other variables. Path analysis (Figure 4-4) revealed that distances from forest edges and from roads had a direct influence on \( C. odorata \) cover as well as an indirect influence through grazing that influenced the biomass of other forest under-storey species. Similarly, forest canopy density indirectly influenced \( C. odorata \) cover through light intensity.

Figure 4-4. Path diagram showing the effect of six variables on the cover of \( C. odorata \). Solid arrows indicate significant effects with path coefficients. Signs indicate negative and positive relationships accordingly, line width is proportional to the size of path coefficients.

Biomass of the other forest understorey species was a variable significantly contributing to the above regression model. It was not however, included in the spatial prediction of \( C. odorata \) cover because it was impossible to map the spatial distribution of this factor. Only light intensity, canopy density and distance from forest edges and roads were mappable. Hence, we used stepwise linear regression to select the best fitting model (Equation 4-4) using these variables, which explained 64% of the variation of \( C. odorata \) cover abundance:

\[
y = -9.56 + 3.14 x_1 - 0.005 x_2 \tag{4-4}
\]

where \( x_1 = \) Light intensity and \( x_2 = \) distance from forest edge

4.3.3 Seed productivity of \( C. odorata \)

The seed production per plant differed between highly and poorly reproductive populations by more than five orders of magnitude. The reproductive biometry of \( C. \)
odorata was significantly related to a number of environmental variables (Table 4-2).

Table 4-2. Correlation between six environmental variables and the logarithm of five biometric properties and the seed production per plant (SPP) of C. odorata. Significance levels: *p< 0.05, **p< 0.01 and ***p<= 0.001

<table>
<thead>
<tr>
<th>Environmental variable</th>
<th>Chromolaena odorata</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Flowering stems</td>
<td>Flowering branches</td>
<td>N inflorescence</td>
<td>N Capitula</td>
<td>N Cypsela</td>
<td>SPP</td>
</tr>
<tr>
<td>Forest canopy density</td>
<td>-0.84***</td>
<td>-0.85***</td>
<td>-0.84***</td>
<td>-0.80***</td>
<td>-0.70***</td>
<td>-0.86***</td>
</tr>
<tr>
<td>Light intensity</td>
<td>0.85***</td>
<td>0.87***</td>
<td>0.85***</td>
<td>0.79***</td>
<td>0.69***</td>
<td>0.86***</td>
</tr>
<tr>
<td>Grazing intensity</td>
<td>0.17*</td>
<td>0.18*</td>
<td>0.15 ns</td>
<td>0.14 ns</td>
<td>0.12 ns</td>
<td>0.16*</td>
</tr>
<tr>
<td>Distance road/trail</td>
<td>-0.54***</td>
<td>-0.47***</td>
<td>-0.54***</td>
<td>-0.54***</td>
<td>-0.53***</td>
<td>-0.55***</td>
</tr>
<tr>
<td>Distance forest edge</td>
<td>-0.27***</td>
<td>-0.22**</td>
<td>-0.27**</td>
<td>-0.25**</td>
<td>-0.24**</td>
<td>-0.25**</td>
</tr>
<tr>
<td>Under-storey biomass</td>
<td>-0.16*</td>
<td>-0.17*</td>
<td>-0.08 ns</td>
<td>-0.01 ns</td>
<td>0.09 ns</td>
<td>-0.11 ns</td>
</tr>
</tbody>
</table>

Light intensity and forest canopy density, which were strongly inter-correlated (Pearson r = 0.98), had a stronger relationship with these biometric properties than any other environmental variable. Figure 4-5 reveals sigmoid patterns in the relation between light intensity and the five reproductive properties of C. odorata. All five properties reduced to almost zero at light intensity below 6.5 mJ m⁻² day⁻¹.
Figure 4.5. Relation between light intensity (mJ m$^{-2}$ day$^{-1}$) and the log$_{10}$ of: A) number of flowering stems per plant, B) number of flowering branch per flowering stem, C) number of inflorescence per flowering branch, D) number of capitulum per inflorescence and E) number of cypsela per capitulum.
Multiple multiplicative factor (MMF) and logistic models best described the relation between light intensity and *C. odorata* reproductive properties (Table 4-3).

### Table 4-3. Regression equations of the best fitting non-linear model between light intensity (X) and reproductive properties of *Chromolaena odorata* (Y)

<table>
<thead>
<tr>
<th>Dependent: Log10(Y+1)</th>
<th>Equation</th>
<th>Type</th>
<th>R2</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>N flowering stem</td>
<td>(-0.09 + 2645 + 1.34 X 3.86)/ (2645 + X 3.86)</td>
<td>MMF</td>
<td>0.86</td>
<td>0.17</td>
</tr>
<tr>
<td>N flowering branch/stem</td>
<td>1.24/(1+203.5<em>Exp(-0.67</em>X))</td>
<td>Logistic</td>
<td>0.86</td>
<td>0.17</td>
</tr>
<tr>
<td>N head/branch</td>
<td>(-0.04 + 65850 + 1.39*X 5.69)/ (65850+X 5.69)</td>
<td>MMF</td>
<td>0.92</td>
<td>0.13</td>
</tr>
<tr>
<td>N capitulum/inflorescence</td>
<td>(-0.03<em>238039 + 0.99</em> X 6.66)/ (238039+X 6.66)</td>
<td>MMF</td>
<td>0.90</td>
<td>0.11</td>
</tr>
<tr>
<td>N cypsela/capitulum</td>
<td>1.48/(1+9706186.4<em>Exp(-2.66</em>X))</td>
<td>Logistic</td>
<td>0.92</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Hence, light intensity was significantly related to five independent biometric properties of *C. odorata*, which together determine its seed productivity. These biometric properties were combined in a reproductive index (see section 4.2.2) reflecting the seed production per plant. Figure 4-6 reveals that *C. odorata* did not produce seed below light intensity of 6.5 mJ m$^{-2}$ day$^{-1}$.

![Figure 4-6. Relation between light intensity and the logarithm of the seed production per plant (SPP) of *C. odorata*. The solid line represents the selected MMF model, while the dotted line indicates the light intensity threshold of 6.5 mJ m$^{-2}$ day$^{-1}$ separating reproductive and non-reproductive populations of *C. odorata.*](image-url)
The relation between the seed production and light intensity was best explained by an Multiple Multiplicative Factor model (Equation 4-5):

\[
\log_{10}(Y + 1) = \frac{-6624.39 + 6.11 \times X^{0.219}}{2890.4 + X^{0.219}}
\]

Equation 4-5

where, Y is the seed production per plant and X is light intensity received at the forest floor.

The equation explained 93% of the variation in \(\log_{10} Y+1\). Further analysis revealed that none of the other variables in Table 4-2 was related to the residuals of the seed-light model described in equation 4-5.

### 4.3.4 Other factors affecting seed productivity of Chromolaena odorata

The results presented above indicate that \(C.\) odorata produced seed at light intensities above 6.5 mJ m\(^{-2}\) day\(^{-1}\). This does not imply however, that \(C.\) odorata was always present above or absent below this threshold. Out of 153 cases, \(C.\) odorata was absent in 22 cases where light conditions were suitable for seed production. In addition, the species was present in 17 cases where light conditions were unsuitable for seed production.

Why was \(C.\) odorata absent from sites suitable for seed production? Logistic regression (Equation 4-6) revealed that the presence of \(C.\) odorata (Y) in areas with light intensity above 6.5 mJ m\(^{-2}\) day\(^{-1}\) was significantly related to the biomass (X) of the forest understorey vegetation (-2LL = 44.08, df = 1, p<0.0001; McFadden’s Rho\(^2\) = 0.38):

\[
y = \frac{\exp^{4.99–3.65\times X}}{1 + \exp^{4.99–3.65\times X}}
\]

Equation 4-6

We classified the probabilities values predicted by the logistic regression into cases of ‘predicted presence’ and ‘predicted absence’. To do this classification, a threshold probability had to be determined. We chose the threshold that produced the highest value for Cohen’s Kappa. The threshold for classifying the predicted probabilities into cases of ‘predicted presence’ and ‘predicted absence’ was 0.74 and produced a Kappa value of 0.56. Table 4-4 presents the model confusion matrix which shows that the model predicts \(C.\) odorata to be absent from sites with a high biomass of other herb and shrub species.
Table 4-4. Logistic regression model confusion matrix

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Observed</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Absence</td>
<td>17</td>
<td>13</td>
</tr>
<tr>
<td>Presence</td>
<td>5</td>
<td>86</td>
</tr>
</tbody>
</table>

4.3.5  Spatial prediction of cover and potential seed productivity of *C. odorata*

Figure 4-7A shows the cover percentage of *C. odorata* was predicted based on Equation. 4-4. Figure 4-7B shows the potential for seed production by *C. odorata* as predicted from light intensity using Equation 4-4 and 4-5 and Figure 4-7B shows the potential seed production based on *C. odorata* cover and light suitability map.

Figure 4-7. Map of A) potential cover % of *C. odorata* and B) Potential areas of seed producing *C. odorata*.
Our predictive map shows that reproductive populations of *C. odorata* currently present along forest edges and roads/trails, however it has a high potential to substantially increase its range. It could potentially invade large areas of the forest interior which are suitable for seed production.

### 4.4 Discussion

This study revealed a strong relationship between light and cover abundance and seed production of *C. odorata*. Light intensity influenced four out of five plant architectural characteristics determining total seed output per plant: the number of flowering stems, branches, the number of inflorescences and capitulum increased with light intensities. The number of cypsela (seed) per capitulum was genetically determined hence, not related to light intensity. These findings confirm Witkowski et al. (2001), who reported significant differences between sun, semi-shade and shaded sites for flower head, capitula and seed per plant but not seeds per capitula.

A positive influence of light intensity on the growth and seed production has been reported for various invasive species characteristic of forest understorey and forest clearings (Bush and Van Auken 1986, Silander and Klepeis 1999, Meekins and McCarthy 2000). Many of these species have a ruderal strategy (Grime 1979), characterized by high reproductive potential, excellent dispersal, fast germination, rapid initial growth and a high morphological and physiological growth plasticity. *C. odorata* combined all of these. The marked response to light of four out of five plant architectural characteristics demonstrated its extremely high morphological growth plasticity.

*C. odorata* thrived in areas with high light intensities, which corresponded to reduced canopy density. Light intensity under closed canopy in natural forest remained below the threshold for seed production. Open canopies with sufficient light reaching the understorey were predominantly found outside conserved forests. Here canopy density was reduced due to logging and lopping (Joshi, pers. obs.).

*C. odorata* was not always present in forests, that would otherwise have been suitable for seed production given their understorey light climate. Path analysis showed that grazing indirectly influenced the cover of *C. odorata*, most likely through its impact on the biomass of other understorey species. *C. odorata* was absent in the understorey of natural forest gaps in well conserved areas such as Chitwan National Park where native grass species reached a height of 2 m. Outside
these well-conserved areas most of the forest was intensively grazed and the density and height of the other grass and herb species was generally much lower (Joshi, pers. obs.). We therefore suggest that these other species control and suppress *C. odorata* through competitive exclusion in the absence of grazing, whereas grazing breaks the dominance of these other species thus creating the conditions for unpalatable *C. odorata* to rise to dominance. Following this, we further suggest that the intensive grazing of the *S. robusta* forest in the Nepalese Terai may well have been a secondary factor responsible for the invasive success of *C. odorata*.

Our results indicate that *C. odorata* was frequently observed in forest too shaded for seed production. Anatomical analysis of the corm (an underground swollen stem base specialized for food storage, detail in Chapter 5) exhibited continuously developed increment zones (Figure 4-8).

![Figure 4-8. Cross sections (A) and radial sections (B) of the xylem of corm of *C. odorata*. Increment zones (arrows) are labeled ray parenchyma with reduced cell lumina and dark stained accessory compounds within (ray parenchyma).](image)

Counting the number of increment zones found in the xylem at the shoot-root transition zone of plants indicated the annual formation of “tree rings” in the xylem of *C. odorata*. Tree ring analyses revealed that plants recorded under these conditions were mostly young and few old plants were found sterile. The presence of *C. odorata* under conditions unfavourable for seed production implies continuous re-colonization of such sites from adjacent seed producing populations. Blackmore (1994) reported that wind disperses seed up to 80m as short distance dispersal agent, while animals, people and vehicles transport seeds over significantly greater distances. The observation that *C. odorata* distribution was generally restricted to the first few metres along tracks in dark forest supports the importance of local
people and domestic as well as wild animals as long-distance dispersal agents and forest canopy density as a factor limiting the invasion ability of C. odorata.

The above indicates that C. odorata maintains sterile populations in shaded forests, which are maintained through continuous colonization from adjacent seed producing populations. This implies that C. odorata is locally segregated into source and sink populations. The source-sink concept (Pulliam 1988) is interesting when applied to invaders, since source populations pose a risk of further spread and infestation while sink populations do not. Sink populations could rapidly develop into source population if trees are removed.

Our results indicated that C. odorata thrives in relatively open forest with sufficient light penetration, and suggested that competitive exclusion of C. odorata by other understorey species is prevented by grazing. The canopy of well-protected natural S. robusta forest is closed and its understorey hardly grazed. We suggest that it is the lopping and logging of the trees and grazing by livestock which degrade the forest canopy and understorey and creates conditions which allows C. odorata to dominate. On the one hand, it could be argued that the success of C. odorata depended on the degradation of the canopy and understorey of these forests, which created optimal conditions for C. odorata. Following this, it could be argued that the condition and degradation of the environment played a primordial role. On the other hand, it could be argued that seed dispersal and a strong reaction of seed production to light conditions point at an important role of the inherited traits of C. odorata. We think that the degradation of the forest environment which created the conditions allowing C. odorata to express its latent invasiveness. Hence, it could also be argued that degradation created an invadable environment which offered C. odorata to express its latent invasible traits.

Although, Civco (1993), reported that neural networks were under certain circumstances less accurate than conventional approaches for classifying land cover, several researchers have demonstrated that neural networks allow the combination of multi-source spatial data into the same classification or estimation (Benediktsson et al. 1993, Wilkinson 1993). A potential seed production map was created using a neural network, an approach generally leading to more accurate results than other traditional land cover classification techniques (Hepner et al. 1990b, Bischof et al. 1992, Atkinson and Tatnall 1997). The seed production of C. odorata was predicted from maps displaying light intensity reaching the forest understorey.
Perhaps the broadest use of remote sensing has been to identify and map vegetation types. In this study, we mapped the degradation stages of one particular vegetation type, rather than multiple separate vegetation categories. In forestry, remote sensing has been used for a long time to monitor deforestation (Tucker et al. 1984). More recently, however, it has been recognized that gradual forest degradation is a process deserving equal attention (Souza Jr. et al. 2003). Remote sensing techniques to map forest canopy density have been developed in response to this. Approaches to map forest canopy density, produced categorical maps with two (Boyd et al. 2002) or more classes (Rikimaru 1996, Rikimaru et al. 2002) rather than a continuous variable. We argued in chapter 3 that canopy density should be treated as a continuous rather than discrete variable.

This study indicates that an indirect approach could be very successful to predict life cycle attributes of invasive species. This success could possibly be due to a number of factors such as C. odorata being a shade tolerant species, the strong relationship between seed production and light intensity proved surprisingly strong and light intensity and the ability to reliably predict light intensity. We further suggest that there are possibly many more species that react in similar ways and the success of this approach might well be applicable to other cryptic invasive species.

We demonstrated the possibility to map and localize source and sink populations in plant species using remote sensing and GIS techniques. The reproductive success in many species is determined by physical factors such as light, moisture or nutrient availability. Remote sensing offers continuously improving possibilities to map such physical variables across landscapes (Baker et al. 2000, Corsi et al. 2000, Guisan and Zimmermann 2000). We therefore suggest that there is wider application for the indirect mapping approach described in this study. This could be helpful in invasive species management to direct interventions aiming at eradication or control to those areas which produce viable seeds and pose the greatest risk for further spread.

The findings of our study illustrate how remote sensing and GIS technologies can provide ecologists and land managers with an innovative perspective with which to study the factors influencing the patterns of invader population dynamics at local landscape scales. Furthermore, We suggested that forest canopy density, inter-specific competition and anthropogenic factors might account for the differences in size and productivity of C. odorata populations.
CHAPTER FIVE

Morphological plasticity and age structure of corms in enhancing invasion of Chromolaena odorata

This Chapter is based on:
Morphological plasticity and age structure of corms in enhancing invasion of *Chromolaena odorata*

Abstract

In this paper, we investigate the vegetative growth of *Chromolaena odorata* and the influence of light intensity on the understorey environment of *Shorea robusta* forest at Chitwan on south-central Terai, Nepal. *C. odorata* is a clonally growing shrub and typically consists of several clones with an underground "cormous organ" (a modified stem to store food reserve; hereafter "corm") belonging to the identical genet. In *C. odorata*, the biomass of such corms varied across the light gradient. The number of shoot described a strong logarithmic relation with biomass of corm. Under open forest canopy environment, corm biomass was strongly correlated with the number of shoots and the corm's age. However, under dense forest canopy, there was no significant relationship between corm biomass and its age. This result shows that corms of *C. odorata* were capable of maintaining their viability for a long period even under closed canopy environment. Any disturbances in forest canopy density would ultimately trigger its clonal growth capability. This plasticity of corms appeared to be a key strategy for invasion success of this species. Comparison of these results further indicates the importance of canopy density in determining invasion success of *C. odorata*.

Key words: Corm anatomy, "corm ring", *Chromolaena odorata*, clonal growth, invasion, light intensity, plant age, size plasticity

5.1 Introduction

The establishment of invasive plant species starts with the arrival of propagules, typically in the form of seeds (Ridley 1930). Once established, invaders may attain local dominance through sexual or vegetative regeneration (Cousens and Mortimer 1995). It has been repeatedly acknowledged that vegetative reproduction may be as valuable as seed production, as it makes the species less dependent on germination chance (Bunting 1960). Vegetative growth facilitates the penetration into adjacent vegetation under more stressful conditions (D'Antonio 1993).

un-colonized areas through dispersal of stolons, rhizomes, tubers or corms (Sachs and Novoplansky 1997). Clonal growers are typically strong competitors (Auge and Brandl 1997, Pysek 1997) The combined ability of spreading and rising to dominance makes clonal growers invaders with a potentially strong influence on their direct adjacency. However, the role of clonal growth in invasiveness and invasibility has also been little explored (Alpert 1995, Shumway 1995, Pysek 1997).

Environmental conditions influence the production of clonal dispersal organs (De Kroon and Hutchings 1995, Sachs and Novoplansky 1997). Under suitable conditions, above ground parts allocate resources to produce clonal reproductive organs. Individuals growing under less favourable environmental conditions may not be able to allocate sufficient resources. Hence, heterogeneity in environmental conditions might generate spatial variation in the relative growth rate of clonal reproductive organs (Hutchings and De Kroon 1994, Hunt and Cornelissen 1997). Spatial variation in environmental conditions are thus expected to result in spatial variability of the rates of clonal growth of plants, particularly when factors are involved influencing their ecophysiology.

Native forest understorey species live under shaded conditions. Opening of forest canopy, due to logging or natural disturbances results in increased light intensities and change in species composition. Typically ruderal and heliophytic species rise to dominance when light intensity increases (Bayfield 1980, Appleby 1998, Kobayashi and Kamitani 2000). A number of exotic plant species such as Chromolaena odorata have successfully established as invaders under conditions of degraded canopy and forest clearing. Several of such clonal growers have been spreading vegetatively after initial establishment through seeds. The increased light intensities are postulated to trigger their rate of clonal growth.

Remote sensing has frequently been used to map invasive species. Applications have been restricted to localizing the distribution of invasive species (Everitt and Nixon 1985, Ustin et al. 2002). It has been argued that it would also be useful to a manager to know where invasive species spread into unoccupied areas through sexual or vegetative reproduction. In chapter 4, we demonstrated that it was possible to map seed production of a forest understorey species Chromolaena odorata. So far, no attempts have been made to map the rate of clonal growth in invaders.

Chromolaena odorata (L.) RM King & Robinson (King and Robinson 1970) is one of the world’s one hundred worst invasive species (ISSG 2004) Originating from
Central America it now occurs in the humid tropics around the world (Muniappan 1988, Gautier 1992b, Kriticos et al. 2005). It has a ruderal strategy and occurs in a wide range of environments including road verges, neglected agricultural fields and as an understorey species in forest. As a heliophyte (Gautier 1992a), it requires sufficient light to grow and produce seeds (Witkowski and Wilson 2001). Because of this it becomes invasive in forest where the canopy has been broken up (De Rouw 1991).

*C. odorata* plants in Nepal are composed of one or more genetically identical clones (Figure 5-1). Every clone has a root system supporting a corm (an underground swollen stem base specialized for food storage) from which shoots emerge (Figure 5-1, left). Buds located belowground on the corm allow *C. odorata* to escape the dry season with its frequent fires. This strategy to escape the adverse season classifies *C. odorata* as a geophyte (Raunkiaer 1937).

Figure 5-1. Morphology of *C. odorata* consisting of a single clone (left) and a genet of multiple clones (right). Photos taken at start of the rainy season show the corm, previous seasons’ and newly emerging shoots.

Single clone *C. odorata* plants develop into genets (Kays and Harper 1974) of multiple clones. After a number of years clones decay and split into two or more new clones spaced typically 5 to 10 cm apart. Older plants because of this consist of a dense crowd of clones together forming one genet that may reach up to several meters in diameter (Figure 5-1, right). Stems of *C. odorata* grow up to 2 m in height.
In this paper, we investigate and model the biomass of corms of *C. odorata* to light intensity and corm age in *Shorea robusta* forests in Southern Nepal. Corm age was established using “corm rings”, which we describe in this article. We next use remote sensing image to predict light intensity in the forest understorey. Finally, we predict the spatial variation in clonal growth rate from the light intensity map.

### 5.2 Methods and materials

#### 5.2.1 Study area

The study was executed in a tropical forest corridor north of Chitwan National Park (27° 31´ to 27° 44´ N and 84° 24´ to 84° 31´ E), 140 km SW of Kathmandu, Nepal. The forest was dominated by *Shorea robusta*, while the understorey was invaded by *C. odorata*.

#### 5.2.2 Data collection

The study area was visited twice. In September and October 2003, 275 plots were visited to measure forest canopy density percentage and light intensity at 1.2 m above the ground using hemispherical photography taken with fisheye lens attached to a Nikon digital camera.

In April-May 2005, we collected 237 corms of *C. odorata* plants. We measured the diameter of the corm and recorded the number of new shoots. The number of rings in the corm was counted on a transverse section. The corms were dried for 40 min in a microwave and dry biomass (g) measured. Morphology and phenology of *C. odorata* were described following several years of intensive study of the species.

Meteorological data on the monthly maximum and minimum temperatures, relative humidity, precipitation and evapotranspiration recorded for an average of 36 years at Rampur weather station were obtained from the Department of Meteorology, HMG, Nepal. Map of cover abundance of *C. odorata* was used from chapter 4.

#### 5.2.3 Anatomical analyses

The anatomy of corms was further investigated at the Federal Research Centre for Forestry and Forest Products, Institute for Wood Biology and Wood Preservation, Hamburg, Germany. The anatomical structure of the xylem of the shoots and of the corms was investigated by light microscopy in order to prove the suitability of tree
ring analyses for age determination in *C. odorata*. The shoot/corm was divided into segments of 1 cm length each. The samples were fixed in a FAA solution. The samples were embedded in polyethylen glycol (PEG 1500) with increasing concentration (PEG 1500:H2O, 1:2, 1:1, 2:1, 1:0, 1:0). For light microscopy and for the histometrical analyses of the xylem cells, transverse and radial sections (10 µm) were prepared by a microtome (Reichert, Austria). For light microscopy unstained and stained (safranine/astrablue (1:1)) slides were used. Histometrical measurements were carried out with an image analyser.

5.2.4 Data analysis

Total light intensity was calculated from the digital hemispherical photographs using Gap light analyzer software version 2 (Frazer *et al*. 1999, Frazer 2001). For ANOVA, we classified the light intensity in the forest understorey into three categories: high or full light (above 13 mJ m⁻² day⁻¹), moderate light or semi-shade (7-13 mJ m² day⁻¹) and low light or full shade (below 7 mJ m⁻² day⁻¹).

We used two way ANOVA to investigate to what extent the biomass of *C. odorata* corm was related to light intensity and its age. We used curve expert (Hyams 2005) to select the best fitting curve describing the relation between number of shoots and biomass of the corm.

5.2.5 Mapping Light Intensity

Field measurements on light intensity were combined with an ETM+ image to produce a map of light intensity in the forest understorey. A three-layer feedforward backpropagation artificial neural network (ANN) consisting of an input, a hidden and an output layer was used for image classification (Skidmore *et al*. 1997). The Landsat ETM+ image of October 24, 2001 was registered with subpixel accuracy (±17m). The first seven bands were used as input to the network. Light intensity calculated from the hemispherical photographs was used to train the ANN. The total data set of 275 samples was randomly divided into two groups. One subset of 138 samples was used for training and the other 137 samples for testing. The best results were obtained with a learning rate of 0.9, a momentum of 0.7 and two hidden nodes. Finally 20 iterations of 7000 epochs were performed (the RMSE stabilized after approximately 7000 epochs) and we selected the best classification based on least root mean square error (RSME). Forest canopy density in percentage was also calculated using the same data set and procedure.
5.3 Results

5.3.1 Climate and *Chromolaena odorata* phenology

The season of heavy rainfall with precipitation higher than evapotranspiration extends in southern central Nepal from July to September (Figure 5-2). Significant rains may start in May and extend until November. The dry season extends from December to May. The season of active growth extends for *C. odorata* from May to October. Flowering starts in December and seeds ripen in February. After seed rippling, the stems die and drop off. Forest fire frequently destroys this decayed above-ground growth. New shoots develop from the resources stored in the corm in April, just before the start of the rainy season. If not destroyed by fire old stems may persist. Old bushes thus form a tangled mass of old and new stems.

![Figure 5-2. Monthly mean (1968-2004) precipitation and temperature for Rampur station (27°37’ N, 84°25’ E). The numbers on the vertical line denotes degree Centigrade for the Temperature (mean temp) and centimetres for Mean Precipitation (Mean prec), Maximum Precipitation (Max prec), Minimum Precipitation (Min prec) and Evapotranspiration (Evapotrans) for the curves.](image)

5.3.2 Corm anatomy

Distinct increment zones were found in the xylem of the shoot and in the xylem of the corms of *C. odorata*. Increment zones in the xylem of *C. odorata* are labeled by fibres and ray parenchyma with reduced cell lumina as well as by wider rays (Figure 5-3a-d). The shoot/corm samples exhibited continuously developed increment zones (Figure 5-3b, d). Counting the number of increment zones found in the xylem at the shoot-root transition zone of plants of known age indicated the annual formation of “corm rings” in the xylem of *C. odorata*. Corm ring analyses showed that the oldest plants considered in our study had an age of 5 years. However, due
to a very inhomogeneous pattern of ring width over the stem cross section and along the corm axis, corm ring analyses was not suitable to quantify the biomass allocation in the corms on an annual scale.

Figure 5-3. Cross sections (a/b) and radial sections (c/d) of the xylem of corm of C. odorata (sample 107). Increment zones (arrows) are labeled fibres and ray parenchyma with reduced cell lumina and dark stained accessory compounds within (ray parenchyma). Scale bars: (a/c) = 500 µm, (b/d) = 100 µm.

5.3.3 Corm and shoot dynamics

The maximum age of corms observed under full light was five years. Parts of these corms had decayed, leaving fragmented living tissue supporting vital shoots. Maximum observed corm age under full shade was also five years. However, these corms looked rotten, with little live tissue remaining.

Figure 5-4 shows corm biomass in relation to age and light intensity. Log transformation was used because it equalized group standard deviations, which originally varied by more than an order of magnitude. The figure suggests that corm
biomass increases when plants age under full light or semi shaded conditions, but not under full shade.

Figure 5-4. Corm biomass in relation to age of *C. odorata* and light intensity: ■ = full light, ▲ = semi-shade, ● = full shade.

This was confirmed by analysis of variance (Table 5-1). Both light and corm age had a highly significantly effect. The significant interaction implied that the increase of corm biomass with age changed with light intensity. While corm biomass differed significantly between two, three, four and five year old plants in the semi-shade (one-way ANOVA; p = 0.000) and in full sun-shine (p = 0.003), it did not in the full shade (p = 0.22). Hence, corms do apparently not grow in full shade while they do under semi shaded and lighter conditions.

Table 5-1. ANOVA of Log10 corm biomass in relation to corm age and light intensity

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>55.08</td>
<td>2</td>
<td>27.90</td>
<td>330.29</td>
<td>0.000</td>
</tr>
<tr>
<td>Corm age</td>
<td>3.14</td>
<td>3</td>
<td>1.04</td>
<td>12.40</td>
<td>0.000</td>
</tr>
<tr>
<td>Light * Corm age interaction</td>
<td>1.17</td>
<td>6</td>
<td>0.19</td>
<td>2.32</td>
<td>0.033</td>
</tr>
<tr>
<td>Error</td>
<td>19.05</td>
<td>225</td>
<td>0.08</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
One might expect that larger corms support larger plants. Figure 5-5 reveals that the number of shoots (y) produced by of *C. odorata* increased with the biomass of its corm (x). The relation was best described by the following Horel model (Equation 5-1), that explained 82% of variation in shoot number:

\[ y = 2.501 \times 1.001^x \times x^{0.266} \]  

Equation 5-1

If low light constrains the growth of corms and subsequently shoot numbers, one would expect no enlargement of shoot numbers over time under low light conditions. Figure 5-6 reveals that this is the case indeed. The annual rate of increase of shoot numbers was significantly related to light conditions. Number of shoots increase with age only under semi shaded or full light conditions.
Figure 5-6. Relation between shoot number in relation to plant (corm) age and light intensity: ■ = full light, ▲ = semi-shade, ● = full shade in C. odorata.

Table 5-2 conformed that there is no significant difference in shoot numbers between two, three four and five year old shaded plants. While number of shoots differed significantly between two, three, four and five year old plants in the semi-shade (one-way ANOVA; p = 0.000) and in full sun-shine (p = 0.000), it did not in the full shade (p = 0.29). These results indicate that number of shoots almost not increase in plants growing in the shade. It does increase for plants growing under semi-shade and full sunshine.

Table 5-2. ANOVA of number of shoots in relation to corm age and light intensity

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>2517.13</td>
<td>2</td>
<td>1259</td>
<td>429.76</td>
<td>0.00</td>
</tr>
<tr>
<td>Corm age</td>
<td>220.36</td>
<td>3</td>
<td>73.5</td>
<td>25.08</td>
<td>0.00</td>
</tr>
<tr>
<td>Light * corm age interaction</td>
<td>148.31</td>
<td>6</td>
<td>24.7</td>
<td>8.44</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>658.92</td>
<td>225</td>
<td>2.93</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.3.4 Mapping forest understorey light intensity

Figure 5-7 and Figure 5-8A presents the performance of the artificial neural networks in scatterplots of observed versus predicted light intensity and the map produced by ANN classifier. It revealed that the prediction of light intensity by the artificial neural network was unbiased. The t-statistic of the slope (b) and intercept (a) reveal that these did not differ significantly from 1 and 0 respectively ($a = -0.002$, $SE_a = 0.005$, $t_a = -0.361$, $b = 1.003$, $SE_b = 0.035$, $t_b = 0.086$, $r^2 = 0.81$).

5.3.5 Spatial prediction of rate of clonal growth of C. odorata

Number of shoots per year produced by the plant was utilized for spatial prediction of rate of clonal growth of C. odorata. The relation was best described by the following modified power model (Equation 5-2) which explained 73% of variation in clonal growth rate:
We inverted this model to predict rate of clonal growth of *C. odorata* in the Chitwan region of Nepal. Map (Figure 5-8B) revealed that the current clonal growth rate of *C. odorata* was high along the forest edge and road, however, it has a high potential to substantially increase its range towards forest interior. It could potentially invade large areas of the forest interior which are climatically suitable for clonal growth in terms of size and number of corms as well as increase in occupied areas by stems.

5.4 Discussion

The results presented in this study indicate that light intensity controls the growth of the corms of *C. odorata*. Our results further reveal that the size of the corms determines the number of next seasons’ shoots. Plants growing under full light conditions thus enlarge their canopy, which in turn allows them to allocate more
resources to the corm, which next year produces an even larger canopy. This positive feedback loop continues for a maximum of five years, after which the clone splits in two or more offspring starting the cycle anew. Over time, this leads to continuous enlargement of *C. odorata* genets.

Our results revealed by contrast that plants growing under shaded conditions do not enlarge their corm. Consequently, their number of shoots remains stagnant and hence no enlargement takes place. Our observation on the decaying condition of five-year old corms under shaded conditions suggests that they probably succumb within five years. The fact multi-clone genets were never observed under shaded conditions fits into this picture.

*C. odorata* thus manages to grow vegetatively under medium to full light conditions. These conditions rarely exist in natural forest. In forests, under shaded conditions one expects *C. odorata* populations to consist of young single clone genets, which is indeed the case. Under canopy openings however, *C. odorata* would receive sufficient light for vegetative expansion. Conditions of canopy opening widely occur in *S. robusta* forests in the Nepalese Terai. Not surprisingly, *C. odorata* populations here consist of multi-clonal genets, sometimes several meters in diameter. Figure 5-9 summarizes the effect of light intensity at different stages of the development of *C. odorata* linking to clonal growth and its vegetative invasion.

![Figure 5-9](image)

**Figure 5-9.** Spatial and temporal dynamics of corm of *C. odorata* under high light environment. A) An establishment of a mother corm in a new environment by long or short distance seed dispersal. B) Development and growth of daughter corms. C) Growth and range expansion of daughter corms of the identical genet. D) Death of mother corm and range expansion of new daughter corm populations.

What makes *C. odorata* such a successful invader in the *S. robusta* forests of the Nepalese Terai? *C. odorata* invades through its huge production of achenes, and its corm production and vegetative spreading were promoted by human disturbances
through altering forest understorey light regime (opening up of forest canopy that benefit its competition and dominance among native plant communities). Furthermore, deliberate fire destroys native vegetation and most of the upper parts of *C. odorata* bush, leaving the basal stem unaffected. These stems regenerate shoots in the rainy season enabling the species to become the first dominant in the next growing season (Liggitt 1983) Grazing on neighbouring plant species further enhances its clonal growth by reducing inter-specific competition as the leaves and young shoots of *C. odorata* are poisonous to livestock (Sajise et al. 1972).

Comparisons of the traits of different invaders suggest that some species are more invasive in a particular environment than others. A wide range of species traits may underline these differences, including ruderal nature, wide seed dispersal mechanism, producing large amount of seeds, or allocation of resource during favourable conditions or long survival in the system (Grime 1979, Richardson and Bond 1991, Roche et al. 1997). All these characters interact with each other and with the environmental factor making it difficult to identify the cause of invasiveness in individual cases. However, our results show the primary importance of biomass allocation in *C. odorata* in determining spatial patterns of vegetative reproduction along light gradients. *C. odorata*'s ability to store energy enhances the early clonal growth in the next growing season. This competitive ability appears to be an important key to understanding its behaviour as an invader. If openings present in a stand, *C. odorata* becomes established and outcompetes previously established native species.

Mapping the rate of clonal growth could be well applied to other invasive species. Clonal reproduction in many species is determined by physical factors such as light, moisture nutrient availability or distance related seed dispersal mechanisms. Spatial distribution of these factors are increasingly available or can be mapped using remote sensing (Robinson and Valentine 1979, Dennis and Brusven 1993, Austin et al. 1996, Stone et al. 1997, Baker et al. 2000, Corsi et al. 2000, Guisan and Zimmermann 2000, Kerr and Ostrovsky 2003). Our study showed how these physical factors, may linked to map the clonal growth rate of an invasive species. Incorporation of remote sensing techniques with species biometry yield instantaneous, useful, cost effective, multi-scale and temporal information on clonal growth dynamics of an invasive species.

Mapping clonal growth rate in *C. odorata* population could significantly reduce control cost by allowing one to concentrate control efforts to manage habitats so as to curtail the spread of invasive species. In this respect, the immediate benefit of
this research has been to contribute to the knowledge base of land managers by providing improved information on the rate of spatial and temporal spread of clonal population *C. odorata*, which will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems.
CHAPTER SIX

Interrelated causes of invasibility of tropical forest ecosystems of Nepal

This Chapter is based on:
Chudamani Joshi, Jan De Leeuw, Andrew K. Skidmore, Iris C. van Duren, Jelle G. Ferwerda.
Submitted to Agriculture, Ecosystems and Environment
6 Interrelated causes of invasibility of tropical forest ecosystems of Nepal

Abstract

The spread of invasive species has been attributed to intrinsic “aggressive” species traits, the extrinsic susceptibility of the recipient environment and the lifting of distribution barriers. People have stimulated invasions while lifting barriers and changing environmental conditions. In this paper, we investigate the hypothesis that environmental change as a result of disease control facilitated invasion. The study was executed in Chitwan district in central Nepal. Malaria control increased human population growth rates to levels exceeding 10% per year in the 1960’s. This resulted in land use change and scarcity of grazing lands outside forests. The increasing demand for grazing and wood resources resulted in an opening up of the forest canopy. It is deduced that the pressure to exploit the forests for grazing increased over time as a result of land use change and increased human population density. Our results indicate that the neo-tropical shrub *Chromolaena odorata* maintains invasive populations at canopy densities below 60%, which prevail in forests with opened canopies. We therefore argue that invasion of *C. odorata* accelerated a result of canopy degradation which was caused by change in land use and demography triggered by malaria control.

Key words: Landuse change, Malaria control, *Chromolaena odorata*, Population migration, Forest canopy

6.1 Introduction

Few exotic species become successful invaders (Veltman 1996). Groves (1991) estimated that while 10% of all alien species get established, only 1% become invasive. Lodge (1993) therefore concluded that exotic species differ in their ability to establish and invade local communities.

What makes an exotic species a successful invader? Some researchers stressed the importance of the intrinsic ability of species to invade (di Castri 1989, Williamson 1996, Kolar and Lodge 2001). Among the traits promoting establishment of populations are a ruderal strategy (Grime 1979), rapid germination, and initial growth rate and high production and efficient dispersal of seeds. Others (Groves and Burdon 1986, Macdonald et al. 1986, Mooney and...
Drake 1986, Hengeveld 1989, Lonsdale 1999a) stressed the importance of propagule pressure and invasibility or the susceptibility of ecosystems to invasion.

Invasions do occur naturally (Botkin 2001, Schullery 2001), since plants and animals disperse across the globe. The rate of species invasion however has been greatly accelerated by humans. The most frequently cited anthropogenic enhancement of invasions is the moving of species across geographical barriers previously restricting distribution and by modifying the recipient ecosystem (Johnstone 1986, Hobbs 2000b, Vila´ and Pujadas 2001). Several studies attributed the invasive success of exotic species to disturbance or degradation imposed by people (Elton 1958, Huston 1994, Hobbs 2000b). Knops (1995) reported a higher frequency of introduced plant species in disturbed than in undisturbed areas. Nowadays mankind influences ecosystems worldwide (Vitousek 1997) through land use change. Land use change in turn is caused by a complex interaction of demographic and socio-economic drivers, the study of which recently gained more attention (Pino 2005). So far, however, few attempts have been made to relate invasion, ecosystem degradation and land use change to these more distant socio-economic drivers. Land use change alters the existing environmental conditions which creates opportunities for invasive species to establish (Hobbs and Huenneke 1992).

In many parts of the world, disease control has resulted in rapid immigration, and penetration of the agricultural frontier into more natural ecosystems. Tsetse control in Ethiopia, for example, increased the rate of human migration and the progression of agriculture and settlements (Reid et al. 1997). In Zimbabwe, the rate of immigration was more than doubled by tsetse control (Govereh 1999). Though recent reports have described the relation between land use change following disease control (Muriuki et al. 2005), there is so far little evidence to support the hypothesis that land use change induced by disease control triggered the invasion of exotic species.

In this study, we investigate the chain of interrelated causes that made lowland forest ecosystems in Nepal susceptible to invasion. We describe how malaria control and government resettlement policies contributed to increased human population density that triggered changes in land use that resulted in the degradation of the forest environment. We finally outline how the degradation and opening of the canopy of lowland Nepalese forests facilitated invasion of a cryptic weed, *Chromolaena odorata*. 
6.2  Material and methods

6.2.1  Chromolaena odorata  (L.) R M. King & Robinson

Chromolaena odorata is ranked among the world’s worst invasive species (ISSG 2004). Native to Central America it is currently found throughout the tropics of Asia and Africa (Muniappan 1988). It dominates in open and degraded forest, but remains virtually absent from closed canopy forest (Chapter 4; Witkowski and Wilson 2001). C. odorata is a heliophyte, capable of producing millions of seeds under optimal light conditions (Erasmus 1985, Gautier 1992b, Witkowski and Wilson 2001). Dispersal over limited distances occurs through wind, while short hooks clinging seeds to animal fur, clothes, etc facilitate zoochoric dispersal over longer distances. C. odorata is a short-lived perennial with above ground parts dying off in the dry season and re-sprouting at the start of the rains from reserves of starch stored in its roots.

6.2.2  Study area

The study was conducted in Chitwan district, Nepal. The forests are dominated by Shorea robusta, a deciduous tree species shedding its leaves in February - March during the second part of the dry season. The district was chosen because the Nepalese malaria control programme was initiated here in 1955 (Jung 2001). Previously the district was densely forested, but rapid deforestation occurred shortly after the start of the malaria control. A degraded narrow forest passage in the middle of the district (Figure 6-1) is the last remaining corridor linking the Royal Chitwan National Park and Indian Wildlife Sanctuaries to the south to the wider pre Himalayan mountain ecosystem in the north. In recent years, the area has been invaded by C. odorata, which makes this forest corridor an ideal site for this study.
6.3 Data

6.3.1 Field observations

In September-October 2003 directly after the end of the rainy season when trees and *C. odorata* were in full leaves, we estimated forest canopy density (Chapter 3) and *C. odorata* cover in 153 randomly located plots of 30 by 30m. Furthermore, in 2005, a circular plot with an area of 500 m² was used to record the number of trees >10 cm diameter at breast height (DBH). From the centre of this larger plot, a smaller plot of 200 m² was constructed to record trees between 2-10 cm DBH. We also recorded number of cut tree stumps for sign of logging and looped tree branches for sign of lopping.
6.3.2 Maps and Imagery

Aerial photographs, land utilization maps, topographic maps, TM, ETM+, Aster satellite images and Corona satellite photographs (Table 6-1) were used to reconstruct the spatial and temporal change in land use and land cover in the study area.

Table 6-1. Satellite images, maps and aerial photographs used for the study and their date and source of acquisition and spatial scale or resolution

<table>
<thead>
<tr>
<th>SN</th>
<th>Data type</th>
<th>Date</th>
<th>Scale/resolution</th>
<th>Rescale</th>
<th>Source*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ASTER 14 bands</td>
<td>25/2/2005</td>
<td>15m, 30m, 90m</td>
<td>15m</td>
<td>ITC</td>
</tr>
<tr>
<td>2</td>
<td>ETM+ 7 bands</td>
<td>24/10/2001</td>
<td>28.5m, 57m</td>
<td>30m</td>
<td>GLCF</td>
</tr>
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<td>3</td>
<td>Topographic maps</td>
<td>1994</td>
<td>25000</td>
<td>25000</td>
<td>DoS</td>
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<tr>
<td>4</td>
<td>TM 7 bands</td>
<td>12/10/1988</td>
<td>30m, 90m</td>
<td>30m</td>
<td>ITC</td>
</tr>
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<td>5</td>
<td>Land utilization map</td>
<td>1982</td>
<td>50000</td>
<td>25000</td>
<td>LRMP</td>
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<td>6</td>
<td>Aerial photographs</td>
<td>1978</td>
<td>50000</td>
<td>12000</td>
<td>DoS</td>
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<td>7</td>
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<td>28/10/1976</td>
<td>60m, 90m</td>
<td>30m</td>
<td>GLCF</td>
</tr>
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<td>1964</td>
<td>12500</td>
<td>12000</td>
<td>DoFR</td>
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<td>Corona photographs</td>
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<td>1.04 m</td>
<td>15m</td>
<td>USGS</td>
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<tr>
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<td>Topographic maps</td>
<td>1958</td>
<td>63000</td>
<td>25000</td>
<td>DoS</td>
</tr>
</tbody>
</table>


6.3.3 Demography and epidemiology

Data from population censuses executed between 1930 to 2001 and migration data from 1952 to 2001 were obtained from the Central Bureau of Statistics (CBS 1958, 1961, 1971, 1984, 1985, 2001) of Nepal. Data related to malaria were derived from the annual reports of Department of Health Services, Ministry of Health, HMG Nepal and from Jung (2001).
6.3.4 Interviews

During the field visit in February-April 2005, 5 retired forestry personnel and 29 old farmers who herded livestock in the 1950’s and 1960’s were interviewed. The following questions were asked to the farmers:

- Did you graze your animals in the forest prior to malaria control (1955) campaign? If not, why not?
- Where did your animals graze before they started grazing the forest?
- How many years after opening up the forest canopy did the composition of the vegetation change?
- What was the type and grazing quality of the vegetation when you first started grazing?
- Did you start to graze your animals in the forest because of shortages of grazing resources outside? If yes, what caused these shortages?

6.3.5 Map production

Various maps were produced to reconstruct the land use change in Chitwan district. Satellite images (Table 6-1) were geometrically corrected to the Nepalese National Grid (Projection: Transverse Mercator, Ellipsoid: Everest India 1830, False easting: 500000, False northing: 0, Central meridian: 84°E, Central parallel: 0°N, Datum: India-Bangladesh). They were re-sampled to 30 (Landsat) and 15 m (Aster) pixel size respectively. Radiometric and atmospheric corrections were applied (NASA 2005).

Stereo-pairs of aerial photographs of 1964 were used to estimate canopy density using a canopy closure template. The photographs covering the study area were then scanned, geo-referenced and glued into an orthophoto mosaic. Similarly, training samples of canopy density were generated from aerial photographs of 1976 and 1989 to classify MSS and TM images of 1976 and 1988 respectively. Forest canopy density maps for 2001 and 2005 were generated from an ETM+ image of 2001 and an Aster image of 2005 respectively using field observation data from 2003 and 2005 (detail in Chapter 3). All these various images were classified into seven land cover classes using eCognition 4.0 software that we found to be an appropriate tool for this study. The software is based on the concept that important semantic information necessary to interpret an image is not represented in single pixels but in meaningful image objects and their mutual relations for land cover mapping (eCognition 2003). First, image segments were defined and calculated. For
each image, parameters were defined for the scale, shape and spectral properties. These image segments were calculated on several hierarchical levels in a “trial and error” process to result in final image segments to represent single objects of interest. The organization of the workflow is as follows: 1) Input images, 2) Multiresolution segmentation, 3) Image object hierarchy, 4) Creation of class hierarchy, 5) Classification using training samples and standard nearest neighbour, 6) Classification base segmentation, 7) Repeat steps for best result, and 8) Final merge classification (Laliberte et al. 2004).

Additionally, 36 Herbarium specimens of C. odorata housed at National Herbarium (KATH), Kathmandu, Nepal and Herbarium of the Natural History Museum (BM), London were examined. The date and place of collection recorded with each specimen was converted to a point map. The point map was subsequently converted to a raster map using point interpolation method (ILWIS 2005) which showed a chronology of the invasion of C. odorata in tropical regions of Nepal.

6.3.6 Data analysis

From the five measured biometric properties of a plant, the average seed production per plant (SPP) was calculated. Regression technique was used to analyze the relation between light intensity, forest canopy density and seed productivity of C. odorata (detail in Chapter 4). Two-sample t-test was used to analyse logging and looping variables, and Mann-Whitney U test for comparing stem densities within and outside the National Park.

6.4 Results and discussion

Figure 6-2 shows a strong relation between forest canopy density and the number of seeds produced per C. odorata plant as (Equation 6-1):

\[
\log_{10} y = a - \frac{b}{1 + c \exp \frac{a x}{c}}
\]

Equation 6-1

where, \( x \) = forest canopy density; \( y \) = seed production per plant, \( a = 6.47 \), \( b = 7.21 \), \( c = 648.51 \), \( d = 0.11 \); \( r^2 = 0.86 \), \( SE = 0.79 \).

The seed production per plant differed six orders of magnitude between highly and poorly reproductive populations, a contrast which was also reflected by the size and architecture of plants. Up to one million seeds per plant were produced in areas with open forest canopy, while no seeds were produced in forest with a canopy density over 60% (Figure 6-2). We indicated (Chapter 4) that forest canopy density
was strongly correlated \((r=0.98)\) to light intensity penetrating into the forest understorey. They also reported that 93\% of the variation in seed productivity could be explained by light intensity alone. We further demonstrated that sterile *C. odorata* plants existed at light intensity below 6.5 mJ m\(^{-2}\) day\(^{-1}\). These sterile populations can only be sustained through continuous immigration of seeds from elsewhere. Livestock and wildlife may well be the agents responsible for this seed dispersal. In chapter 4, we suggested that *C. odorata* is structured by forest canopy density into source and sink populations.

The foregoing indicates that *C. odorata* maintains invasive populations at canopy densities below 60\%. Figure 6-3 shows that now a days, canopy densities below 60\% are very common in areas with open access to inhabitants such as the forests in the Barandabhar forest corridor. Analysis of the historic maps reveals that the canopy closer of the forests in this corridor was above 60\% in the 1960’s (Figure 6-3A).
Figure 6-3. Land cover change in the Chitwan region between 1962 and 2005. Source data:
A) Corona satellite photography 1962; B) Landsat MSS 1976; C) = Landsat TM 1988; D) Landsat ETM+ 2001; E) = Aster 2005 and F) represents legends of all the maps.

Comparison of the later maps (Figure 6-3B, C, D and E) indicates that the canopy opened up since the early 1960’s. This was confirmed through interviews with retired forestry staff employed in the area in the 1950 and 60’s who reported that they witnessed the opening up of the *S. robusta* forests. They furthermore informed us that the legal protection of the dominant tree species *S. robusta* in 1961 had an
un-anticipated side effect. The legal protection of *S. robusta* implied all other non-
protected tree species were free to be logged, and thus caused the opening of the

Logging resulted in a decline of stem density per unit area. Hence, one would expect
a relation between canopy density and stem density per unit area. Figure 6-4
confirms there is a positive relation between stem and canopy density. The
regression equation is (Equation 6-2):

\[ y = 62.24 \times \exp^{-0.024 \times x} \]

Equation 6-2

where \( X = \) Number of stems per ha and \( Y = \) Forest canopy density, \( SE = 10.8, r^2 = 0.73. \)

The figure also reveals that forests inside Chitwan National Park had canopy and
stem density of over 40% and 500 individuals per ha respectively while forest
outside were more open and had lower stem densities.

![Figure 6-4. Relation between forest canopy density and stem density per hectare (DBH >2
cm) for *S. robusta* forests in Chitwan region (NP = Royal Chitwan National Park, and NF =
National forest/Bharandabhar forest corridor area) of Chitwan, Nepal.](image)

What exactly happened next in the 1960’s and 1970’s? Figure 6-3 reveals that the
amount of arable land increased at the expense of forest and particularly
grasslands. Interviews with farmers herding livestock in the 1950’s and 1960’s
revealed that the recently opened forests attracted them because of the good
quality of tall grasses. Farmers also indicated that, dry season grazing resources
became more difficult to obtain because natural grasslands gradually disappeared (Figure 6-3). In response, they converted forest to grassland south of the Rapti river. The closing of access to these grasslands when they became part of Chitwan National Park in 1976 further reduced the area of available grazing land. This resulted in a severe shortage of grazing resources in the encroaching agricultural landscape and pushed the herdsmen to turn towards the recently opened forests.

Not surprisingly, 24 out of 29 interviewed herdsmen confirmed that they reduced the number of cattle because of these forage shortages. They also reported that the tall grasses, which initially dominated the forest understory replaced by shorter species of lower grazing quality.

Under natural conditions, open forest closes through recruitment of trees. A comparison of tree sapling (DBH = 2-5cm) density in grazed (outside the National Park) and non-grazed (inside the National Park) areas revealed that the sapling density was significantly higher inside the National park (Mann-Whitney U test, test statistic = 404, P <0.001). We therefore conclude that very limited number of tree seedlings attend mature in grazed areas. The natural regeneration and growth of tree species in these sylvo-pastoral systems is effectively suppressed (Joshi, pers. obs.), possibly as a result of grazing of the understory vegetation.

Canopy gaps could also be closed through enlargement of existing crowns. However, lopping of the trees for fodder or fuel wood prevented this. The percentage of trees with signs of lopping was significantly higher (14.2% versus 0%) in open access than in protected areas (two sample t-test, t = 5.64, p<0.01). The interviewed herdsmen confirmed that this practice was introduced in the 1950’s and continues outside the National park to this day. Lopping provides another benefit, while the young leaves of S. robusta are highly nutritious fodder in a period at the end of the dry season when little other good quality forage is available.

Together, logging, lopping and suppression of regeneration due to grazing (Figure 6-5) thus well explain why the open canopy structure of the S. robusta forests has been maintained. It is not surprising that people started to graze their animals in the forest. Animals play an important role in the agro-ecosystems of the Terai. Bovine species are used as labour force and for the provision of milk. These animals grazed in the natural grasslands which according to the 1962 map (Figure 6-3A) fringed the edges of the forest. Today these grasslands have been transformed into rice paddies, while the number of animals increased along with the number of households. While paddies provide forage during harvest in early dry season, they
fail to do so during the height of the dry season. Interviewed herdsman further stated that at the middle of the dry season most cattle graze inside the forest. The remnant forest patches in this intensifying paddy agro-ecosystem thus became increasingly attractive alternative grazing lands.

Figure 6-5. Logging (left), lopping (centre) and grazing (right) in the study area.

How was this canopy opening related to socio-economic drivers and why did it occur in this particular period? Until the 1950’s, the Terai was densely forested and sparsely populated because of hyperendemic malaria (Peters et al. 1955, Brydon 1961, Darsi Jr and Pradhan 1990). The indigenous Tharu, noted for their resistance to malaria, occupied pockets of clearings in a matrix of malaria bearing forest. A national campaign aiming at control of malaria was started in 1955 in Chitwan district (Isaacson et al. 2001). The infection rate in the Nepalese Terai reduced from almost 90% in the early 1950’s to much lower levels in the 1970’s and thereafter (Figure 6-6).

![Graph showing change in percentage of the population infected by malaria parasites in the Nepalese Terai between 1955 and 2003.]

Figure 6-6. Change in percentage of the population infected by malaria parasites in the Nepalese Terai between 1955 and 2003.

The control of malaria in the lowlands was followed by rapid immigration from the higher parts of Nepal (Ghimire 1992). The construction of the East–West Highway in
the early 1970s and the promise of new land prompted further waves of immigration. This immigration was extremely pronounced in Chitwan district. As a result overall population growth rate increased from 1.17% before 1941 to 6 and 10% during the 1950’s and 1960’s respectively (Figure 6-7). Furthermore, malaria control doubtlessly reduced infant mortality rates from 70% before 1957 towards zero in the early 1970’s (Jung 2001, Guyatt and Snow 2004). This contributed to increase the autonomous population growth rate.

The population grew slowly before the malaria control. Growth rates accelerated in the 1950’s and 1960’s and population increased more than 10 fold within forty years since 1941 (Figure 6-8). We also simulated what would have been the population size without immigration and the growth rate maintained at pre-malaria control level of 1.17% annually. The figure shows that the population of Chitwan district would have been much lower today when the pre 1950’s growth rates of 1.17% annually would have been maintained.

The rapid immigration was not only triggered by malaria control alone. By 1960, the Rapti Valley Development Project (1955 - 1964) had distributed 27,759 ha forest land to 5,233 families (Müller-Böker 1991, Guneratne 1994). Isaacson et al. (2001) confirmed that both “malaria control and Rapti Valley rural development encouraged the opening of the Terai, while supporting increased agricultural production and the formation of industrial towns”. As a result, within three decades Chitwan district was transformed from a poorly inhabited jungle into one of the most heavily settled regions of the country.

Figure 6-7. Average annual rate of population growth (%) in Chitwan district and Nepal for seven inter-census periods between 1931 and 2001.

The rapid immigration was not only triggered by malaria control alone. By 1960, the Rapti Valley Development Project (1955 - 1964) had distributed 27,759 ha forest land to 5,233 families (Müller-Böker 1991, Guneratne 1994). Isaacson et al. (2001) confirmed that both “malaria control and Rapti Valley rural development encouraged the opening of the Terai, while supporting increased agricultural production and the formation of industrial towns”. As a result, within three decades Chitwan district was transformed from a poorly inhabited jungle into one of the most heavily settled regions of the country.
When did *C. odorata* invade Nepal? The flora of Nepal has been systematically surveyed since 1803 (Rajbhandari 1976). Herbarium records show that species went unnoticed till 1964 (Wallich 1824-1826, Don 1825, Wallich 1829-32, Hooker 1882). John David Adam Stainton recorded the first specimen from Nepal (Stainton 1964) in 1956 (No. 14, BM; Figure 6-9A). Nowadays, *C. odorata* is common in tropical regions of central and east Nepal. Based on the 36 herbarium records (KATH and BM), a chronology of the spread of *C. odorata* in Nepal is presented in Figure 6-9B.

Figure 6-9. A) The earliest collected *C. odorata* specimen from Nepal housed in the Herbarium of the Natural History Museum (BM), London collected by J.D.A. Stainton in 1956, B) Chronology of the invasion of *C. odorata* in Nepal.
Our historical land cover change analysis revealed that forests were opened up somewhere between the 1960’s and 1970’s. Hence, the period when the canopy of forests opened coincided with the spread of *C. odorata* into the region. We argue that this is not a mere coincidence. Canopy opening created the light conditions in the forest environment required for establishment and reproduction of *C. odorata*. We therefore argue that the degradation of the canopy triggered the invasion success of *C. odorata* into the lowland forests of Nepal. In other words, *C. odorata* did not become a successful invader because of its traits alone, but rather because of the combination of these traits and the degradation of the forest environment. We further demonstrated that the control of malaria increased human population density, which according to Guneratne (1994), Müller-Böker (1991) and Soussan et al. (1995) triggered land use changes and forest degradation. We finally argue that this sequence of events leading to forest degradation contributed to the invasion of *C. odorata* in the lowland forests of Nepal. We summarizes the hypothesized cause and effect relationships linking malaria control, population growth and forest degradation to the invasion of *C. odorata* in Figure 6-10.

We are not aware of other cases where a claim has been made that the invasive success of exotic species was facilitated by the control of infectious diseases and the related changes in human demography. Control of infectious diseases has opened up large previously uninhabitable areas of the tropics. Tsetse control in East and Southern Africa for instance, triggered immigration into previously scarcely populated areas resulting in rapid change in land use (Murwira 2003). It would be interesting to further investigate the invasive success of exotics in disease control areas.
Figure 6-10. Scheme showing hypothesized cause and effect relationships linking malaria control, population growth and forest degradation to the invasion of C. odorata.
CHAPTER SEVEN

Modeling the spatial distribution of Chromolaena odorata in Nepal

This Chapter is based on:

And

Modeling the spatial distribution of *Chromolaena odorata* in Nepal

Abstract

Remote sensing and GIS driven bioclimatic variables and their application in predicting presence and absence of invasive species are increasing, however, only few studies have explored the effect of multi-collinearity in model outputs. We developed three models: an expert model, an empirical expert model and a fully empirical model using the first ten components derived from the PCA to predict presence and absence of *C. odorata* in Nepal. Selection of input variables was largely based on our understanding of species autecology from the literature and empirical observation. High resolution interpolated climate surfaces derived from the SRTM and interpolated climate surfaces and a combination of altitude and length of growing season for *C. odorata* allowed us to predict the distribution of *C. odorata* distribution with 80% accuracy. The principal component analysis could predict its distribution with 85% accuracy. This suggests that the use of very few climatic variables could potentially predict the presence and absence of *C. odorata* with high accuracy. Furthermore, very high resolution interpolated surfaces data are more robust in delineating climatic variability within which *C. odorata* could thrive. Coarse scale for species prediction is not appropriate for country similar to Nepal where topographic and climatic variation is high because course scale can not deal with all response shape. The worldwide distribution nature of *C. odorata* populations indicates that bioclimatic variables and their respective resolutions are carefully chosen for model production. Our results indicate that, for modeling the spatial distribution of *C. odorata* having worldwide distribution, one should employ a modeling method whose results are more contributing to ecological explanation than models produced by a ‘black box’ algorithm.

**Key words:** Bioclimatic models, Predicting species presence absence, *Chromolaena odorata*, Nepal
7.1 Introduction

Mapping the potential distribution of invasive species has recently gained interest. This interest emerged from the concern that exotic species might, when left uncontrolled, infest areas so far not invaded. Invasion risk maps predict areas at risk of invasion. Typically these are based on a model describing the environmental conditions under which the invasive species has been observed to occur. This model is then used to search for other areas with similar conditions.

Climatic variables have frequently been used to predict potential invasive species distribution (Pysek et al. 1998, Higgins et al. 1999, Baker et al. 2000). Climate based invasion risk assessment has typically been established at small geographical (e.g. (sub) -continental) scale. This predominance of small scale studies is the result of a number of factors. Firstly, studies assessing the potential distribution of invasive species have been called for by national authorities having responsibility over large areas of land. CSIRO for instance developed invasive species risk assessment for the whole of Australia (Sindel 2000, Groves et al. 2001, CSIRO 2005). A second reason is that climate impacts on species distribution become in general apparent only over longer distances. A final reason might be that it is easier to obtain maps displaying species distribution and climatic variables at small than at large geographical scale.

Recently, climate databases have been developed with a resolution of 1 km². This WORLDCLIM dataset offers the opportunity to model species climate relationship at finer resolution (Hijmans et al. 2005). This would be attractive, particularly in countries with complicated topography where climatic conditions change over short distances.

Nepal is such a country. It’s complicated topography causes strong climatic variation over short distance. Climate conditions change in relation to elevation, as well as from the humid southern slopes exposed to the monsoon to the arid trans-Himalayan plains in the north. The monsoonal influence also changes from the east to the west of the country. This extreme climatic variation is one of the factors explaining Nepal’s high biodiversity. The country hosts floral and faunal elements from a wide variety of bio-geographical provinces in Asia. The wide range of eco-climatological zones also implies that the country could potentially host a large part of the world’s flora and fauna. So far however, no attempts have been made to assess the invasion risk at country level.
Invasion risk assessments have been made for the world or individual continents such as Asia. Recently an invasion risk model was established for instance for *Chromolaena odorata* RM King & Robinson in Asia (Kriticos et al. 2005). This CLIMEX model predicts the worldwide distribution of *C. odorata* with a 0.5 degree resolution, which is by far too course to account for the topoclimatic variability of Nepal.

It would be tempting to use the 1 km² WORLDCLIM database to develop a fine resolution invasion risk models. The WORLDCLIM dataset however, has been developed through interpolation climate stations using elevation as a co-variate. This implies that climate variables might be highly correlated among each other. Multi-collinearity or correlation among predictor variables (Buckland and Elston 1993) inflates the estimation of regression coefficients and may bias models. The WORLDCLIM database also offers tens of variables. Exploring for significance in a large sample of dependent variables increases the danger of type II error e.g. deciding there is a relationship while in reality there is not.

In this paper we investigated the correlation between high resolution climate surfaces for Nepal and developed and compared climate based distribution models for *C. odorata* in Nepal.

### 7.2 Material and Methods

#### 7.2.1 Nepal and *Chromolaena odorata*

Nepal has a complex topography and climate varies accordingly from tropical to alpine and humid to arid. This high climatic variation makes the country highly attractive not only for tourists but also for species originating from other parts of the world. Many exotic species have found their way into the Nepalese flora and fauna, and an increasing number of these become invasive (HMGN/MFSC 2002).

One of the established invasive species is *C. odorata* commonly known as Banmara or killer of the forest (Figure 7-1). This shrub invaded the tropical forests around the world. Originating from South America it is now considered to be one of the world’s 100 worst invaders. *C. odorata* entered the Indian sub-continent around Calcutta prior to 1840 as an ornamental garden plant (Hooker 1882, Prain 1906, McFadyen and Skarratt 1996). From there it spread into lower Burma and Malaysia, and north India (Gautier 1992c, McFadyen and Skarratt 1996). The plant naturalized in the
Ganges flood plain by the 1870s (Clarke 1876). Nowadays, it is common in central and east tropical regions of Nepal (Joshi, pers. obs).

Figure 7-1. Life cycle of *Chromolaena odorata* recorded in the tropical region in the Chitwan region of Nepal 1) A one year old corm and growth of a new shoots in Mar-Apr, 2 and 3) Vegetative growth (Mar-Nov) 4) Flowering (Nov-Feb) 5) Fruiting and seed shedding (Feb-Mar) 6) Death of aerial part (Mar-Apr).

7.2.2 Distribution of *Chromolaena odorata*

We compiled a dataset of 773 sites located throughout Nepal for which we recorded the presence and absence of *C. odorata*. Part of these site descriptions were obtained during botanical surveys undertaken by the first author prior to 2001. Also included were the sites of herbarium records from the National Herbarium in Kathmandu (KATH) and the British Museum (BM). A further sample of 594 site observations was captured during various surveys in 2002, 2003 and 2004. Geographical locations were recorded using Garmin GPS. This sample was used to develop and validate the distribution models for *C. odorata*.

7.2.3 Elevation

An elevation model of the study area was created from 26 scenes of SRTM (Shuttle Radar Topography Mission) images downloaded from Global Land Cover Facility site (GLCF 2004). The 26 scenes were mosaiced and an elevation model of Nepal was derived using ArcGIS 9.0 (ESRI 2004).
7.2.4 Climate data

We compiled a dataset with ~1 km\(^2\) resolution of fifty years average of monthly precipitation, potential evapotranspiration, minimum, mean and maximum daily temperature. Temperature and precipitation surfaces with 1 km\(^2\) resolution were downloaded from the WORLDCLIM database (www.worldclim.org/), described by (Hijmans et al. 2005). The New LOCCLIM software from FAO site (www.fao.org/sd/2002/en1203a_en.htm) was used to generate local climate data of mean monthly potential evapotranspiration and length of growing season for 4550 geographical locations systematically distributed across the country. These point data were converted into point maps. Co-Kriging point interpolation method was applied in a GIS environment using elevation as a co-variable. All raster maps were then resampled to a 1 km\(^2\) grid. The details of the data type, date of acquisition and the source is presented in Table 7-1.
Table 7-1. Description of the data used in this study

<table>
<thead>
<tr>
<th>SN</th>
<th>Data type</th>
<th>Date</th>
<th>Source*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>SRTM images (Elevation)</td>
<td>2000</td>
<td>USGS / GLCF</td>
</tr>
<tr>
<td>2</td>
<td>Monthly Precipitation</td>
<td>50 years average</td>
<td>(Hijmans et al. 2005)</td>
</tr>
<tr>
<td>3</td>
<td>Monthly Temperatures</td>
<td>50 years average</td>
<td>(Hijmans et al. 2005)</td>
</tr>
<tr>
<td>4</td>
<td>Monthly Evapotranspiration</td>
<td>50 years average</td>
<td>New LocCLIM (FAO)</td>
</tr>
<tr>
<td>5</td>
<td>Length of growing season</td>
<td>50 years average</td>
<td>New LocCLIM (FAO)</td>
</tr>
<tr>
<td>6</td>
<td>Topographic maps</td>
<td>1996</td>
<td>DoS</td>
</tr>
<tr>
<td>7</td>
<td><em>Chromolaena odorata</em></td>
<td>Field observation</td>
<td>2002-2005</td>
</tr>
<tr>
<td>8</td>
<td>Herbarium records</td>
<td>1954-2005</td>
<td>KATH, BM</td>
</tr>
</tbody>
</table>


7.2.5 Length of growing season (LGS)

The length of growing season (number of days) for each spatial location was computed (Figure 7-3) using Local Climate Estimator (New LocClim software) developed by FAO.

Figure 7-3. Average growing season, precipitation and potential evapotranspiration pattern in the tropical region of A: west Nepal (81 degree Longitude), B) Central Nepal (85 degree Longitude) and C) East Nepal (87 degree Longitude). The numbers on the vertical line denotes degree Centigrade for the Temperature (mean temp) and centimetres for Mean Precipitation (Mean prec), Maximum Precipitation (Max prec), Minimum Precipitation (Min prec) and Evapotranspiration (Evapotrans) for the curves.
7.2.6 Principal component analysis

We calculated 10 principal components (PC) using all environmental variables (monthly mean temperatures (mean, maximum and minimum), monthly mean evapotranspiration, mean monthly precipitation) to reduce data dimensionality. Principal components analysis (PCA) is a multivariate technique that produces a set of components (variables) called principal components which are weighted linear combinations of the original variables (Chatfield and Collins 1980, James and McCulloch 1990).

7.2.7 Model development

We developed three different models: an expert model (Model 1), an empirical expert model (Model 2) and a fully empirical model (Model 3) using the first ten components derived from the PCA.

What factors are considered to limit the distribution of *C. odorata*? The distribution of *C. odorata* has been related to average annual precipitation. Reported precipitation thresholds vary from 1500mm in Nigeria (Ivens 1974), 1200 mm worldwide reported by MacFayden (1989), 1100 mm in Ivory Coast (Gautier 1992a) and 700 mm for Corpus Christi in Texas, reported in Gauthier (Gautier 1992a). The distribution of *C. odorata* has also been related to elevation. It occurs in the Himalayas up to an elevation of 1100 m (Moni & George 1959, cited by (Kriticos et al. 2005)). They attributed this to sensitivity to frost. Gauthier (1992a) referred to a third factor when mentioning that *C. odorata* occurs in West Africa in areas with a dry season not exceeding five months.

We combined these variables as inputs in an expert model to predict the distribution of *C. odorata* in Nepal. We considered an area suitable when mean annual precipitation was >1200mm, elevation below 1100m and the length of the growing season at least 7 months (210 days). The length of the growing season was excluded from the expert model, because it remained subjective how to relate the suggestion of Gauthier (1992a) about the importance of the duration of the dry season to the LGS estimates, because duration of the dry season was not defined.

The empirical expert model used annual precipitation, elevation and LGS. These were used as inputs in a logistic regression, which was then used to estimate the coefficients. The fully empirical model was a logistic regression model using the first ten components of the PCA as inputs. The data set had a sample size of 773. A sub-
sample of 387 records (50%) was used to develop the models described above. The remaining 50% of the sample was used to validate the models (see below).

7.2.8 Model evaluation

The accuracy of the predictions obtained with the three models was evaluated using overall accuracy and Kappa. A Kappa based z test has traditionally been used to assess whether the alternative methods differ in accuracy. De Leeuw et al. (2006) recently indicated that the Kappa z test is appropriate when comparing independent error matrices. The three confusion matrices used in this study used the same sub set of observations. The data are therefore likely to be dependent. We used a chi square test to test for dependence among the error matrices. We followed De Leeuw et al. (2006) who recommended utilizing the more sensitive McNemar test in case of dependent error matrices.

7.3 Results

7.3.1 Correlation between climatic factors

Figure 7-4 shows a matrix revealing the pairwise correlation between the fifty-year averages of monthly potential evapotranspiration, precipitation and the monthly mean of minimum, maximum and average daily temperatures. Also included are altitude, length of the growing season and latitude/longitude in Nepal. The matrix shows all monthly temperature values were extremely highly correlated. Correlation between temperature and precipitation and potential evapotranspiration was lower.

The length of the growing season showed low to intermediate correlation to the above-mentioned climatic variables. Elevation, latitude and longitude generally showed lower correlations to climate variables. This figure shows that multicollinearity would be a real problem when entering these climate variables as independent variables in a statistical analysis.

The figure also reveals the correlation of the first ten principal components derived from the climate data. PC 8 and PC 10 were highly correlated to thermoclimate. The other components were showing medium correlations to precipitation in various months. The figure reveals that the principal components were not or poorly correlated among each other.
Figure 7-4. Matrix revealing the Pearson correlation between pairs of A) climate variables, length of the growing season, elevation and latitude and longitude. Abbreviations: PET = mean monthly potential evapotranspiration; P = mean monthly precipitation; PC = Principal components (1-10).

Figure 7-5A shows the distribution of *C. odorata* in Nepal. The figure suggests a relation with longitude and elevation, which is confirmed in Figure 7-5B.
Figure 7-5 A) Distribution of *C. odorata* in Nepal according to 773 records throughout the country. B) Relation of the observed distribution with longitude and elevation.

The expert system (Model 1) predicted the distribution of *C. odorata* using an environmental envelope with elevation <1100 m and annual precipitation >1200 mm/yr. Figure 7-6 shows the distribution of *C. odorata* predicted by this model.

The prediction had a low kappa accuracy of 36%. Figure 7-7 reveals the reason for this poor performance: *C. odorata* distribution was poorly related to annual precipitation. Elevation was a better predictor.
We next investigated empirically whether the three variables proposed by experts were related to the distribution of *C. odorata*. Stepwise forward logistic regression confirmed a significant contribution of all three variables (Table 7-2). The model was significantly better than the null model (-2*(LL3-LL0) = 294.42, df = 3, p<0.000) and had a McFadden’s Rho² = 0.61. Figure 7-8 shows the distribution of *C. odorata* predicted by this model.
Table 7-2. Results of logistic regression between C. odorata presence absence and three explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-29.71</td>
<td>4.14</td>
<td>-7.16</td>
<td>0.000</td>
</tr>
<tr>
<td>LGP</td>
<td>0.1399</td>
<td>0.0214</td>
<td>6.52</td>
<td>0.000</td>
</tr>
<tr>
<td>Annual rainfall</td>
<td>0.0054</td>
<td>0.0010</td>
<td>5.28</td>
<td>0.000</td>
</tr>
<tr>
<td>Altitude</td>
<td>-0.00512</td>
<td>0.00074</td>
<td>-6.90</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Figure 7-8. Observed (test sample) and empirical expert model based predicted distribution of C. odorata in Nepal at pixel resolution of 100 m.

Six components were selected when running a logistic regression model with the first ten principal components as dependent variables (Table 7-3). This model was significantly better than the null model ($-2 \times (LL_{6} - LL_{0}) = 357.98$, df = 6, p<0.000) and had a McFadden’s $R^2 = 0.74$. The distribution resulting from this model is displayed in Figure 7-9. The Figure reveals a close match between observed and predicted distribution.

Table 7-3. Results of logistic regression between C. odorata presence absence and principal components

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-13.52</td>
<td>7.630</td>
<td>-1.77</td>
<td>0.071</td>
</tr>
<tr>
<td>PCA 1</td>
<td>0.023</td>
<td>0.003</td>
<td>6.69</td>
<td>0.000</td>
</tr>
<tr>
<td>PCA 5</td>
<td>0.045</td>
<td>0.010</td>
<td>4.48</td>
<td>0.000</td>
</tr>
<tr>
<td>PCA 6</td>
<td>-0.113</td>
<td>0.032</td>
<td>-3.45</td>
<td>0.000</td>
</tr>
<tr>
<td>PCA 7</td>
<td>-0.117</td>
<td>0.019</td>
<td>-5.90</td>
<td>0.000</td>
</tr>
<tr>
<td>PCA 8</td>
<td>-0.264</td>
<td>0.058</td>
<td>-4.53</td>
<td>0.000</td>
</tr>
<tr>
<td>PCA 10</td>
<td>0.054</td>
<td>0.025</td>
<td>2.15</td>
<td>0.031</td>
</tr>
</tbody>
</table>
Assessment of the accuracy of the predictions made by the three models revealed that the empirical model based on PCA had the highest accuracy, followed by the empirical expert model (Table 7-4).

Table 7-4. Overall and kappa accuracy and its standard error (SE) for maps classified by three models

<table>
<thead>
<tr>
<th>Model</th>
<th>Overall Accuracy</th>
<th>Kappa</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expert</td>
<td>78%</td>
<td>0.36</td>
<td>0.0495</td>
</tr>
<tr>
<td>Empirical expert</td>
<td>90%</td>
<td>0.74</td>
<td>0.0386</td>
</tr>
<tr>
<td>PCA</td>
<td>94%</td>
<td>0.86</td>
<td>0.0289</td>
</tr>
</tbody>
</table>

McNemar’s test inferred a significant difference between models 1 and 2, 1 and 3 and 2 and 3.

Table 7-5 shows that model 1 and 2 disagreed for 51 observations. Model 1 classified 3 observations correctly which had been misclassified by model 2, while model 2 had 48 observations correctly classified which had been misclassified by model 1. McNemar’s test revealed that there was a significant difference between the two models ($\chi^2$ McNemar symmetry = 39.7; df = 1, p<0.000). Similarly model 1 and 3 showed a significant difference in models performance ($\chi^2$ McNemar symmetry = 52.4; df = 1, p<0.000). The test also revealed a significant difference between the performance of model 2 and 3 ($\chi^2$ McNemar symmetry = 8.53; df = 1, p<0.0034).
Table 7-5. Cross table displaying the frequency of correctly and wrongly classified observed (test sample) points according to the three classification method.

<table>
<thead>
<tr>
<th></th>
<th>Expert</th>
<th></th>
<th>Empirical expert</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wrong</td>
<td>Correct</td>
<td>Wrong</td>
<td>Correct</td>
</tr>
<tr>
<td>Empirical expert</td>
<td>35</td>
<td>48</td>
<td>3</td>
<td>300</td>
</tr>
<tr>
<td>PCA</td>
<td>17</td>
<td>66</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>298</td>
<td>23</td>
<td>341</td>
</tr>
</tbody>
</table>

Figure 7-10 compares the distribution of *C. odorata* as predicted by CLIMEX (Kriticos et al. 2005) at coarse resolution of 0.5 degree with the high spatial resolution model based on principle component analysis described above. The figure shows a remarkable difference between the outputs of the two models, both in terms of spatial resolution as well as predicted distribution.

Figure 7-10. Probability of presence and absence of *C. odorata* in Nepal predicted by Climex model (Kriticos et al. 2005) at a scale of 0.5 degree (A) and by PCA model at fine scale of 100 m (B).
7.4 Discussion

Our results demonstrated that identifying spatial extent of potential *C. odorata* invasion over large areas can be successfully accomplished using a very few climatic variables. In this study, we also demonstrated that very high resolution interpolated climate surfaces derived from the SRTM and weather stations allowed us to predict the distribution of *C. odorata* with 86% accuracy. Furthermore, higher resolution interpolated climate surfaces have potential to map climate boundaries with higher precision in terrain with complicated topography such as Nepal. As a measure of the proportion of presence or absence that is predicted by a model, McNemar’s statistics offer a meaningful numerical variable for intercomparison between models. The evaluation of map accuracy revealed clear differences in performance between different modeling approaches. Models derived from empirical expert knowledge and computer simulated data model performed better than models derived from expert knowledge only.

The expert model is computationally simplistic approach to analyse minimum number of predictive variables, however it failed to produce high accuracy predictive maps of presence and absence of *C. odorata* when compared with empirical expert or PCA based models. The PCA based model yielded highest accuracy predictive map, however their input is a “black-box approach”.

We attribute the differences in model performance to a number of issues related to the worldwide distribution of *C. odorata* and other issues related to the input variable to the algorithm. Certainly, image resolution, and predictor variables are two components that must be carefully chosen when constructing any distributional model. Species, for instance *C. odorata* having worldwide distribution may not allows us to draw a climatic envelop. Based on the expert knowledge on the ecology of *C. odorata* we could not draw a fine line of climatic envelop. The problem in mapping of the presence and absence of a species at national or regional scale could be solved by using finer resolution interpolated climate surfaces or remote sensing images which usually provides better predictive ability in models (Guisan and Thuiller 2005). Thus, an increase in spatial resolution of climate data is one of the primary factors necessary to increase model prediction accuracy, particularly for areas with microtopographic variation (Guisan and Zimmermann 2000). The climate data layers used for modeling are available at various resolutions, but even the highest resolution, multi-collinearity among the predictive variables could easily mislead our judgment.
High bioclimatic variation and altitudinal gradient in the Nepalese mountains would suggest that ecological effects on organisms should be strong. This means the potential for effective modeling should be high. However, spatial scale certainly plays a significant role since climate could change within a distance of few hundred meters. The high-altitude distribution limits of a species can be constrained by the low winter temperatures or the amount of frost below which level a plant species could stop its photosynthetic activity or simply could not survive. *C. odorata* could not survive above frost line. Our model assumes that lower lethal temperature could be the strongest influential climatic variable, which limits *C. odorata*'s vertical distribution i.e. northern boundary. This is reasonable because many literatures mentioned that *C. odorata* couldn’t survive at this temperature (Kriticos *et al*. 2005). Our empirical observation also showed that *C. odorata* was not observed beyond 1100 m altitude. Our analysis showed that altitude and temperature variables were highly correlated among each other. Hence, using any one of these variable could equally predict the presence and absence of *C. odorata*, which would reinforce our conclusions regarding the reduction of effect of multi-collinearity among climatic variables.

Temperatures or altitude limits did not predicted the horizontal distribution of *C. odorata* because altitude does not change horizontally in Nepal. However, length of growing season for *C. odorata* significantly differs. *C. odorata* needs length of main growing season of at least 7 months time to complete its life cycle. The summer monsoon (summer rainy season), a strong flow of moist air from the southwest, follows the pre-monsoon season. The arrival of the summer monsoon can vary by as much as a month, in Nepal, it generally arrives in early June starting from Eastern Nepal and lasts through September, when it begins to recede. The plains and lower Himalayas receive more than 70% percent of their annual precipitation during the summer monsoon. The amount of summer monsoon rain generally declines from southeast to northwest as the maritime wedge of air gradually becomes thinner and dryer. Although west Nepal receives sufficient pre and post monsoon rain, the main growing season for most of the areas are below 150 days, which is not long enough where *C. odorata* could complete its life cycle. A long dry season between winter and summer monsoon season could potentially prevent *C. odorata* invasion in west Nepal.

Our study revealed that a box classification approach focusing on generalized climatic stress factors only, did not successfully forecast the distribution of *C. odorata* in Nepal. Consideration of length of the growing period significantly
improved the predictions. Kriticos et al. (2005) predicted that west Nepal was partly suitable. Our first two models do also predict this, with higher spatial resolution. An empirical expert model is better than the expert model, which is attributable to the inclusion of length of growing season. Principal component based model does not predict suitability in west Nepal. The accuracy assessment assesses how well the three models mimic the current distribution. The PCA model does this better than the two other models. It does not assess which model assesses climatic suitability. Climate based potential distribution models assume that we are able to define the climatic boundaries, which restrict the distribution of a species. This is a reasonable assumption in case distribution is indeed determined by climatic factors. This assumption is not necessarily true. It may be false in case of a recent invader which has not yet reached the limits of its envelope. It may also not be true for species which are absent from parts of its climatic envelope for other reasons. In conclusion, computer simulated models using enormous number of climatic variables serve as valuable tools in the invasion ecology, researchers must increase their emphasis on the applicability of predictions generated from these models. The failure to address proper applicability issues will only weaken the potential utility of such models and ultimately will result in models of limited usefulness. All models we presented or discussed may have some importance in scientific understanding, however, there real test of their accuracy will depend on the usefulness and applicability of these predictive models in invasive species management.

C. odorata is a problem worldwide. It invades natural ecosystems and poses a serious threat to the maintenance and enhancement of biodiversity values of native vegetation. Land managers currently control the spread of invasive non-native plant species after they have already become established instead of trying to prevent the establishment of the species, but its management requires preventative approaches, both at the local and national level. The early detection of new species invasions and the development of rapid response plans are vital for successful eradication programmes. We argue that predictive maps as a result of “box classification” and without considering useful spatial scale, could potentially influence management programme. Because if a species presence absence map is used for management purposes, both failure to correctly predict locations of observed presence and the prediction of false presence will be ‘expensive’ for planning, management and implementation of eradication/control programme. In our view, this is a simplistic approach of detecting actual and potential area under invasion with high precision. This is highly crucial for invasive species management, since limitation of resources forces invasive species managers to carefully plan and prioritize interventions in areas more severely affected by invaders or localize areas
requiring interventions most urgently. And they could focus their precious funds and efforts to control the spread of this species and so that the control methods are cost effective and practical. The approach we presented can be well applied for mapping of other species if their biometry and environmental requirement is known.
CHAPTER EIGHT

An integrated assessment of deforestation and forest degradation for biological conservation in the Terai of Nepal

This Chapter is partly based on:
8 An integrated assessment of deforestation and forest degradation for biological conservation in the Terai of Nepal

Abstract

Deforestation and forest degradation are associated processes, which frequently have been studied in isolation. The objective of this study was to assess the spatial extent and severity of both of these processes in the twenty districts in the Terai of Nepal using field survey records, existing vegetation maps, and remote sensing data. Forest canopy density was recorded at 329 sites from west to east Nepal using hemispherical photography. An artificial neural network was used to predict forest canopy density in four classes using a mosaic of 16 Landsat ETM+ images captured around the year 2000. Forest canopy density class was predicted with 82% overall accuracy. Data analysis revealed that the forested area reduced from 21774 km² in 1958 to 12649 km² in 2000 corresponding to an annual rate of decline of 1.38%. Our analysis further revealed that 70% of the forested area outside conservation areas had canopies with density below 60%, thus confirming widespread degradation. More surprisingly fifty percent of the forested area inside protected areas had similar open canopies. Our analysis revealed that canopy opening prevailed as well in these communities. We argue that from a biodiversity point of view conservation effort should focus on the preservation and restoration of these forests. The forest degradation maps presented in this article could serve as a start to prioritize such interventions.

Key words: Forest degradation, Deforestation, Remote sensing, Terai Nepal, Biological conservation

8.1 Introduction

Deforestation and forest degradation are two different processes, which are frequently linked together. Deforestation is the conversion of forest to another land cover types (Allen and Barnes 1985). It is widely recognized a critical environmental problem with serious long-term economic and social consequences (Siebert 1987, Saunders et al. 1991, Ojima et al. 1994). More recently, concern has been expressed about forest degradation, a more gradual process, which negatively affects many forests. Both processes occur worldwide but are most prominent in...
the tropics, where land is cleared to supply resources and free space for a rapidly growing population.

Concerns over the impacts of deforestation and forest degradation creates demand for accurate statistics describing the distribution and rates of these processes (Geist and Lambin 2002). Achard et al. (2002) reported a rate of decline of humid tropical forest of 4.9 million ha per year, a statistic 23% lower than the FAO (2001) estimate of 6.4 million ha per year. Percentage of the total forest area annually disappearing was higher in Asia (0.71%) than Africa (0.36%) or Latin America (0.33%).

Forest degradation, is a more subtle process. It may involve opening of the canopy, modification of the vertical structure of the forest or change of other attributes. The forest however remains intact and somehow discernable from the surrounding environment. As such, forest degradation is less straightforward to assess from satellite imagery and rates of forest degradation are harder to obtain. Remote sensing has however been used to assess forest canopy density as an indicator of forest degradation. Intensity of canopy degradation makes the remote sensing measurement sensitive to the state of the underlying ground. There exists a variety of empirical approaches to map forest canopy density. An object based classification (Dorren et al. 2003), artificial neural network, fuzzy logic (Pierce et al. 1994), linear regression (Iverson et al. 1989, Zhu and Evans 1994, DeFries et al. 1997, Levesque and King 2003), decision tree classification (Souza Jr. et al. 2003), radar backscattering (Saich et al. 2001), geometric-optical model (Scarth and Phinn 2000), digital surface models (Gong et al. 2002) and a biophysical model based deductive approach (Rikimaru and Miyatake 1997) are some of the methods which were used in mapping forest canopy density. Achard et al. (2002) estimated an annual rate of forest degradation in the humid tropics of 2.3 million ha or 0.20% of the total forest area. Rates differed between continents, with Asia (0.42%) having higher rates than Africa (0.21%) and Latin America (0.13%).

Confronted with these trends national and international communities called for interventions to stop both processes. Legislation aiming to conserve forest has been introduced in many countries and increasingly large stretches of forested land are being protected. Management may vary from production systems to forests protected for strict biological conservation. While restoration may be achievable in degraded production forest, this may not be the case for biological conservation areas, once species are extinct.
While deforestation and forest degradation are a point of concern for management of both conservation categories, there would be a need to more closely monitor biological conservation areas, because of the potentially irreversible impacts of deforestation and forest degradation. So far, remotely sensed deforestation and forest degradation investigations have rarely been combined with conservation status, in order to assess the impacts on biodiversity resources.

In this study, we assess the rate of deforestation and the current degree of forest degradation in Nepal. We investigate whether the historic rate of deforestation and current forest degradation status differs between areas protected for biological conservation (e.g. National Parks and wildlife reserves) and those demarcated as production forests.

8.2 Material and methods

8.2.1 Study area

Nepal extends approximately 885 km from east to west and covers an area of 147180 km². The Himalayas and the trans-Himalayan plains form the northern two-thirds of the country. The study was executed in twenty districts in the Terai area to the south (Figure 8-1), which consist of pre-Himalayan footslopes extending into the Indo-Gangetic plain in India.

The Nepalese government confronted with this deforestation, legally protected the remaining forests in the 1961. Initially this was motivated from a perspective of resource conservation, while the lowland Terai forests deliver commercially valuable timber such as Sal (Shorea robusta). Later on biodiversity values further supported the urgency for conservation. The National Parks and Wildlife Conservation Act of 1973 provided the legal basis for the establishment of a number of National Parks aimed at biological conservation. Since then the remaining forest has been placed under two broad management categories – approximately one third of the forest area is conserved as National Parks and wildlife reserves while most of the remaining area is protected as national forest.

Widespread poverty in the Terai, with many landless families, puts a high pressure on these remnant forest ecosystems. Many forests have been degraded as a result. We used remote sensing imagery (chapter 3) to assess the degree of forest degradation in Eastern Chitwan district. So far, forest degradation has not been assessed for the whole of the Nepalese Terai.

8.2.2 Data

8.2.2.1 Historic forest maps

A digital map displaying the distribution of forest in 1958, derived from 1: 63,360 topographic maps produced by the Survey of India was obtained from the Worldwide Fund for Nature (WWF), Nepal. Dobremez et al. (1975), Dobremez (1976), Dobremez and Shakya (1977), Dobremez and Shrestha (1980), Dobremez (1984) and Dobremez et al. (1984) produced maps of the actual and potential distribution of forests in Nepal. A digital version of these maps updated by IUCN (Nepal), ICIMOD and HMG, Nepal (unpublished) is referred to in this article as the Dobremez forest community map.
8.2.2.2 Satellite imagery

We selected 16 Landsat ETM+ images captured around the year 2000 (Table 8-1) to study the recent extent and degradation status of the Terai forests. Some forest types show considerable phenological variation over the year, due to shedding of leaves in March (Singh and Kushwaha 2006). This may complicate the consistency of image classification between scenes. We therefore selected images from the same season (October to December) shortly after cessation of the monsoon but before leaf fall. The first seven bands of all images were atmospherically corrected, georeferenced, resampled to 30m pixel size and combined into one mosaic using Erdas 8.7.

Table 8-1. Landsat ETM+ Images used in this study, including path and row number, acquisition date and source

<table>
<thead>
<tr>
<th>SN</th>
<th>Path/row</th>
<th>Acquisition date</th>
<th>Producer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>139/041</td>
<td>12/26/2000</td>
<td>EarthSat</td>
</tr>
<tr>
<td>2</td>
<td>139/042</td>
<td>11/6/1999</td>
<td>USGS / GLCF</td>
</tr>
<tr>
<td>3</td>
<td>140/041</td>
<td>10/30/2000</td>
<td>EarthSat</td>
</tr>
<tr>
<td>4</td>
<td>140/042</td>
<td>10/28/1999</td>
<td>EarthSat</td>
</tr>
<tr>
<td>5</td>
<td>141/040</td>
<td>11/22/2000</td>
<td>EarthSat</td>
</tr>
<tr>
<td>6</td>
<td>141/042</td>
<td>10/24/2001</td>
<td>EarthSat</td>
</tr>
<tr>
<td>7</td>
<td>142/040</td>
<td>12/13/1999</td>
<td>EarthSat</td>
</tr>
<tr>
<td>8</td>
<td>142/041</td>
<td>12/13/1999</td>
<td>EarthSat</td>
</tr>
<tr>
<td>9</td>
<td>143/039</td>
<td>10/3/2000</td>
<td>EarthSat</td>
</tr>
<tr>
<td>10</td>
<td>143/040</td>
<td>12/25/2001</td>
<td>EarthSat</td>
</tr>
<tr>
<td>11</td>
<td>143/041</td>
<td>10/17/1999</td>
<td>EarthSat</td>
</tr>
<tr>
<td>12</td>
<td>144/039</td>
<td>10/13/2001</td>
<td>EarthSat</td>
</tr>
<tr>
<td>13</td>
<td>144/040</td>
<td>11/9/1999</td>
<td>USGS</td>
</tr>
<tr>
<td>14</td>
<td>144/041</td>
<td>11/11/2000</td>
<td>EarthSat</td>
</tr>
<tr>
<td>15</td>
<td>145/039</td>
<td>10/15/1999</td>
<td>EarthSat</td>
</tr>
<tr>
<td>16</td>
<td>145/040</td>
<td>10/15/1999</td>
<td>USGS</td>
</tr>
</tbody>
</table>

8.2.2.3 Field observations

Forest canopy density was recorded at 329 sites from west to east Nepal in Sept-Oct 2003 and 2004. A digital camera (Nikon coolpix 995) with fisheye lens attached was used to take skyward photographs of the canopy. The camera, positioned at 1.2 m height, produced hemispherical circular images recording gaps in the forest canopy. Canopy density (%) was computed from the digital photographs using Gap Light Analyzer (GLA) software version 2 (Frazer et al. 1999). A view angle of 114° was used for canopy density calculation. This corresponded to estimating canopy density for a 900m² canopy area for an average tree height of 22.5m. These canopy density estimates were subsequently classified in four classes of <20%, 21-40%, 41-60% and >60% density. From this larger sample of 329 sites one sub-sample of
50% (n=165) was randomly selected to train an artificial neural network to predict canopy density. The remaining sub-set of 164 sites was used to validate the predictions of the neural net.

### 8.2.2.4 Image classification and data analysis

Artificial neural networks are neurologically inspired statistical mechanisms which has been employed in classification of forest cover using various sensors (Barrow et al. 1993, Boyd et al. 2002). Here, a three-layer feedforward error-backpropagation artificial neural network implemented in Interactive Data Language (IDL) was used in order to predict forest canopy density in the four classes mentioned above. The algorithm minimizes the root mean square error between the actual output of the multi-layered feed forward perceptron and the desired output (Skidmore et al. 1997). The field observations were used to train a neural network. We followed (Atkinson and Tatnall 1997) to search for system parameters to increase the accuracy of the method and avoid overtraining of the neural network. The neural network was trained with canopy density and the reflectance values for the seven ETM+ bands for the sub sample of 165 sites. Another subsample of 164 observations was used in post-classification cross-validation. The best combination of optimum learning rate and momentum to minimize the root mean square error (RSME) was empirically established. The best results were obtained with a learning rate of 0.7, a momentum of 0.7 and four hidden nodes. The RSME stabilized after approximately 3000 epochs. Twenty iterations of 3000 epochs were performed and the best one was selected based on root mean square error.

Finally, a standard majority filter was run through the classified image for smoothing. It works in a 3x3 pixel matrix environment and selects the predominant (most frequently occurring) value or class name of a pixel to the centre pixel in the output map (ILWIS 2005). The validation data set was used to compile a confusion matrix. Accuracy and associated errors of commission and omission and the Kappa statistic was calculated as a measure of actual agreement and chance agreement between training data and classified according to Cohen (1960).
8.3 Results

Figure 8-2 reveals a considerable forest decline in the Nepalese Terai between 1958 and 2000. The forested area reduced from 21774 km² in 1958 to 12649 km² in 2000. This corresponds to a 41.9% decline in 42 years, or an annual rate of decline of 1%.

Figure 8-2. Forest distribution (black) in the Nepalese Terai in 1958 (derived from 1:63,360 topographic maps) and 2000 (Landsat ETM+ imagery).

Figure 8-3. Distribution of the forest communities of Terai districts of Nepal in 2000, derived while combining figure 2B with the Dobremez forest community map.

Figure 8-3 shows the actual distribution of ten forest communities in 2000. This map was used to produce Table 8-2, which shows the aerial extent of the ten forest communities in 1958 and 2000 and their annual rate of change. The table reveals a decline of forest area for eight out of the ten forest communities.
Table 8-2. Extent (Km²) in 1958 and 2000 and annual rate of change for ten forest types in the Terai districts of Nepal

<table>
<thead>
<tr>
<th>Forest community</th>
<th>1958</th>
<th>2000</th>
<th>Decline</th>
<th>Decline%</th>
<th>% Yr-1</th>
<th>CV*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chir Pine</td>
<td>863.9</td>
<td>664.4</td>
<td>-199.5</td>
<td>-23.09</td>
<td>-0.63</td>
<td>2</td>
</tr>
<tr>
<td>Chir Pine-Broad Leaved</td>
<td>324.6</td>
<td>321.3</td>
<td>-3.3</td>
<td>-1.01</td>
<td>-0.02</td>
<td>3</td>
</tr>
<tr>
<td>Hill Shorea</td>
<td>6607.1</td>
<td>5447.7</td>
<td>-1159.4</td>
<td>-17.55</td>
<td>-0.46</td>
<td>1</td>
</tr>
<tr>
<td>Terai Shorea</td>
<td>12866.4</td>
<td>5354</td>
<td>-7512.4</td>
<td>-58.39</td>
<td>-2.09</td>
<td>1</td>
</tr>
<tr>
<td>Riverine Broad Leaved</td>
<td>68.4</td>
<td>35.3</td>
<td>-33.1</td>
<td>-48.41</td>
<td>-1.57</td>
<td>3</td>
</tr>
<tr>
<td>Riverine Khair-Sissoo</td>
<td>681.1</td>
<td>469.9</td>
<td>-211.2</td>
<td>-31.01</td>
<td>-0.88</td>
<td>1</td>
</tr>
<tr>
<td>Upper Tropical Riverine</td>
<td>66.6</td>
<td>48.3</td>
<td>-18.3</td>
<td>-27.51</td>
<td>-0.76</td>
<td>2</td>
</tr>
<tr>
<td>Schima-Castanopsis</td>
<td>260.4</td>
<td>285.2</td>
<td>24.8</td>
<td>9.54</td>
<td>0.22</td>
<td>4</td>
</tr>
<tr>
<td>Lower Temperate Oak</td>
<td>30.9</td>
<td>18.2</td>
<td>-12.7</td>
<td>-41.16</td>
<td>-1.26</td>
<td>3</td>
</tr>
<tr>
<td>East Himalayan Oak-Laurel</td>
<td>4.2</td>
<td>5.3</td>
<td>1.1</td>
<td>26.79</td>
<td>0.55</td>
<td>4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>21773.6</td>
<td>12649.6</td>
<td>-9124.0</td>
<td>-41.90</td>
<td>-1.29</td>
<td></td>
</tr>
</tbody>
</table>

*Commercial value: 1= very high, 2 = High, 3 = Moderate, 4 = Low

**Terai S. robusta** forest community was affected most with annual transformation rate of 2%. The Oak-Laurel and Schima-Castanopsis forest types increased in size during this period with an average annual rate of 0.55 %. The rate of forest decline was close to significantly related to the commercial value of the forests (Spearman correlation, r = -0.62, n = 11, p = 0.054).

Figure 8-4. Forest canopy density in the Terai in 2000. Red lines represent boundaries of National Parks and wildlife reserves.

Figure 8-4 presents the spatial distribution of forest canopy density within and outside the protected areas. Accuracy assessment (Table 8-3) revealed that the canopy classes were mapped with high accuracy. 135 out of 164 observations had
been correctly classified. The confusion matrix analysis yielded an overall accuracy of 82.3%.

Table 8-3. Error matrix for observed versus predicted canopy density class by an artificial neural network

<table>
<thead>
<tr>
<th>Forest canopy density</th>
<th>Other</th>
<th>&lt;20%</th>
<th>21-40%</th>
<th>41-60%</th>
<th>&gt;60%</th>
<th>Total</th>
<th>Commission error</th>
<th>Producer’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other</td>
<td>26</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>32</td>
<td>18.75</td>
<td>81.25</td>
</tr>
<tr>
<td>&lt;20%</td>
<td>2</td>
<td>14</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>22.22</td>
<td>77.78</td>
</tr>
<tr>
<td>21-40%</td>
<td>1</td>
<td>2</td>
<td>21</td>
<td>7</td>
<td>0</td>
<td>31</td>
<td>32.26</td>
<td>67.74</td>
</tr>
<tr>
<td>41-60%</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>23</td>
<td>6</td>
<td>31</td>
<td>25.81</td>
<td>74.19</td>
</tr>
<tr>
<td>&gt;60%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>51</td>
<td>52</td>
<td>1.92</td>
<td>98.08</td>
</tr>
<tr>
<td>Total</td>
<td>29</td>
<td>21</td>
<td>26</td>
<td>31</td>
<td>57</td>
<td>164</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8-3 further shows that the <20% and 21-40% canopy density class were classified with producer’s accuracy of over 77% and 67% respectively with much of the error attributed to confusion with the other and 40-60% canopy density class. The high canopy density class (>60%) had the larger producer’s accuracy of 98%.

Table 8-4. Frequency distribution (%) of ten forest communities over four canopy closure classes

<table>
<thead>
<tr>
<th>Forest community</th>
<th>&lt;20%</th>
<th>21-40%</th>
<th>41-60%</th>
<th>&gt;60%</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chir Pine</td>
<td>27.96</td>
<td>35.29</td>
<td>18.31</td>
<td>18.45</td>
<td>100</td>
</tr>
<tr>
<td>Chir pine - Broad leaved</td>
<td>21.37</td>
<td>35.86</td>
<td>18.87</td>
<td>23.90</td>
<td>100</td>
</tr>
<tr>
<td>Oak-Laurel</td>
<td>0.00</td>
<td>11.20</td>
<td>27.13</td>
<td>61.67</td>
<td>100</td>
</tr>
<tr>
<td>Hill Shorea</td>
<td>12.65</td>
<td>29.10</td>
<td>26.56</td>
<td>31.68</td>
<td>100</td>
</tr>
<tr>
<td>Lower Temperate Oak</td>
<td>29.74</td>
<td>36.12</td>
<td>21.50</td>
<td>12.64</td>
<td>100</td>
</tr>
<tr>
<td>Terai Shorea</td>
<td>13.71</td>
<td>22.82</td>
<td>24.73</td>
<td>38.74</td>
<td>100</td>
</tr>
<tr>
<td>Riverine Broad leaved</td>
<td>8.63</td>
<td>16.84</td>
<td>26.49</td>
<td>48.03</td>
<td>100</td>
</tr>
<tr>
<td>Acacia-Dalbergia</td>
<td>4.44</td>
<td>11.04</td>
<td>36.36</td>
<td>48.15</td>
<td>100</td>
</tr>
<tr>
<td>Schima-Castanopsis</td>
<td>29.13</td>
<td>42.20</td>
<td>18.87</td>
<td>9.80</td>
<td>100</td>
</tr>
<tr>
<td>Upper Tropical Riverine</td>
<td>6.79</td>
<td>26.30</td>
<td>35.01</td>
<td>31.91</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>14.23</td>
<td>26.58</td>
<td>25.37</td>
<td>33.82</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 8-4 shows forest canopy of all seven communities of Terai districts of Nepal was open (except Oak-Laurel and Riverine forest). Visual analysis (Figure 8-4) further indicated that closed canopy forest can exist only inside the protected
areas. The canopy closing outside protected forests was significantly lower than the protected ones.

Figure 8-5 revealed that 70% of tropical forest outside the protected areas had a canopy density below 60%. A larger proportion of the forest inside conservation areas had canopy density above 60%. However, within protected areas almost 50% of the forest area had a canopy density below 60%.

![Figure 8-5. Proportion of four forest canopy density classes in and outside National parks and wildlife reserves in the Terai districts of Nepal in 2000.](image)

8.3.1 Discussion

This study demonstrated that the forested area in the Terai reduced by 41% between 1958 and 2000. Deforestation in the Terai has been reported before by Myers (1986) and Isaacson et al. (Isaacson et al. 2001). Estimates of deforestation rates and the area of remaining forest differ however between studies, most likely because of different definitions of “forest area” and “deforestation”. The impact of definitions is exemplified by the discrepancy between forest cover estimates at a national scale. The FAO and the Land Resources Mapping Project (LRMP) using a 50% and 40% crown cover criterion estimated 29.1 and 28.1% forest cover in Nepal in 1976 and 1985 (Metz 1991). The government of Nepal using a threshold of 10% crown cover estimated that 38.1% of Nepal was forested in 1985/86. The National Planning Commission of Nepal estimated the forest cover of Nepal declined from 60% to 19% between 1961 and 1980, corresponding to an annual rate of decline of 5.7%. The claim of Karan and lijhna (1985) that one-fourth of the forests had been cut in the preceding decade corresponds to 2.9% annual decline. A slower rate
of 1.4% was reported by the World Bank stating that 25% of the forest has been lost in the last 20 years (IBRD 1979). A higher estimate of 4.6% was reported by Allan (1986) who reported that "over 50% of the forests have been destroyed in 15 years".

The observed deforestation may be attributed to a number of factors. The Terai had lower population until the 1950’s due to the prevalence of malaria (Peters et al. 1955, Brydon 1961, Darsi Jr and Pradhan 1990). Only the Tharu, a tribe resistant to malaria practiced shifting cultivation (Guneratne 1994). Malaria control, started in 1956 in the Rapti valley (Jung 2001) was soon extended to the whole of the Terai. The control was followed during the 1960s and 1970s by resettlement programs encouraging immigration to bring additional lands under cultivation. Together these two policies, malaria control and creation of settlement opportunities drew immigrants from the hilly parts of Nepal. The population of the Terai increased five fold in forty years time (Isaacson et al. 2001). Lands were cleared for agriculture, resulting in the deforestation reported in this study.

The forests of Nepal became national property in 1957. The first national Forest Act came into force in 1961. These were general acts, which did not foresee demarcation of land to be protected or conserved. Realizing the rapid deforestation, the Nepalese government responded by declaring a National Parks and Wildlife Conservation Act, 1973, and first National Park (Royal Chitwan) was established in the same year. The Act established and demarcated protected areas within forest. In 1993, forest rules were amended (Forest Act, 1993 and its Regulations, 1995) to legally protect the remaining forests. Deforestation in the Terai is at present effectively halted, as all the remaining forest has been demarcated and protected either as nature conservation areas or as a national forest.

Natural undisturbed forest in the Terai typically has canopy closure above 60% (Joshi, personal observation). Our results revealed that 66% of the forests in 2000 had canopies with a closure below 60%. Canopy openings occurring naturally due to storms or dying of trees could bring the canopy density of individual pixels of the satellite image below 60%. However, such canopy gaps of natural origin are a local phenomenon, affecting a small portion of the area at a time. It is unlikely that the 66% of forest area with canopy closure below 60% could be of natural origin. Hence we consider the opening of the canopy of these forests as a sign of degradation. As such our results indicate that forest degradation appears to be a widespread phenomenon in the Nepalese Terai.
Malaria control and an active resettlement policy drew immigrants to the Terai. As a result, the Terai was transformed within three decades from a jungle into one of the most heavily settled regions of the country. Many people are landless, while many those who own land have small holdings only. Confronted with extreme poverty people turned to the forests to complement their livelihood. Although formally forbidden, such utilization by the local poor people was tolerated in most of the national forests. Utilization included collection of secondary forest products, grazing livestock on understorey biomass and logging and lopping of the forest canopy. The forests degraded as a result, a situation continuing until this day. The poverty of the surrounding populations forms the root cause maintaining the Terai forests in this degraded state.

Our study reveals that forests outside national parks were more degraded than inside. National parks have far more staff than other forests to ensure effective control. The vulnerability of the national forests led the government to a strategic plan to control the degradation under the Forest Act of 1993. The act is clear: it prohibits deforestation, grazing, and illegal removal of products from government forest land. It did however not stop the degradation, most likely because it did not address the underlying driver, the poverty of the people.

Our results also revealed that 50% of the forest area inside the national parks had an opened canopy. This is alarming. It indicates that protection within parks, notwithstanding better control, falls short. The degradation of the canopy of these forests negatively affects their productivity and potential for wood supply. Primarily however these forests have been protected as National Parks for biological conservation purposes. Degradation of their canopy may have negative implications for their biodiversity value. Johns (1992) and Kellman and Tackaberry (1999) reported that low density extraction of trees may have severe declines of biodiversity. Malcolm and Ray (Malcolm and Ray 2000) suggested that canopy degradation is the most appropriate measurement of anthropogenic disturbance to forests. No specific research has been done so far on this issue in the Terai but we (Joshi, pers. obs.) observed that forests with opened canopies have strongly reduced richness of the epiphytic flora. At the level of ecosystem diversity the Nepalese Terai is of international importance for three forest ecosystems mentioned in this study: the tropical deciduous riverine forest, tropical monsoon forest and tropical evergreen forest (HMGN/MFSC 2002).
A number of heliophytic invasive species are commonly found under opened canopies, e.g. *Chromolaena odorata*, *Lantana camara* L. and *Mikania micrantha* Kunth. They are unpalatable and rise together with unpalatable native species (e.g. *Clerodendrum viscosum* Vent.) to dominance only in heavily grazed areas. The associated reduction of the forage quality reduces the potential of the understorey to provide benefits to the local communities. Deprived of palatable forage for their cattle, local people started to lop trees to collect leaves to supply to their cattle. This lopping avoids closure of the opened canopy.

The current study thus reveals the ubiquitous presence of forest degradation in the Terai of Nepal. At present, with protected areas and national forests being demarcated, deforestation may no longer be the issue of primary concern. Control of forest degradation deserves to be moved to priority number one of the administration. Our study revealed that remote sensing could be applied to efficiently collect information on degradation status and could thus be used as a tool to demarcate areas deserving intervention and to monitor the success of such interventions.

What could be done to reverse this trend? Law enforcement apparently does not work to achieve the policy and objectives to put a halt to degradation. Community based management starts with the assumption that poverty can be alleviated while exploiting natural resources, while at the same time maintaining the ecological integrity of the ecosystem. A panacea to this problem remain exclusive, but balancing strong protection with recognition of human rights and cultural differences in approaches to forest management, must remain the starting point.
CHAPTER NINE

Mapping cryptic invaders and invasibility of tropical forest ecosystems: Synthesis
9 Synthesis

9.1 The challenge of mapping cryptic invaders

Invasive species management initially aimed at eradication. One century of experience has learned however, that except for very few cases this is not achievable. Currently, invasive species management aims at control and mitigation rather than eradication. Limitation of resources forces invasive species managers to carefully plan and prioritize interventions. Ideally, priority should be given to interventions optimizing benefits in terms of damage reduction, durability and cost effectiveness. This could typically more easily be realized in areas most severely affected by invaders. Maps predicting the distribution of invaders and severity of the impact and damage could thus be used to localize areas requiring interventions.

The distribution of invasive species has been mapped from large (local) to small (global) geographical scale. Small-scale invasive species maps either generalize the known geographical range across a continent or the world or indicate areas at risk of invasion. Invasion risk is generally predicted while establishing the climatic envelope within which a species occurs in its realized range. This climatic envelope is then used to delineate areas with similar climatic conditions, which if not yet invaded would be at risk of invasion. Remote sensing has been applied to map the actual distribution of exotic species, generally at relatively large geographical scales.

Applications of remote sensing to invasive species mapping so far focused on detection of species dominating the upper layer of the invaded community. In this thesis, however, we observed that 67% of the world’s 100 worst invasive species (ISSG 2004) do not dominate the ecosystem canopy. Most of invaders are cryptic, either because they are small or because they are hidden from detection by remote sensing devices (Pysek and Prach 1995, Gerlach 1996, Chittibabu and Parthasarathy 2000).

We introduced a classification of invasive species based on their remotely sensed canopy reflectance response. Class I includes species dominating the canopy and forming homogeneous single species stands. Class II includes mixed canopy dominant species that are members of a multi-species canopy and still directly contribute to the reflected electro-magnetic radiation. Class III includes species not reflecting, but influencing the reflective properties of canopy members, while Class IV finally includes non-canopy dominant species that neither “reflect light” nor influence the reflective properties of other canopy dominant species.
Remote sensing for invasive species mapping thus focused on canopy-dominant species, while most of the IUCN’s worst invaders appear to be cryptic species, beyond detection for straightforward application of remote sensing. Mapping the distribution of cryptic invaders would thus be a challenge, a challenge we have taken up in this thesis while exploring alternative methods to map invaders at local scale.

What alternative possibilities do we have to map invasive species distribution at local scale? A first important observation is to note that invasive species are not distributed at random. Similar to other species they occur in certain environments while not in others. Local variation in environmental conditions thus relates to and sometimes causes their distribution across landscapes. If this assumption would be true, one could use environmental variables to predict the distribution of species across landscapes.

This idea, attractive as it appears, has thus far little been explored in large-scale invasive species mapping. This is probably because the invasive species community has been struggling with a gene or environment debate, while focusing on the question “What makes exotic species successful invaders?”. Some researchers stressed the importance of the intrinsic traits and the inherited ability of species to invade (di Castri 1989, Williamson 1996, Kolar and Lodge 2001). Others maintain that the recipient environment determines whether an exotic species will be established or not (Lonsdale 1999b, Alpert et al. 2000, Vila´ and Pujadas 2001).

9.2 Species-environment relationships across scale

Above we already noted that different environmental factors determine the distribution of species at different scales. Climatic factors determine species distribution at continental level, while environmental variables varying across landscapes such as the availability of nutrients or other resources may determine species distribution at local level. Figure 9-1 schematically represents the factors determining invasive species distribution at various scales. The global species pool is split up in a number of regional species pools, which evolutionary speaking developed because of their isolation and remained segregated from each other through geographical barriers. Movement of species across such barriers occurred but at low rates, which maintained the segregation of floras and faunas.
Mankind greatly speeded up the movement of species across barriers. Exotic species have been entering and continue to enter regional species pools. Once a bridgehead population establishes the new territory lays open and the exotic may disperse as far as climatic constraints allow. The speed of dispersal will depend on the invaders dispersal mechanisms. Climatic conditions within the local area may act as a sieve. It allows those species to invade the local area which manage to establish and reproduce under these climatic conditions. We used an environmental sieve model (van der Valk 1981, Zobel 1997, Van Andel and Aronson 2005a) to illustrate this; some invaders may find the climatic conditions of a local area suitable, others not.

To invasive species, the local area may still be a highly heterogeneous environment, notwithstanding its relatively homogeneous climate. Environmental factors such as water level, soil aeration, nutrient levels etc. may vary across the landscape. Such environmental conditions make a site within such a landscape suitable for certain species while it remains hostile and uninhabitable to others. Hence, landscape-related environmental variation may act as a second level sieve allowing certain species from the local species pool to enter the species assemblage of a site.

At the level of a site, species compete for resources and the better competitors would come to dominance if undisturbed. Disturbance such as grazing and fire modify competitive relationships, and the actual species composition will be the outcome of both these processes.

Below we review the outcomes of our thesis research in the perspective of the scheme presented in Figure 9-1.
Figure 9-1. Scheme showing factors controlling the distribution of invasive species at various geographical scales.

### 9.3 The distribution of *Chromolaena odorata*

Our study dealt with *C. odorata*, one of the world’s worst invasive species which has invaded tropical forests understorey around the world (Goodall and Erasmus 1996, McWilliam 2000). Our research empirically established two environmental sieves,
which constrain the distribution of *C. odorata* in the forests of Nepal. Climatic conditions and heterogeneity in light intensity at landscape level formed two distinct environmental sieves.

A number of authors investigated the climatic constraints to the distribution of *C. odorata*. Its worldwide distribution has been related to total annual rainfall (Muniappan 1988, Goodall and Erasmus 1996), frost incidence (Goodall and Erasmus 1996). Kriticos (2005) predicted the worldwide distribution of *C. odorata* using a number of empirically derived climatic variables. The predictions had a spatial resolution of 30 min, which is rather course for a country with a complex topography like Nepal. In chapter 8, we developed 1 km resolution models predicting the climatic boundaries of the distribution of *C. odorata* in Nepal. *C. odorata* disappears at elevations above 1100 m, most likely because of frost sensitivity. The species is also absent from West Nepal. The length of growing season for *C. odorata* in west Nepal is shorter than in the east. The model had an accuracy of 80% and the 1 km climate data thus allowed to model *C. odorata* distribution realistically (Figure 9-2).

![Figure 9-2. Climatic suitability of Nepal for *Chromolaena odorata*.](image)

*C. odorata* occurs in the lowland forests of Nepal, where it shows a remarkable response to light (Chapter 4). It remains virtually absent from dense forest, but dominates and vigorously produces seed in forest clearings and ruderal environments with more open canopies. This suggests that light intensity determines the competitive and reproductive traits of *C. odorata*. We demonstrated
a very strong relationship between light intensity and the sexual and vegetative reproduction of *C. odorata* and concluded that this factor controls the invasion of the species in the forest environment. Light intensity was strongly related to the number of seeds produced per plant (Figure 9-3). *C. odorata* is a clonal grower and we demonstrated that the rate of clonal growth was positively related to light intensity as well.

![Figure 9-3](image)

**Figure 9-3.** Relation between the number of seeds produced per plant (SPP) and light intensity and forest canopy density. The dotted line indicates the light intensity threshold of 6.5 mJ m⁻² day⁻¹ and forest canopy density threshold of 60% separating reproductive and non reproductive populations of *C. odorata*.

Light intensity in the forest is determined by canopy density. Canopies of most forest had been opened up, due to logging and other utilization. We predicted forest canopy density and light intensity reaching the understorey while classifying Landsat imagery using a neural network. These forest canopy density and light intensity maps could then be used to predict the distribution of *C. odorata* populations at local level.

We next mapped the forest in the whole of the Nepalese *Terai* and used Landsat images to assess the degree of canopy degradation (Chapter 8). We further upscale this map up to the climatic suitability limit in Nepal for *C. odorata*. 
Figure 9-4. Forests canopy density map of Nepal within the suitability range of *C. odorata*.

Derived from this we produced a map showing the suitability of forest to maintain seed producing populations of *C. odorata* (Figure 9-4). This thus corresponds to the second environmental sieve constraining the distribution of *C. odorata*.

Figure 9-5. Suitability of forests of Nepal for invasion by *C. odorata* considering forest canopy density in Terai districts.
Finally, we combined these two environmental sieves into a map showing the potential distribution of *C. odorata* in the forests of Nepal. It predicts the distribution of *C. odorata* while considering climatic constraints and the influence of light intensity due to the degradation of the forests (Figure 9-5).

The map displays the suitability of the forest understorey for *C. odorata*. Its actual presence and abundance depends on the interaction with other species. We noted that *C. odorata* was absent from suitable sites within well-protected areas with little human interference. Here native grass species dominated the forest understorey. People who collect forest products and allow their animals to graze however heavily utilize most of the forests. *C. odorata* is an unpalatable species. Intensive grazing causes the disappearance of the replacement of the original vegetation by unpalatable species like *C. odorata*. Frequent fire used to manage the sylvo-pastoral system further favours *C. odorata*, which is well adapted to survive fire in the dry season.

We argue that opening up of the canopy alone is not enough to explain the widespread invasion of *C. odorata* in the forests in the Terai. We hypothesize that overgrazing and management of the forest understorey enabled *C. odorata* to outcompete the native flora and rise to dominance. Or in terms of Figure 9-1, management of the understorey modified the competitive relationships in favour of *C. odorata*. The above assumptions were inferred from field observations. It would be interesting to confirm these supposed causal links through experimentation.

The findings of our study illustrate how remote sensing and GIS technologies can provide ecologists and land managers with an innovative perspective with which to study the factors influencing the patterns of invader population dynamics at local landscape scales. Furthermore, we suggest that forest canopy density, inter-specific competition and anthropogenic factors might account for the differences in size and productivity of *C. odorata* populations. This study shows how these physical factors linked to map the clonal growth rate of an invasive species. Incorporation of remote sensing techniques with species biometry yields instantaneous, useful, cost-effective, multi-scale and temporal information on clonal growth dynamics of an invasive species. Mapping clonal growth rate in *C. odorata* populations could significantly reduce control costs by allowing one to concentrate control efforts to manage habitats so as to curtail the spread of invasive species. In this respect, the immediate benefit of this research has been to contribute to the knowledge base of land managers by providing improved information on the rate of spatial and
temporal spread of clonal populations of \textit{C. odorata}, which will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems.

### 9.4 Invasibility of the \textit{Terai} forests

Above we indicated that \textit{C. odorata} invaded the \textit{Terai} forests where the canopy had been broken up. This allows light to penetrate the under story, thus enabling \textit{C. odorata} to reproduce seeds and become invasive.

Analysis of historic maps reveals that the canopy of the forests in \textit{Terai} region of Nepal was more closed (>60% closure) in the 1960s. Today canopy densities below 60% are very common in areas with open access to inhabitants such as the forests in the Barandabhar forest corridor in Chitwan district of Nepal. This suggests that \textit{C. odorata} invaded the forests in the \textit{Terai} because they were degraded.

Our historical land cover change analysis reveals that forests were opened up somewhere between the 1960s and 1970s. Hence, the period when the canopy of forests opened coincided with the spread of \textit{C. odorata} into the region. We suggest that this is not a mere coincidence. Canopy opening created the light conditions in the forest environment required for establishment and reproduction of \textit{C. odorata}. We therefore argue that the degradation of the canopy triggered the invasion success of \textit{C. odorata} into the lowland forests of Nepal. In other words, \textit{C. odorata} did not become a successful invader because of its traits alone, but rather because of the combination of these traits and the degradation of the forest environment. We further demonstrated that the eradication of malaria increased human population density, which - according to Guneratne (1994), Müller-Böker (1991) and Soussan et al. (1995) - triggered land use changes and forest degradation. We finally argue that this sequence of events leading to forest degradation contributed to the invasion of \textit{C. odorata} in the lowland forests of Nepal. Hence, human plays a significant role in invasions by exotic species than previously thought (Blumenthal 2005).

### 9.5 Ecological restoration

Repeated disturbance, typically grazing, logging and lopping will continue to provide suitable light intensity for colonization by \textit{C. odorata} in the forest understorey. Well-established genets of \textit{C. odorata} will eventually be present in the disturbed neighbourhood of forest understorey, because the high light intensity and high levels of continuous disturbance provide long-term habitat. Despite growing
awareness and the extensive amount of research carried out on *C. odorata* worldwide, the spread of this species has not been curbed by any chemical, mechanical or cultural control means (Goodall and Erasmus 1996). Even though biological agents - for instance the arctiid moths *Pareuchaetes pseudoinsulata*, *Acaultus adoratus* and *Actinote anteas* - have been introduced for reducing aboveground vegetative biomass and seed production of *C. odorata* with variable success (Kluge 1991, Kluge and Caldwell 1993, McFadyen et al. 1996), invasive corms of *C. odorata* pose a continuous threat under light conditions sufficient for growth. Therefore, in order to understand the invasion success of *C. odorata*, the plasticity in corm morphology and the long-term impact of biological agents on resource allocation dynamics must be taken into consideration. We conclude from our study, that both vegetative propagation of corms and aboveground growth and seed production of established *C. odorata* populations decline after recovery or restoration of the disturbed forest until a canopy density of over 60% has become re-established.

This work is one-step further to succeed in efforts to answer the question of how to mitigate the effects of invasive species on tropical forest ecosystems and how to make those ecosystems less prone to invasion. Deliberate introduction of biological agents, as occurs now in biological control efforts will surely be less needed (if they are well effective) if we understand how control of species can be enhanced through the local knowledge and management measures. Similarly, this approach could help in controlling the excessive use of toxic bio-chemicals in suppressing species invasion.

Successful restoration of sustainable communities and *de novo* creation of persistent complex systems that provide essential ecosystem services in novel environments are considered the true tests of our understanding of forest dynamics. That, in short, as Van Andel and Aronson (2005b) explained, is the shared frontier of community ecology and ecological restoration. We need to know which aspects of community structure are restorable once dissembled, and which are not. In our view, after this study, we have that understanding.

### 9.6 Perspective: science and society

Many of the following recommendations are specific to the tropical region of Nepal. Species and invasion dynamics may differ depending on climatic conditions or the disturbance history. Nonetheless, the conceptual framework for developing *C. odorata* management strategies demonstrated in this study will be appropriate in
many other settings. Experience from other tropical countries shows that chemical and mechanical or biological eradication of *C. odorata* seems to be impossible. We propose a feasible strategy in which active control efforts are directed toward infestations that pose the greatest threat to the biological values of the Nepalese tropics. In addition, more passive control methods can be employed to manage less critical but more widespread infestations.

With the support of remotely sensed images, GIS and modeling tools, we developed and supplied the technical information for cryptic invaders to design and implement a comprehensive system that enables the local, regional and national managers to predict, prevent, and rapidly respond to new incursions of invasive species, thus minimizing their spread and impact.

This research gives a new perspective of the capabilities of indirect use of remote sensing tools in mapping and management of invasive species. We believe that this insight will allow the remote sensing community, ecologists and land managers to enhance their skills in understanding invasibility of ecosystems and mapping other cryptic invaders that pose an immediate threat to the recipient ecosystems. This strategy engenders the following recommendations.

- Any disturbances in forest canopy promote invasion of *C. odorata* by increasing the invasibility of such forest communities. Tropical ecosystems of Nepal are highly productive. Effective shading is one of the most effective ways of suppressing the cover abundance of *C. odorata*. Mapping the presence of reproductive populations of this species could significantly reduce the size of area infested by *C. odorata*, which could help in formulating a management strategy and in focusing on areas most requiring interventions. Hundreds of governments and non-government organizations focus on forest management issues independently. These efforts can easily be redirected for the dual purpose, i.e. sustainable management of forests and control of invasive species.

- Control measures will not be necessary for sink populations. Forest with above 60% canopy cover does not support reproductive populations of *C. odorata* probably because the light intensity is too far below the level of its reproductive growth.

- *C. odorata* is well established abundantly at highly grazed areas throughout the entire tropical region of east and central Nepal. However, our observations suggest that *C. odorata* is incapable of establishing its abundance under dense grassland, hence long-term exclusion of grazing and fire, which kills most of the understory vegetation, could significantly reduce its abundance.
• C. odorata is also abundant along roadsides, forest edges and most of the neglected areas with no agriculture. These populations may not be controlled easily, so targets for intensive control efforts must be prioritized. Fast-growing trees or development of fruit orchards could help in controlling its further abundance and spread.

• The presence of C. odorata to the forest interior suggests that the species may invade these areas in the future in case of disturbance. Disturbance associated with livestock grazing may provide C. odorata with a bare-soil niche for generative regeneration and for corm invasion and vegetative reproduction. C. odorata invasion into such areas can be curtailed by active management by leaving sufficient forest understorey vegetation for more inter-specific competition.

We tried to resolve debates (at least in case of C. odorata) about what makes an area susceptible for invasion. As the human population persistently grows, its cumulative impact on the Earth's resources goes up as well. Multiple disturbances have a complex effect on both physical and biotic processes as they interact. Because disturbance alters resource levels, effective management requires understanding of the ecology of disturbance. Tropical forests are experiencing an unprecedented level of impact in both ways from land use change and exotic species invasion. Both natural and anthropogenic disturbance regimes accelerate invasion, which physically influence the ground.

Bio-invasion is a by-product of globalization (Wilson 1995). Prevention becomes a more formidable challenge (Meyerson and Reaser 2002). Eradication of invasive species is an illusion. Hence, the continued persistence of potentially harmful species at tolerable levels could be an ultimate strategy. However, the ability of land managers to combat invasive plants is persistently limited by funding constraints. Information to suggest low-cost control measures and a system to prioritize labour-intensive site-specific eradication could be vital. Through this thesis, we offered an understanding why C. odorata is so successful an invader in tropical forest ecosystems of Nepal. This understanding is essential to controlling its further spread. Furthermore, this technique can be equally useful in understanding, detecting and managing other cryptic invasive species.

This thesis highlights the needs and challenges involved in local to regional-scale modeling of plant invasion as a response to land use change. Output from analysis of remotely sensed images and models should be a primary tool for researchers and decision makers to evaluate the question of sustainable resource utilization and safe rates of land use change, and associated impacts on biodiversity, protection of species, and other resource issues and their management.
The ability of the Earth to support more humans is dependent on the ability of humans to manage natural resources wisely. Hence, there is a fundamental need to bring together existing information on invasion processes and vulnerability of ecosystems. Perhaps more urgent at this time is the need to provide information on the management of these ecologically pivotal resources.


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Epilogue*

Traveling downhill, “the big B” and my journey to PhD

Traveling downhill

“Do not chase monkeys, or they will attack you”. That was my mother’s advice when I left for school. However, my worries actually concerned a scary monitor lizard family who lived in a huge dead tree trunk along the trail on my way to school. Those were the days in 1972 when my family migrated from high mountains to the flat plains so called Terai (Terai: a narrow belt of alluvial and fertile flat plain of the southern border of Nepal extends from the westernmost part of the country to the eastern limit and covers about 17% of the total land) south of the Himalayas.

I was born in a remote village in the middle mountains in the west of Nepal. My family was fortunate since my father inherited sufficient land, which had not been divided among an increasing heir because my father, grandfather and great-grandfather were the only child in their family. Other families in our village, however, were less well off. Lack of land and low grain production mashed farmers with poverty and unemployment. As a result, many poor families from the hills migrated since the 1950’s towards the Terai region.

This migration in Nepal resulted from ‘push’ factors such as poverty and food insecurity and ‘pulls’ factors for instance availability of land and employment elsewhere. Plenty of fertile land was located in the lower foot slopes of the Himalayas. Until the 1950’s, this so called Terai was little populated. Indigenous malaria was preventing people from settling here. Only indigenous malaria resistant people such as the Tharu, occupied pocket settlements in dense jungles. For the others the Terai remained a forbidden frontier.

My brother, who later became a medical doctor, first told me about the malaria control programme. This USAID supported programme, aiming at malaria control first started in the central Terai in 1955, followed by others parts areas in 1963. Control activities included spraying of DDT and pyrethrum in addition to prophylactic treatment with paludrine tablets. By the mid 1960’s most of the Terai was declared save and freed of malaria.

The rumour quickly spread that fertile uninhabited lands freed of malaria were available in the Terai. It also reached my village. Many families abandoned their homes looking for brighter opportunities downhill. Soon our village was running empty. My parents, owning the better land in the village stayed until 1972. By that year, we were among the very few families remaining. Belonging to a so-called Brahman cast, my parents were not supposed to plough the field and we were always dependent on others to work for us. We decided to follow the others, not so much because of the opportunities, but of the dying social life in the village. My first brother (who is 20 years older than me) was the first migrant in my family. He was appointed as a school teacher in one of the Tharu villages. He claimed a small piece of land by cutting away some trees in the very dense jungle near Mahendranagar in 1968. I joined him with my parents in 1972.

* This epilogue is submitted to the WOTRO Newsletter
Initially, we were living amidst dense forest. Plenty of wildlife was still around. Out there, next to our big wooden house, I was fascinated by a flying fox family. They lived in a giant Shorea robusta tree and glided every evening for foraging. A vulture family worked hard to collect enormous amounts of heavy branches to build their nest on top of a Terminalia alata tree. Whenever I had some free time, I joined my playmate who never attended school. He was however, an expert “hunter”. We always looked for parrot nests and played “hide and seek” with the woodpeckers. They moved around tree trunks as we tried to glimpse them. A little further, a giant Adina cordifolia tree with a big hole in its trunk created a sort of “cave” - the perfect hiding place for us. Part of our game was to press the lateral side of Chilanthus (silver fern) leaves on our arms to create a beautiful silvery temporary “tattoo”. We were a disaster for the termite family since we constructed a “Ghusudi” or slide and with this, destructed the home of the termites.

Prior to 1961, Mahandranagar (my home town and the head quarter of the region which is named after late King Mahendra in 1961) was known as Ghusudi bazaar, where probably someone prior to us constructed a Ghusudi on some tall termite mountains.

My family cleared the forest to claim more and more land. Every Saturday, I was allowed to join them to set fire on dead trees and branches. Also, we collected latex of Pterocarpus marsupium, a valuable medicinal tree of which people believed to be a blood purifier or Ophioglossum plants for my grandmother, a wild vegetable for delicacy. We enjoyed the amazingly bright red and blue coloured fruits of Rauvolfia serpentina. Sometimes we raised our cattle in a near by part of the jungle, later gazetted as Royal Suklaphanta National Park and Wildlife Reserve.

Days passed and the forest disappeared quickly, as did my childhood. I had completed my secondary education in 1980 and went to India for higher education. Here, I graduated as a biologist in 1985 and immediately joined the National Herbarium and Plant Research Laboratories, under the Department of Plant Resources, Ministry of Forest and Soil Conservation as an assistant botanist. The forests, their ecology and Biodiversity -“the big B” became part of my professional life and drive. I explored my country in many botanical expeditions and started to appreciate its biodiversity when realizing there were more than 7000 flowering plant species out there.

Then I was appointed in the far west, the area where I spend my childhood. I found the forest all gone. Settlers had cleared it to plant their crops, and timber companies had seen to the rest. Yet I now realized that this was the very spot where in 1876 the first Rana Prime Minister Jang Bahadur had taken the Prince of Wales (later Edward VII) hunting for big game. The Royal party, transported through the woods and swamps by an army of 800 elephants, had on that occasion bagged a leopard, twenty Royal Bengal tigers and no less than a hundred deer.

In vain, I tried to find my lizard family, the Terminalia tree and the flying fox, the Adina “cave”, the vulture family, Pterocarpus, Ophioglossum, woodpeckers and termite mountains. Everything had changed, big concrete blocks of houses replaced all those species. Our family land was taken back by the government and two huge university campus complexes had been established there. However, I could see that the two mango trees planted by my brother and me were still standing just in front of the university canteen, the only witness of my childhood. The moist loving Cheilanthus farinosa (the juice of the plant is used as ear drops in the treatment of earache) had disappeared, replaced by Ipomoea fistulosa a useless exotic invasive species from tropical America.
Then, I looked at my neighbours. The land was dotted were thousands of houses, a pattern reminding me of the gone termitaria. The big pieces of land owned by their parents had been fragmented into small parcels. The house of the friends of my youth had been deprived. The forest were gone and where fragments remained there were holes in the canopy (Figure 9-6 left). I realized that the few remnant forest fragments were in poor condition. Even there, however, few of the original species survived. Instead the forests were degraded and disturbance loving species including invaders from the other side of the globe dominated the remnants of this part of our natural heritage.

Working in central Nepal I got particularly stuck by the widespread dominance of *Chromolaena odorata*, a major invasive weed of pasture, forest clearings, roadside and forest plantations, disturbed land and other similar land uses. No vegetation survives beneath its 2–3 m high dense thickets (Figure 9-6 right). Grasslands under disturbed forest environment are rapidly invaded, the grass shaded out and completely replaced by it. Bitter tasting pyrrolizidine alkaloids do not allowed animals to graze it and if cattle do eat it, the alkaloids progressively destroy their liver, and animals die. If forest degradation continues, soon *C. odorata* will replace native biota as well as valuable pasture by its dense growth, leaving the livestock to starve and the villagers further deprived of their source of milk, meat, cash income, non-timber forest products or medicinal plants.

Why was this? What were the root causes for this degradation? How and why do these forest canopy holes affect biodiversity. Did the degradation of the forest not affect human well-being as well? Should we blame the poor people for this and their own predicament? How about their government? Have they pursued policies that actually harm rather than sustain development?

Hundreds of these questions were with me when making the first move towards a WOTRO (the Netherlands Foundation for the Advancement of Tropical Research) scholarship. As I had a strong desire to learn about the spatial and temporal dynamics of those ecosystems, I applied for a NFP Fellowship (Netherlands Fellowship Programme) and started another MSc with the International Institute for Geoinformation Science and Earth Observation (ITC), the Netherlands, an international institute dealing with advanced GIS and remote sensing technologies.
Every time I turned on my computer, I experienced something new. Curiosity and fascination were generated by the pixels of satellite images of the country I knew so well. And, the more I experienced, my complex, scattered and multifaceted curiosities only raised my research hunger. My hunger for research was positively appreciated by WOTRO who in 2002 approved a PhD proposal I developed.

Since then as a researcher, I investigated the best way to locate holes in the forest canopy. Also I have answered the question why there are so many holes in those forests. What factors and government policies are responsible in creating such holes? What is the spatial extent of those holes? Why are forests having such holes in their canopy more susceptible to species invasion?

I am eventful to up-scale the spatial pattern of those holes to the national or continental extents. However, I still have to understand why floristic composition under those canopy holes changed. What happened to the Cheilanthes populations, flying fox or the woodpeckers family who prefer dense forest canopies? During my PhD, I became familiar with techniques to address such questions and I feel confident I could support youngsters in Nepal to absorb this European scientific tradition.

Other questions still remain. There is the ambiguous feeling about the migration downhill which resulted in improved living conditions for people but also the vanishing of the friends of my youth. Although, no one will ask me why should the loss of flying fox should concern me? Why the species dynamics under such canopy holes is so important? However, my grandchild will certainly ask me what the flying fox looked like or whether the delicacy of Ophioglossum was compensated by the benefits of the invasive C. odorata?

What next?

This is the personal account of my experiences preceding my journey to my doctoral research in Netherlands. However, it is the story of every person of my age who has migrated from the mountains to the Terai. This “going downhill” is an ongoing process. While I am writing this story, out there some families are on the way to the Terai. They continue to open up patches of forests (Figure 9-7). I doubt however whether the woodpeckers were still there to play “hide-and-seek”, because so many holes pierce the forest canopy these days.

Figure 9-7. A newly settled family house in the dense Shorea forest. I took this photo on 16 May 2005 near my home town Mahendranagar.
Only 40 years of age, I witnessed biodiversity of Nepalese ecosystems going downhill. It was affected as habitat decreased in size and health and the distances between forest patches greatly increased. Looking back, I realize that changes in habitat drove the woodpecker and Ophioglossum populations to local extinction. The disappearance of these species has certainly lowered “the big B”. However, I have no clue to questions for instance how many ecosystems, species and genetic diversity we have scratched. Or what is the impact of the invasive species we have introduced? And how do we keep those unwanted species under control so that they do not pose a further threat?

These questions look simple. However, I have not addressed them in this thesis. Nor has anyone found the answers yet. To me, it is crucial to mitigate the anthropogenic pressures put upon our native ecosystems. How people and their, institutions and organisations can be more effective in managing “the big B” still remains an apprehensive question at another level.

Returning to the Terai of my youth, Ophioglossum no longer grows there. No more safe drinking water left in the lake neighbouring my village due to an invasion of the water hyacinth (Eichhornea crassipes). One of the friends of my youth, Rauwolfia serpentina has been red listed in appendix II of the CITES endangered species list. Growing older I will act while re-introducing *Pterocarpus* to those ecosystems so that my grand children will be able to collect its latex to purify my aging blood.

Enschede, the Netherlands
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Curriculum vitae

Chudamani Joshi was born in 1964 in Jhigni, Devel Dibyapur, Dadeldhura district of Far West Nepal. He completed his primary education at Kedar Primary School, Kholi, Devel Dibyapur (1968-1972) and Baijnath High School, Mahendranagar, Kanchanpur (1972-1980) respectively. He graduate in 1985 with Bachelor of Science degree in Biology and Chemistry from Lucknow University, India. In 1989 he graduate with Bachelor of Legislative Law (specialization in Administrative law) from Lucknow University. In 1995 he joined Tribhuvan University, Kathmandu, Nepal and graduate with MSc in botany (specialization in plant taxonomy) in 1997.

Since 1986 he has been a permanent member of staff of the National Herbarium and Plant Research Laboratories under Department of Plant Resources, Ministry of Forest and Soil Conservation, Nepal and currently working as a research officer. As a manager and researcher he has long experience in botanical inventories, plant systematics, ethno-botanical survey and management of botanical gardens and Herbal farms. Between 1995-1997 he worked as a Botanist/Technical expert with HMGN/FINNIDA (Mitsahallitus, Finland) and involved in national forest inventory programme. He has visited almost all districts of Nepal on foot and collected a large number of plant specimen for National Herbarium, Kathmandu and many other international herbaria. He is author of 4 parts of flora of Nepal, some peer reviewed scientific papers, conference papers, project reports and other publications.

In 1999 he joined ITC for an another MSc course and graduated in Natural Resources Management (specialization in Rural Land Ecology) in 2001. In mid 2002 he received a WORTO fellowship and started his PhD research at ITC and Wageningen University the Netherlands that resulted in this thesis.

He married Geeta in 1989 and he is a father of daughter Richa and son Rishav.
Author’s Publications

Books/chapters


Theses:


Peer review papers:


Peer review conference papers:


Project reports:


Joshi, C. 1998. Description and uses of the non-timber forest products recorded in the NFI of the hilly area of Western Development Region. In: Forest Resources of the Western Development Region 1997, HMGN/FRIS-Project/Finland, Publication No 71.


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