Ela Foundation

Ela Journal of Forestry and Wildlife

ISSN 2319-4361
(Indexed in Google Scholar)
Volume 14 | Issue 2
April - June 2025

A quarterly scientific refereed e-Journal of Ela Foundation and Forest Department, Maharashtra for Nature Conservation through Education and Research

Listed in UGC- CARE

Faecal Microbiota Profiling of Captive Gyr Falcons (*Falco rusticolus*) and Hybrids in Saudi Arabia

Zubair Medammal[1]*, Lysamma Surya[2] and Mohammed Al-Rasheed[3]
[1]Department of Zoology, University of Calicut, Kerala, India. Email: zubairm@uoc.ac.in
[2]Department of Zoology, University of Calicut, Kerala, India. Email: lysuvinu29@gmail.com
[3]Avian Research Centre, King Faisal University, Al Ahsa, Saudi Arabia. Email: malrasheed@kfu.edu.sa

Citation: Medammal Zubair, Surya Lysamma and Al-Rasheed Mohammed. (2025). Faecal Microbiota Profiling of Captive Gyr Falcons (*Falco rusticolus*) and Hybrids in Saudi Arabia. *Ela Journal of Forestry and Wildlife*. 14(2): 1738-1750

Date of Publication: 30 June 2025

ISSN 2319-4361

Abstract

Falcons have been used in falconry for centuries in the Kingdom of Saudi Arabia and other countries in the area. In many of these countries, various falcon species are captive-bred, with the goal of selecting for hunting ability. Purebred Gyr falcons *(Falco rusticolus*), the largest species of falcon, are highly regarded by falconers for their hunting abilities. Gyr falcons that have been captive-bred may live, reproduce, and hunt for longer periods of time, making them more stable. Aspergillosis is a non-contagious fungal disease of wild and domestic birds caused by the Aspergillus fungus. This fungal illness is commercially important since it is the leading cause of mortality in captive birds, particularly falcons. This study examined the effect of nutrition on the intestinal bacterial ecology of Aspergillosis-affected Gyr falcons using faecal culture, as well as the potential for the isolated organisms to transfer to humans and avian species, an important aspect in the One-Health approach which is presently adopted universally. An infected male Gyr and a hybrid female (Gyr and Peregrine - *F. peregrinus*) were fed meat and a fresh chicken-rich diet, and the results revealed an equal distribution of gram-positive and gram-negative bacteria in fecal analysis that were less hazardous. The bacteria discovered here could be temporary flora acquired through food and, under normal conditions, are unlikely to colonize and become permanent inhabitants of the raptorial enteral tract. Thus, supplying falcons with different healthy foods is a better option in captivity, which may assist falconers keep their birds free from infection.

Key words

Captive, Gyr falcons, Aspergillosis, Peregrine, faecal culture.

Introduction

Falcons (Falconidae family) are noted for their amazing speed and agility, which they utilize to pursue other birds and small mammals (Fox *et al*., 1976). There are over 40 species of falcons, including peregrines, Gyr falcons, hobbies, and kestrels (Oberprieler *et al.,* 2009). The Gyrfalcon (*Falco rusticolus*), sometimes known as the "Arctic Falcon," has a vast distribution in the Arctic and sub-Arctic regions of North America, Europe, and Asia. It is considered the world's largest falcon, with females much larger than males. Adult males weigh 800-1300 g and are 48-61 cm long, whilst females weigh 1200-2200 g and are 51-65 cm long. The Gyrfalcon is classified as a species of "Least Concern" by the International Union for Conservation of Nature (IUCN). Throughout the Middle Ages, monarchs would catch and train the Gyrfalcon to be a hunting partner because it was regarded as the bird of kings in traditional falconry. The practice of teaching a falcon to hunt and return to its handler is called falconry. The peregrine falcon, commonly known as the "peregrine" or *Falco peregrinus* is a bird that is widely spread and renowned for its swiftness. The peregrine falcon is a highly prized bird in falconry worldwide because of its exceptional hunting skills, outstanding trainability, adaptability, high success rate in captive breeding, and resulting ease of supply.

Due to stress, wild Gyr falcons kept in captivity are more likely to have illnesses such as Aspergillosis. Gyr falcons raised in captivity are more resilient and have a longer lifespan for hunting and breeding. Without affecting wild populations, captive breeding will produce a steady supply. Many efforts have been made in Saudi Arabia to enhance the management of the Gyrfalcon, despite the fact that the species poses numerous difficulties in terms of infections and captive care. When husbandry conditions expose birds to disease, a fungal disease of both wild and domestic birds, caused by the fungus Aspergillus species, can arise as a flock concern. Decomposing organic matter, especially hay, compost, or wood, contains a lot of the fungus's spores. The danger of infection is increased by inadequate cleanliness and poor ventilation. The fungus is characterized by its major involvement of the respiratory tract, the formation of yellow cheesy plaques, and hard nodular masses in the lungs and air sacs, while it can also commonly impact other organs. Isolating social animals, combining flocks of birds, or beginning training are all possible stressors that could result in immunosuppression and infections. For falconers involved in rehabilitation, bringing sick or injured wild falcons into captivity is a known risk factor for Aspergillosis. One of the main causes of bird mortality in captivity is Aspergillosis, which has important economic ramifications. The purpose of this study was to investigate the intestinal bacterial flora of these raptors through faecal culturing of Aspergillosis affected Gyr falcons. The impact of food on faecal bacteria was also taken into account, and the possibility that isolated organisms could infect people and birds was explored.

Materials And Methods

Aspergillosis was discovered in pet Gyr falcons and Gyr-Peregrine hybrid falcons in a Riyadh, Saudi Arabian bird market according to the study conducted by Rahim *et al*., 2013. After feeding on meat and fresh chicken-rich meals, an infected male Gyr and a hybrid female (Gyr and Peregrine - *Falco peregrinus*) were examined, and samples of their faeces were taken for additional analysis. The samples were examined under a microscope after Gram staining to ascertain whether they were gram-positive or gram-negative. The bacterial culture was maintained at 40°C on a nutrient agar medium using the spread plate method. Microbial colony's appearance and colour were used to diagnose the infection. The test organism was then kept in the refrigerator for later use after being separated from colonies using the streak plating technique. After that, the cells' pure genomic DNA was extracted. Origin Genomic DNA Kit was used for DNA extraction and isolation. Using the PCR method, almost two Nano grams of genomic DNA were amplified. The PCR procedure included a 5-minute denaturation step, 30 cycles of 10 seconds at 95°C, 30 seconds at 55°C, and 45 seconds at 72°C, and a final 3-minute phase at 72°C. To verify the amplification of the target gene, the PCR products were resolved on a 2% TAE-agarose gel. The Mo Bio UltraClean PCR Cleanup Kit (Mo Bio Laboratories, Inc., California) was used to column purify the PCR product. SciGenom Labs Private Ltd. in Cochin performed the sequencing of the purified PCR product. After chromatograms were examined to assess the quality of the obtained sequence, Clustal W was used to combine the forward and reverse sequences, and the consensus was collected for additional analysis. The resultant sequence was analysed for similarity using NCBI's BLAST (www.ncbi.nlm.nih.gov/). MEGA10 software was used to plot the phylogenetic tree using the neighbor-joining method.

Results

These falcons' faecal samples yielded the bacterial isolates shown in Table 1 for samples 1-OR413817 (Figure 1), 2-OR413816 (Figure 2), 3-OR413804 (Figure 3), and 4-OR413813 (Figure 4). Table 2 lists the biochemical assays that were performed on the samples. Figures 1, 2, 3, and 4 represents the quadrant streak colony of the bacterial isolates.

Figure 1. The colony of *Enterococcus faecalis*

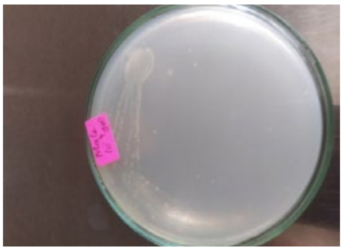


Figure 2. The colony of *Enterobacter sichuanensis*

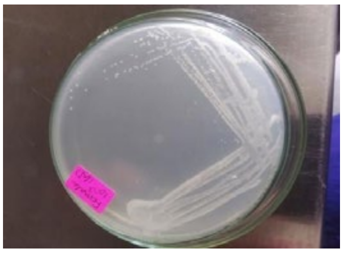


Figure 3. The colony of *Bacillus tropicus*

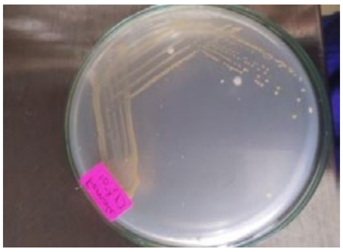


Figure 4. The colony of *Serratia marcescens*

Table 1- The bacterial isolates identified.

Species	Bacteria isolated	Bacteria identified	Nature of the bacteria
Gyrfalcon			
Male	Gram-positive	*Enterococcus faecalis* (sample 1- OR413817)	Opportunistic bacteria used as probiotic
	Gram-negative	*Enterobacter sichuanensis* (sample2- OR413816)	Potential pathogen in humans
Hybrid Female (Gyr and Peregrine - *F. peregrinus*)	Gram-positive	*Bacillus tropicus* (sample 3- OR413804)	Feather-degrading bacteria, a potential pathogen in humans
	Gram-negative	*Serratia marcescens* (sample 4- OR413813)	Opportunistic pathogen causing nosocomial infections

Table 2- The biochemical tests conducted

Biochemical test	Bacteria isolated			
	Enterococcus faecalis	*Enterobacter sichuanensis*	*Bacillus tropicus*	*Serratia marcescens*
Citrate	_	+	+	+
Carbohydrate	+	+	_	+
Catalase	_	+	_	+
Indole	_	_	_	_
Oxidase	_	_	+	_
Methyl-red	_	_	_	_
Starch	+	_	+	+
Urease	_	_	_	_
Voges-Proskauer test	+	+	_	+

Figure 1. Showing OR413817 ***Enterococcus faecalis*** **strain ATCC 19433 16S ribosomal RNA, partial sequence**

Sequence ID: NR_115765.1, Length: 1483Number of Matches: 1				
Score	Expect	Identities	Gaps	Strand
2560 bits(1386)	0.0	1423/1440(99%)	6/1440(0%)	Plus/Plus

```
Query  1    TGCAAGTCGAACGCTTCTTTCCTCCCGAGGGCTTGCACTCAATTGGAAAGAGGAGTGGCG   60
            |||||||||||||||||||||||||  ||||||||||||||||||||||||||||||||
Sbjct  29   TGCAAGTCGAACGCTTCTTTCCTCCCGAGTGCTTGCACTCAATTGGAAAGAGGAGTGGCG   88
Query  61   GACGGGTGAGTAACACGTGGGTAACCTACCCATCAGAGGGGGATAACACGTTGGCAAACA   120
Sbjct  89   ||||||||||||||||||||||||||||||||||||||||||||| |||| ||||| GACGGGTGAGTAACACGTGGGTAACCTACCCATCAGAGGGGGATAACAC-TTGG-AAACA   146
Query  121  GGTGCTAATACCGCTATAACAGCTTTATGCCGCATGGCATAAGAGTGAAAGGCGCTTTCG   180
Sbjct  147  |||||||||||| |||||| ||||||||||||||||||||||||||||||||||||||||| GGTGCTAATACCGC-ATAACAG-TTTATGCCGCATGGCATAAGAGTGAAAGGCGCTTTCG   204
Query  181  GGTGTCGCTGATGGATGGACCCGCGGTGCATTAGCTAGTTGCGTGAGGTAACGGCTCACC   240
Sbjct  205  |||||||||||||||||||||||||||||||||||||||| ||||||||||||||||||||| GGTGTCGCTGATGGATGGACCCGCGGTGCATTAGCTAGTTG-GTGAGGTAACGGCTCACC   263
Query  241  AAGGCCACGATGCATAGCCGACCTGAGAGGGTGATCGGCCACACTGGGACTGAGACACGG   300
Sbjct  264  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AAGGCCACGATGCATAGCCGACCTGAGAGGGTGATCGGCCACACTGGGACTGAGACACGG   323
Query  301  CCCAGACTCCTACGGGAGGCAGCACTACGGAATCTTCGGCAATGGACGAAAGTCTGACCG   360
Sbjct  324  ||||||||||||||||||||| || |||||||||||||||||||||||||||||||||||| CCCAGACTCCTACGGGAGGCAGCAGTAGGGAATCTTCGGCAATGGACGAAAGTCTGACCG   383
Query  361  AGCAACGCCGCGTGAGTGAAGAAAGTTTTCGGATCGTAAAACTCTGTTGTTAGAGAAGAA   420
Sbjct  384  |||||||||||||||||||||| ||||||||||||||||||||||||||||||||||||||| AGCAACGCCGCGTGAGTGAAGAAGGTTTTCGGATCGTAAAACTCTGTTGTTAGAGAAGAA   443
Query  421  CAAGGACGTTAGTAACTGAACGTCCCCTGACGGTATCTAACCAGAAAGCCACGGCTAACT   480
Sbjct  444  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CAAGGACGTTAGTAACTGAACGTCCCCTGACGGTATCTAACCAGAAAGCCACGGCTAACT   503
Query  481  ACGTGCCAGCAGCCGCGGTAATACGTACGTGGCAAGCGTTGTCCGGATTTATTGGGCGTA   540
```

Sbjct	504	||||||||||||||||||||| ||||||||||||||||||||||||| ACGTGCCAGCAGCCGCGGTAATACGTAGGTGGCAAGCGTTGTCCGGATTTATTGGGCGTA	563
Query	541	AAGCGAGCGCAGGCGGTTTCTTAAGTCTGATGTGAAAGCCCCCGGCTCAACCGGGGAGGG	600
Sbjct	564	|||||||||||||||||||||||||||||||||||||||||||||| AAGCGAGCGCAGGCGGTTTCTTAAGTCTGATGTGAAAGCCCCCGGCTCAACCGGGGAGGG	623
Query	601	TCATTGGAAACTGGGAGACTTGAATGCAAAAGAGGATAGTGGAATTCCATGTGTATCGGT	660
Sbjct	624	|||||||||||||||||| |||| |||||| ||||||||||||||| |||| TCATTGGAAACTGGGAGACTTGAGTGCAGAAGAGGAGAGTGGAATTCCATGTGTAGCGGT	683
Query	661	GAAATGCGTAGATATATGGAGGAACACCAGTGGCGAACGCGGCTCTCTGGTCTGTAACTG	720
Sbjct	684	||||||||||||||||||||||||||||| ||||||||||||||||||| GAAATGCGTAGATATATGGAGGAACACCAGTGGCGAAGGCGGCTCTCTGGTCTGTAACTG	743
Query	721	ACGCTGAGGCTCGAAAGCGTGGGGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCCG	780
Sbjct	744	|||||||||||||||||||||||||||||||||||||||||||||| ACGCTGAGGCTCGAAAGCGTGGGGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCCG	803
Query	781	TATACGATGAGTGCTAAGTGTTGGAGGGTTTCCGCCCTTCAGTGCTGCAGCAAACGCATT	840
Sbjct	804	|||||||||||||||||||||||||||||||||||||||||||||||| TAAACGATGAGTGCTAAGTGTTGGAGGGTTTCCGCCCTTCAGTGCTGCAGCAAACGCATT	863
Query	841	AAGCACTCCGCCTGGGGAGTACGACCGCAAGGTTGAAACTCAAAGGAATTGACGGGGGCC	900
Sbjct	864	|||||||||||||||||||||||||||||||||||||||||||||| AAGCACTCCGCCTGGGGAGTACGACCGCAAGGTTGAAACTCAAAGGAATTGACGGGGGCC	923
Query	901	CGCACAAGCGGTGGAGCATGTGGTTTAATTCGAAGCAACGCGAAGAACCTTACCAGGTCT	960
Sbjct	924	|||||||||||||||||||||||||||||||||||||||||||||| CGCACAAGCGGTGGAGCATGTGGTTTAATTCGAAGCAACGCGAAGAACCTTACCAGGTCT	983

Phylogenetic tree

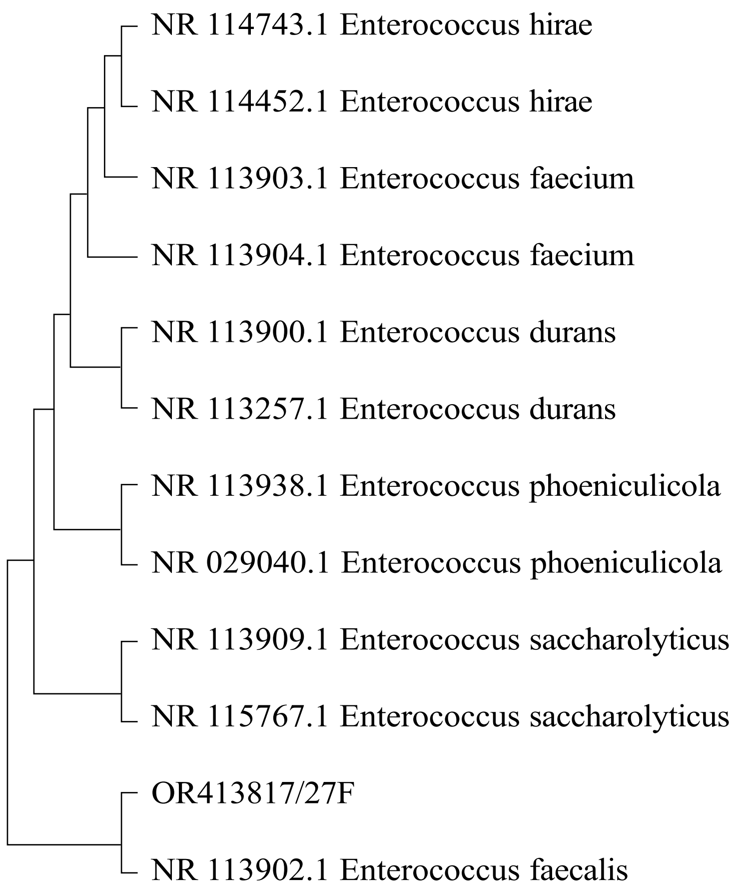


Figure 2. Showing OR413816 ***Enterobacter sichuanensis*** **strain WCHECL1597 16S ribosomal RNA, partial sequence**
Sequence ID: NR 179946.1, **Length: 1528Number of Matches: 1**

Alignment statistics for match #1				
Score	Expect	Identities	Gaps	Strand
1965 bits (1064)	0.0	1115/1140 (98%)	3/1140 (0%)	Plus/Plus

```
Query  1    TGCCTGATGGAGGGGGATAACTACTGGAAACGGTAGCTAATACCGCATAACGTCGCAAGA  60
            ||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  124  TGCCTGATGGAGGGGGATAACTACTGGAAACGGTAGCTAATACCGCATAACGTCGCAAGA  183
Query  61   CCAAAGAGGGGGACCTTCGGGCCTCTTGCCCTCAGATGTGCCCAGATGGGATTAGCTAGT  120
Sbjct  184  |||||||||||||||||||||||||||||||| ||||||||||||||||||||||||| CCAAAGAGGGGGACCTTCGGGCCTCTTGCCATCAGATGTGCCCAGATGGGATTAGCTAGT  243

Query  121  AGGTGGGGTAACGGCTCACCTAGGCGACGATCCCTAGCTGGTCTGAGAGGATGACCAGCC  180
Sbjct  244  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AGGTGGGGTAACGGCTCACCTAGGCGACGATCCCTAGCTGGTCTGAGAGGATGACCAGCC  303

Query  181  ACACTGGAACTGAGACACGGTCCAGACTCCTACGGGAGGCAGCAGTGGGGAATATTGCAC  240
Sbjct  304  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||| ACACTGGAACTGAGACACGGTCCAGACTCCTACGGGAGGCAGCAGTGGGGAATATTGCAC  363

Query  241  AATGGGCGCAAGCCTGATGCAGCCATGCCGCGTGTATGAAGAACGCCTTCGGGTTGTAAA  300
Sbjct  364  ||||||||||||||||||||||||||||||||||||||||||| |||||||||||||||| AATGGGCGCAAGCCTGATGCAGCCATGCCGCGTGTATGAAGAAGGCCTTCGGGTTGTAAA  423

Query  301  GTACTTTCAGCGGGGAAGAAAGGTGTTGTGGTTAATAACCACAGCAATTGACGTTACCCG  360
Sbjct  424  ||||||||||||||| || |||||||| |||||||||| |||||||||||||||||| GTACTTTCAGCGGGG-AGGAAGGTGTTGAGGTTAATAACCTCAGCAATTGACGTTACCCG  482

Query  361  CAGAAGAAGCACCGGCTAACTCCGTGCCAGCAGCCGCGGTAATACAGAGGGTGCAAGCGT  420
Sbjct  483  ||||||||||||||||||||||||||||||||||||||||||||| |||||||||||||| CAGAAGAAGCACCGGCTAACTCCGTGCCAGCAGCCGCGGTAATACGGAGGGTGCAAGCGT  542

Query  421  TACTCGGATTTACTGGGCGTAAAGCGCACACAGGCGGTCTGTCAAGTCAGATGTGAAATC  480
Sbjct  543  || ||||| ||||||||||||||||||| |||||||||||||||||| ||||||||||| TAATCGGAATTACTGGGCGTAAAGCGCACGCAGGCGGTCTGTCAAGTCGGATGTGAAATC  602

Query  481  CCCGGGCTCAACCTGGGAACTGCATTCGAAACTGGCAGGCTAGAGTCTTGTAGAGGGGGG  540
Sbjct  603  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CCCGGGCTCAACCTGGGAACTGCATTCGAAACTGGCAGGCTAGAGTCTTGTAGAGGGGGG  662

Query  541  TAGAATTCCAGGTGTAGCTGTGATATGCGTAGAGATCTGGAAGAATACCGGTGGCGAACG  600
Sbjct  663  |||||||||||||||||| |||| |||||||||||||||| |||||||||||||||| | TAGAATTCCAGGTGTAGCGGTGAAATGCGTAGAGATCTGGAGGAATACCGGTGGCGAAGG  722

Query  601  CGGCCCCCTGGACAAAGACTGACGCTCAGGTGCGAAAGCGTGGGGAGCAAACAGGATTAG  660
Sbjct  723  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CGGCCCCCTGGACAAAGACTGACGCTCAGGTGCGAAAGCGTGGGGAGCAAACAGGATTAG  782

Query  661  ATACCCTGGTAGTCCACGCCGTAAACGATGTCGACTTGGAGGTTGTGCCCTTGAGGCGTG  720
Sbjct  783  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||| ATACCCTGGTAGTCCACGCCGTAAACGATGTCGACTTGGAGGTTGTGCCCTTGAGGCGTG  842

Query  721  GCTTCCGGAGCTAACGCGTTAAGTCGACCGCCTGGGGAGTACGGCCGCAAGGTTAAAACT  780
Sbjct  843  ||||||||||||||||||||||||||||||||||||||||||||||||||||||||  902
            GCTTCCGGAGCTAACGCGTTAAGTCGACCGCCTGGGGAGTACGGCCGCAAGGTTAAAACT
```

```
Query  781   CATATGAATTGACGGGANTCCCACACAATCGGTGGAGCATGTGGTTTAATTCGATGCAAC   840
             || |||||||||||            ||| |||| |||||||||||||||||||||||
Sbjct  903   CAAATGAATTGACGGG-GGCCCGCACAAGCGGTGGAGCATGTGGTTTAATTCGATGCAAC   961
Query  841   GCGAAGAACCTTACCTACTCTTGACATCCAGAGAACTTTCCAGAGATGGATTGGTGCCTT   900
Sbjct  962   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GCGAAGAACCTTACCTACTCTTGACATCCAGAGAACTTTCCAGAGATGGATTGGTGCCTT   1021

Query  901   CGGGAACTCTGAAAACAGGTGCTGCATGGTTGTCATCAGCTCGTGTTGTGAAATGTTGGG   960
Sbjct  1022  ||||||||| | ||||||||||||| |||| |||||||||||||||||||||||||||||| CGGGAACTCTG-AGACAGGTGCTGCATGGCTGTCGTCAGCTCGTGTTGTGAAATGTTGGG   1080

Query  961   TTAAGTCCCGCAACGAGCGCAACCCTTATCCTTTGTTGCCAGCGGTTAGGCCGGGAACTC   1020
Sbjct  1081  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TTAAGTCCCGCAACGAGCGCAACCCTTATCCTTTGTTGCCAGCGGTTAGGCCGGGAACTC   1140

Query  1021  AAAGGAGACTGCCAGTGATAAACTGGAGGAAGGTGGGGATGACGTCAAGTCATCATGGCC   1080
Sbjct  1141  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AAAGGAGACTGCCAGTGATAAACTGGAGGAAGGTGGGGATGACGTCAAGTCATCATGGCC   1200

Query  1081  CTTACGAGTAGGGCTACACACGTGCTACAATGGCGCATACAAAGAGAAGCGACCTCGCGA   1140
Sbjct  1201  ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||   1260
             CTTACGAGTAGGGCTACACACGTGCTACAATGGCGCATACAAAGAGAAGCGACCTCGCGA
```

Phylogenetic tree

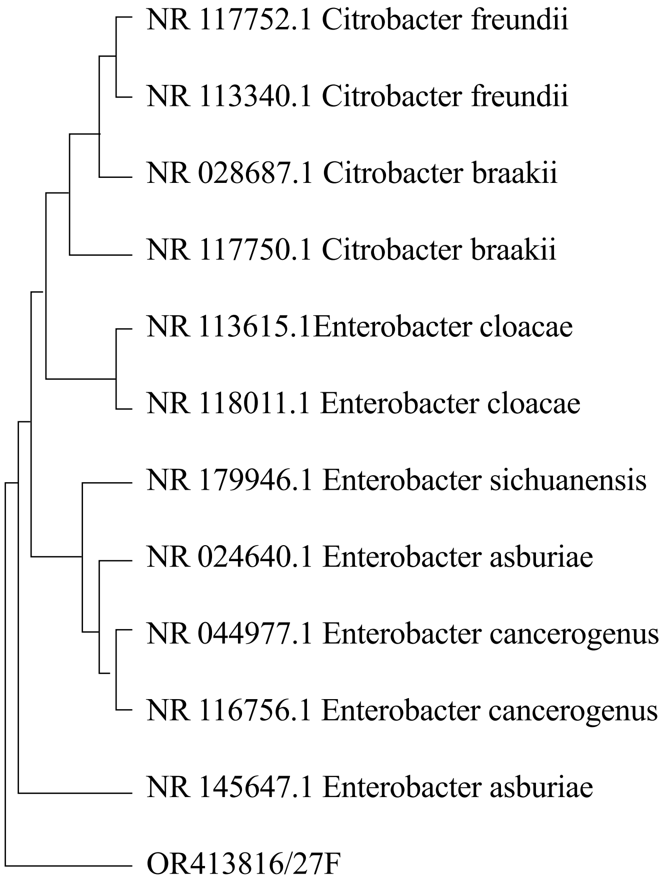


Figure 3. Showing OR413804 ***Bacillus tropicus*** **strain MCCC 1A01406 16S ribosomal RNA, partial sequence**
Sequence ID: NR_157736.1, **Length: 1509Number of Matches: 1**

Alignment statistics for match #1				
Score	Expect	Identities	Gaps	Strand
2495 bits(1351)	0.0	1370/1379 (99%)	1/1379 (0%)	Plus/Plus

```
Query  3     AGTCGAGCGAATGGATTAAGAGCTTGCTCTTATGAAGTTAGCGGCGGACGGGTGAGTAAC   62
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  53    AGTCGAGCGAATGGATTAAGAGCTTGCTCTTATGAAGTTAGCGGCGGACGGGTGAGTAAC   112
Query  63    ACGTGGGTAACCTGCCCATAAGACTGGGATAACTCCGGGAAACCGGGGCTAATACCGGAT   122
Sbjct  113   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| ACGTGGGTAACCTGCCCATAAGACTGGGATAACTCCGGGAAACCGGGGCTAATACCGGAT   172

Query  123   AACATTTTGAACCGCATGGTTCGAAATTGAAAGGCGGCTTCGGCTGTCACTTATGGATGG   182
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||

Sbjct  173   AACATTTTGAACCGCATGGTTCGAAATTGAAAGGCGGCTTCGGCTGTCACTTATGGATGG   232
Query  183   ACCCGCGTCGCATTAGCTAGTTGGTGAGGTAACGGCTCACCAAGGCAACGATGCGTAGCC   242
Sbjct  233   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| ACCCGCGTCGCATTAGCTAGTTGGTGAGGTAACGGCTCACCAAGGCAACGATGCGTAGCC   292

Query  243   GACCTGAGAGGGTGATCGGCCACACTGGGACTGAGACACGGCCCAGACTCCTACGGGAGG   302
Sbjct  293   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GACCTGAGAGGGTGATCGGCCACACTGGGACTGAGACACGGCCCAGACTCCTACGGGAGG   352

Query  303   CAGCAGTAGGGAATCTTCCGCAATGGACGAAAGTCTGACGGAGCAACGCCGCGTGAGTGA   362
Sbjct  353   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CAGCAGTAGGGAATCTTCCGCAATGGACGAAAGTCTGACGGAGCAACGCCGCGTGAGTGA   412

Query  363   TGAAGGCTTTCGGGTCGTAAAACTCTGTTGTTAGGGAAGAACAAGTGCTAGTTGAATAAG   422
Sbjct  413   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TGAAGGCTTTCGGGTCGTAAAACTCTGTTGTTAGGGAAGAACAAGTGCTAGTTGAATAAG   472

Query  423   CTGGCACCTTGACGGTACCTAACCAGAAAGCCACGGCTAACTACGTGCCAGCAGCCGCGG   482
Sbjct  473   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CTGGCACCTTGACGGTACCTAACCAGAAAGCCACGGCTAACTACGTGCCAGCAGCCGCGG   532

Query  483   TAATACGTAGGTGGCAAGCGTTATCCGGAATTATTGGGCGTAAAGCGCGCGCAGGTGGTT   542
Sbjct  533   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TAATACGTAGGTGGCAAGCGTTATCCGGAATTATTGGGCGTAAAGCGCGCGCAGGTGGTT   592

Query  543   TCTTAAGTCTGATGTGAAAGCCCACGGCTCAACCGTGGAGGGTCATTGGAAACTGGGAGA   602
Sbjct  593   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TCTTAAGTCTGATGTGAAAGCCCACGGCTCAACCGTGGAGGGTCATTGGAAACTGGGAGA   652

Query  603   CTTGAGTGCAGAAGAGGAAAGTGGAATTCCATGTGTAGCGGTGAAATGCGTAGAGATATG   662
Sbjct  653   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CTTGAGTGCAGAAGAGGAAAGTGGAATTCCATGTGTAGCGGTGAAATGCGTAGAGATATG   712

Query  663   GAGGAACACCAGTGGCGAAGGCGACTTTCTGGTCTGTAACTGACACTGAGGCGCGAAAGC   722
Sbjct  713   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GAGGAACACCAGTGGCGAAGGCGACTTTCTGGTCTGTAACTGACACTGAGGCGCGAAAGC   772

Query  723   GTGGGGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCCGTAAACGATGAGTGCTAAG   782
Sbjct  773   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GTGGGGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCCGTAAACGATGAGTGCTAAG   832

Query  783   TGTTAGAGGGTTTCCGCCCTTTAGTGCTGAAGTTAACGCATTAAGCACTCCGCCTGGGGA   842
Sbjct  833   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TGTTAGAGGGTTTCCGCCCTTTAGTGCTGAAGTTAACGCATTAAGCACTCCGCCTGGGGA   892

Query  843   GTACGGCCGCAAGGCTGAAACTCAAAGGAATTGACGGGGGCCCGCACAAGCGGTGGAGCA   902
Sbjct  893   |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GTACGGCCGCAAGGCTGAAACTCAAAGGAATTGACGGGGGCCCGCACAAGCGGTGGAGCA   952

Query  903   TGTGGTTTAATTCGAAGCAACGCGAAGAACCTTACCAGGTCTTGACATCTTCTGACAACC   962
```

```
Sbjct  953   |||||||||||||||||||||||||||||||||||||||||||||| |||||||| TGTGGTTTAATTCGAAGCAACGCGAAGAACCTTACCAGGTCTTGACATCCTCTGACAACC   1012

Query  963   CTAGAGATAGGGCTTTTCCTTCGGGAGCAGAGTGACAGGTGGTGCATGGTTGTCGTCAGC   1022
Sbjct  1013  ||||||||||||| |||||||||||||||||||||||||||||||||||||||||| CTAGAGATAGGGCTTCTCCTTCGGGAGCAGAGTGACAGGTGGTGCATGGTTGTCGTCAGC   1072

Query  1023  TCGTGTCGTGAGATGTTGGGTTAAGTCCCGCAACGAGCGCAACCCTTGATCTTAGTTGCC   1082
Sbjct  1073  |||||||||||||||||||||||||||||||||||||||||||||||||||||| TCGTGTCGTGAGATGTTGGGTTAAGTCCCGCAACGAGCGCAACCCTTGATCTTAGTTGCC   1132

Query  1083  ATCATTAAGTTGGGCACTTTAAGGTGACTGCCGGTGACAAACCGGAGGAAGGTGGGGATG   1142
Sbjct  1133  ||||||||||||||||| |||||||||||||||||||||||||||||||||||||| ATCATTAAGTTGGGCACTCTAAGGTGACTGCCGGTGACAAACCGGAGGAAGGTGGGGATG   1192

Query  1143  ACGTCAAATCATCATGCCCCTTATGACCTGGGCTACACACGTGTTCCAATGGACGGTACA   1202
Sbjct  1193  |||||||||||||||||||||||||||||||||||||||||| | ||||||||||||   1252
             ACGTCAAATCATCATGCCCCTTATGACCTGGGCTACACACGTGCTACAATGGACGGTACA
Query  1203  AAGAGCTGCAAGACCGCGAGGTGGAGCTAATCTCATAAAACCGTTCTCAGTTCGGATTGT   1262
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1253  AAGAGCTGCAAGACCGCGAGGTGGAGCTAATCTCATAAAACCGTTCTCAGTTCGGATTGT   1312
Query  1263  AGGCTGCAACTCGCCTACATGAAGCTGGAATCGTTAGTAATCGCGGATCACCATGCCGCG   1322
             |||||||||||||||||||||||||||||||| |||||||||||||||| |||||||||
```

Phylogenetic tree

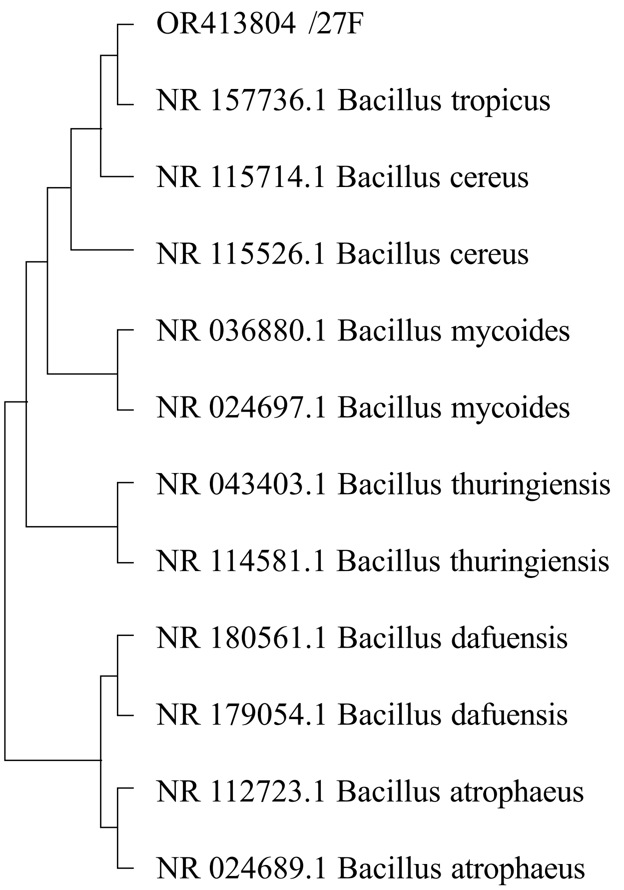


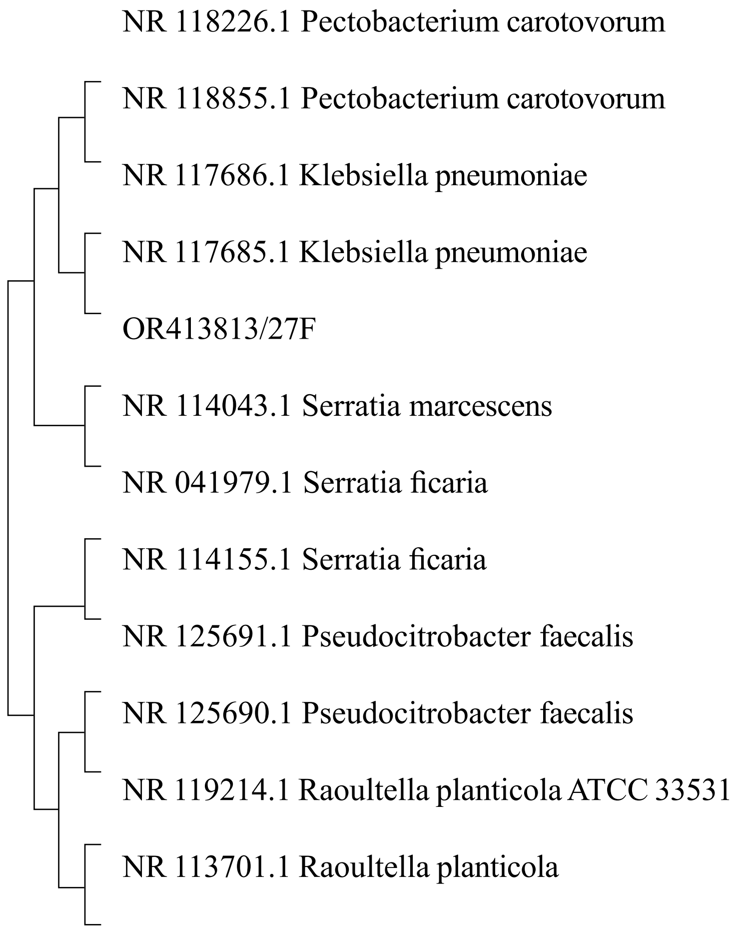
Figure 4. Showing OR413813 Serra*tia marcescens* strain KRED 16S ribosomal RNA, partial sequence Sequence ID: NR_036886.1, Length: 1532Number of Matches: 1

Alignment statistics for match #1				
Score	Expect	Identities	Gaps	Strand
2538 bits(1374)	0.0	1379/1381(99%)	1/1381(0%)	Plus/Plus

```
Query  1    ATGC-AGTCGAGCGGTAGCACAGGGGAGCTTGCTCCCTGGGTGACGAGCGGCGGACGGGT  59
            ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  49   ATGCAAGTCGAGCGGTAGCACAGGGGAGCTTGCTCCCTGGGTGACGAGCGGCGGACGGGT  108

Query  60   GAGTAATGTCTGGGAAACTGCCTGATGGAGGGGGATAACTACTGGAAACGGTAGCTAATA  119
            ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  109  GAGTAATGTCTGGGAAACTGCCTGATGGAGGGGGATAACTACTGGAAACGGTAGCTAATA  168

Query  120  CCGCATAACGTCGCAAGACCAAAGAGGGGGACCTTCGGGCCTCTTGCCATCAGATGTGCC  179
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CCGCATAACGTCGCAAGACCAAAGAGGGGGACCTTCGGGCCTCTTGCCATCAGATGTGCC
Sbjct  169                                                                228

Query  180  CAGATGGGATTAGCTAGTAGGTGGGGTAATGGCTCACCTAGGCGACGATCCCTAGCTGGT  239
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CAGATGGGATTAGCTAGTAGGTGGGGTAATGGCTCACCTAGGCGACGATCCCTAGCTGGT
Sbjct  229                                                                288

Query  240  CTGAGAGGATGACCAGCCACACTGGAACTGAGACACGGTCCAGACTCCTACGGGAGGCAG  299
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CTGAGAGGATGACCAGCCACACTGGAACTGAGACACGGTCCAGACTCCTACGGGAGGCAG
Sbjct  289                                                                348

Query  300  CAGTGGGGAATATTGCACAATGGGCGCAAGCCTGATGCAGCCATGCCGCGTGTGTGAAGA  359
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| CAGTGGGGAATATTGCACAATGGGCGCAAGCCTGATGCAGCCATGCCGCGTGTGTGAAGA
Sbjct  349                                                                408

Query  360  AGGCCTTCGGGTTGTAAAGCACTTTCAGCGAGGAGGAAGGTGGTGAACTTAATACGTTCA  419
Sbjct  409  ||||||||||||||||||||||||||||||||||||||||||||||||||||||| ||| AGGCCTTCGGGTTGTAAAGCACTTTCAGCGAGGAGGAAGGTGGTGAACTTAATACGCTCA  468

Query  420  TCAATTGACGTTACTCGCAGAAGAAGCACCGGCTAACTCCGTGCCAGCAGCCGCGGTAAT  479
Sbjct  469  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TCAATTGACGTTACTCGCAGAAGAAGCACCGGCTAACTCCGTGCCAGCAGCCGCGGTAAT  528

Query  480  ACGGAGGGTGCAAGCGTTAATCGGAATTACTGGGCGTAAAGCGCACGCAGGCGGTTTGTT  539
Sbjct  529  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| ACGGAGGGTGCAAGCGTTAATCGGAATTACTGGGCGTAAAGCGCACGCAGGCGGTTTGTT  588

Query  540  AAGTCAGATGTGAAATCCCCGGGCTCAACCTGGGAACTGCATTTGAAACTGGCAAGCTAG  599
Sbjct  589  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AAGTCAGATGTGAAATCCCCGGGCTCAACCTGGGAACTGCATTTGAAACTGGCAAGCTAG  648

Query  600  AGTCTCGTAGAGGGGGGTAGAATTCCAGGTGTAGCGGTGAAATGCGTAGAGATCTGGAGG  659
Sbjct  649  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AGTCTCGTAGAGGGGGGTAGAATTCCAGGTGTAGCGGTGAAATGCGTAGAGATCTGGAGG  708

Query  660  AATACCGGTGGCGAAGGCGGCCCCCTGGACGAAGACTGACGCTCAGGTGCGAAAGCGTGG  719
Sbjct  709  |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| AATACCGGTGGCGAAGGCGGCCCCCTGGACGAAGACTGACGCTCAGGTGCGAAAGCGTGG  768

Query  720  GGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCTGTAAACGATGTCGATTTGGAGGT  779
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GGAGCAAACAGGATTAGATACCCTGGTAGTCCACGCTGTAAACGATGTCGATTTGGAGGT
Sbjct  769                                                                828

Query  780  TGTGCCCTTGAGGCGTGGCTTCCGGAGCTAACGCGTTAAATCGACCGCCTGGGGAGTACG  839
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TGTGCCCTTGAGGCGTGGCTTCCGGAGCTAACGCGTTAAATCGACCGCCTGGGGAGTACG
Sbjct  829                                                                888

Query  840  GCCGCAAGGTTAAAACTCAAATGAATTGACGGGGGCCCGCACAAGCGGTGGAGCATGTGG  899
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| GCCGCAAGGTTAAAACTCAAATGAATTGACGGGGGCCCGCACAAGCGGTGGAGCATGTGG
Sbjct  889                                                                948

Query  900  TTTAATTCGATGCAACGCGAAGAACCTTACCTACTCTTGACATCCAGAGAACTTTCCAGA  959
            |||||||||||||||||||||||||||||||||||||||||||||||||||||||||||| TTTAATTCGATGCAACGCGAAGAACCTTACCTACTCTTGACATCCAGAGAACTTTCCAGA
Sbjct  949                                                                1008
```

```
Query  960   GATGGATTGGTGCCTTCGGGAACTCTGAGACAGGTGCTGCATGGCTGTCGTCAGCTCGTG  1019
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1009  GATGGATTGGTGCCTTCGGGAACTCTGAGACAGGTGCTGCATGGCTGTCGTCAGCTCGTG  1068
Query  1020  TTGTGAAATGTTGGGTTAAGTCCCGCAACGAGCGCAACCCTTATCCTTTGTTGCCAGCGG  1079
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1069  TTGTGAAATGTTGGGTTAAGTCCCGCAACGAGCGCAACCCTTATCCTTTGTTGCCAGCGG  1128
Query  1080  TTCGGCCGGGAACTCAAAGGAGACTGCCAGTGATAAACTGGAGGAAGGTGGGGATGACGT  1139
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1129  TTCGGCCGGGAACTCAAAGGAGACTGCCAGTGATAAACTGGAGGAAGGTGGGGATGACGT  1188

Query  1140  CAAGTCATCATGGCCCTTACGAGTAGGGCTACACACGTGCTACAATGGCGTATACAAAGA  1199
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1189  CAAGTCATCATGGCCCTTACGAGTAGGGCTACACACGTGCTACAATGGCGTATACAAAGA  1248

Query  1200  GAAGCGACCTCGCGAGAGCAAGCGGACCTCATAAAGTACGTCGTAGTCCGGATTGGAGTC  1259
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1249  GAAGCGACCTCGCGAGAGCAAGCGGACCTCATAAAGTACGTCGTAGTCCGGATTGGAGTC  1308

Query  1260  TGCAACTCGACTCCATGAAGTCGGAATCGCTAGTAATCGTAGATCAGAATGCTACGGTGA  1319
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1309  TGCAACTCGACTCCATGAAGTCGGAATCGCTAGTAATCGTAGATCAGAATGCTACGGTGA  1368
Query  1320  ATACGTTCCCGGGCCTTGTACACACCGCCCGTCACACCATGGGAGTGGGTTGCAAAAGAA  1379
             ||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
Sbjct  1369  ATACGTTCCCGGGCCTTGTACACACCGCCCGTCACACCATGGGAGTGGGTTGCAAAAGAA  1428

Query  1380  G  1380
             |
Sbjct  1429  G  1429
```

Phylogenetic tree



Discussion

Numerous internal and external factors, including host genetics, nutrition, ambient conditions, behavioural patterns, social interactions, age, and sex, affect the makeup of the faecal microbiota. The organisms found in these birds' faeces are therefore determined by a variety of factors, such as geographic location, environmental exposure, and nutrition. It makes sense that the organisms in these birds' excrement would be influenced by a variety of factors, such as geographic location, environmental exposure, and nutrition. The faecal samples taken from the unhealthy captive Gyr falcons fed on a diet high of chicken demonstrated an equivalent distribution of gram-positive and gram-negative bacteria, highlighting the importance of nutrition in the composition of the microbiome. Gram-negative bacteria, however, were the most prevalent in the faeces of 47 healthy raptors kept in captivity in a different study (Bangert et al., 1988) on raptors given professionally cooked chicken. The two gram-positive bacteria, *Enterococcus faecalis*, are used as probiotics, and *Bacillus tropicus* is a feather-degrading bacterium. The other two gram-negative bacteria *Enterobacter sichuanensis* and *Serratia marcescens* can cause nosocomial infections if not properly controlled in captive areas. The results of both studies were similar in that they found a variety of bacterial isolates that were potential pathogens. However, another study (Bangert et al., 1988) on raptors fed professionally prepared chicken found that the most common bacteria in the faeces of 47 healthy raptors housed in captivity were gram-negative. The two gram-positive bacteria, *Bacillus tropicus*, which breaks down feathers, and *Enterococcus faecalis*, are employed as probiotics. If the other two gram-negative bacteria are not adequately managed in captivity, they may result in nosocomial illnesses. Both research' findings were similar in that they identified a range of bacterial isolates that might be harmful.

Conclusion

Numerous bacterial, fungal, and viral illnesses are commonly seen in falcons. In confined falcons, the environment and food quality have a close relationship with nutritional deficiencies and metabolic disorders. Birds raised intensively may become infected with Aspergillosis and other common illnesses due to a variety of circumstances, including cage layout, food preparation and storage, hygiene, stress, and other factors. Nearly every disease can be partially avoided with appropriate care, better personal hygiene, a healthy diet, and routine examinations. If the intestinal biota of the infected falcon enters the humans through the faecal contamination, it may result in serious illnesses, which has significance in the One Health and zoonotic disease perspective.

Acknowledgement

We acknowledge the falcon hospitals, falcon clinics and falcon shops in the Kingdom of Saudi Arabia for permitting us to collect samples.

References

- **Ahmad, A., Ridgeway, S., Shibl, A. A., Idaghdour, Y., &Jha, A.** (2022). Falcon gut microbiome is shaped by diet and enriched in Salmonella. *BioRxiv*, 2022-11.
- **Bangert, R. L., Ward, A. C. S., Stauber, E. H., Cho, B. R., &Widders, P. R.** (1988). A survey of the aerobic bacteria in the feces of captive raptors. *Avian Diseases*, 53-62.
- **Fox, R; Lehmkuhle, S.; Westendorf, D.**(1976). Falcon visual acuity. *Science*. **192** (4236): 263.
- **Hejazi, A., &Falkiner, F. R.** (1997). Serratia marcescens. *Journal of Medical Microbiology*, 46(11), 903-912.
- **Holt, J. G., ed.** (1986). Bergey's manual of systematic bacteriology, Vol. 2. Williams and Wilkins, Baltimore, Md.
- **Khanna, A., Khanna, M., &Aggarwal, A.** (2013). *Serratia marcescens* - a rare opportunistic nosocomial pathogen and measures to limit its spread in hospitalized patients. *Journal of clinical and diagnostic research*: JCDR, 7(2), 243.
- **Needham, J. R., J. K. Kirkwood, and J. E. Cooper.** (1979). A survey of the aerobic bacteria in the droppings of captive birds of prey. *Research. Veterinary. Science*. 27:125- 126.
- **Oberprieler, Ulrich; Cillié, Burger** (2009). The raptor guide of Southern Africa. Game Parks Publishing.
- **Oyedele, O. A., Kuzamani, K. Y., Adetunji, M. C., Osopale, B. A., Makinde, O. M., Onyebuenyi, O. E., & Ezekiel, C. N.** (2020). Bacteriological assessment of tropical retail fresh-cut, ready-to-eat

fruits in south-western Nigeria. *Scientific African*, 9, e00505.

- **Quesenberry, K. E., and B. G. Short.** (1983). Serratia marcescens infection in a Blue and Gold Macaw. J. Am. *Veterinary Medical Association* 183:1302-1303.
- **Rahim, M. A., Bakhiet, A. O., & Hussein, M. F.** (2013). Aspergillosis in a gyrfalcon (Falco rusticolus) in Saudi Arabia. *Comparative Clinical Pathology*, 22, 131-135.
- **Rocas, I. N., SiqueiraJr, J. F., & Santos, K. R.** (2004). Association of *Enterococcus faecalis* with different forms of per radicular diseases. *Journal of Endodontics*, 30(5), 315-320.
- **Sale, Richard**(2016). Falcons (Collins New Naturalist Library, Book 132). HarperCollins UK.
- **The Speed of Animals" in The New Book of Knowledge. Grolier Academic Reference.** 2003. p. 278
- **Winsor, D. K., A. P. Bloebaum, and J. J. Mathewson.** (1981). Gram-negative, aerobic, enteric pathogens among intestinal microflora of wild turkey vultures (Cathartes aura) in west central Texas. *Applied Environment Microbiology* 42:1123-1124.
- **Zubair, M.** (2016). Investigation on Prevalence and Management of Health Impediments in Captive Falcons of United Arab Emirates. *Research Innovator*, Vol.3 (6) Pp. 46-57.

A Baseline Survey of Freshwater Fish Fauna in the Krishna River of Northern Western Ghats up to Wai tehsil

Sachin Shelake*[1,2], Vishwas Deshpande[1] and Ranjit More[3]
[1]Yashwantrao Chavan Institute of Science, Satara, India 415001
[2]Yashwantrao Chavan Mahavidyalaya, Halkarni, Chandgad, Kolhapur, India 416552
[3]Arts, Science and Commerce College, Indapur, Dist. Pune, India 413106
***Corresponding author:** Sachin K. Shelake
E-mail: sachinshelake1993@gmail.com

Citation: Shelake Sachin, Deshpande Vishwas and More Ranjit. (2025). A Baseline Survey of Freshwater Fish Fauna in the Krishna River of Northern Western Ghats up to Wai tehsil. *Ela Journal of Forestry and Wildlife*. 14(2): 1751-1758

Date of Publication: 30 June 2025

ISSN 2319-4361

Abstract

Indian freshwater supports diverse Ichthyofauna (more than 1000 species; as per FishBase) and thus broadly classified as “freshwater eco-region”. This study aimed to assess the freshwater fish diversity of the Krishna River at Wai and the upstream Dhom Reservoir was assessed during January 2021 to December 2022, revealing a total of 56 species distributed across 14 families and 33 genera. Among these, 13 species are endemic to the Western Ghats of India, while two species are exclusive to the Krishna river system. The study identified five globally threatened species *Hypselobarbus curmuca, Labeo potail, Schismatorhynchos nukta, Tor khudree* and *Parapsilorhynchus discophorus* with populations ranging from moderate to rare. The fish fauna of this region is under significant threats from five introduced species, *Clarias gariepinus*, *Cyprinus carpio*, *Hypophthalmichthys molitrix*, *Oreochromis mossambicus* and *Oreochromis niloticus*. Anthropogenic activities such as overfishing, habitat degradation, and pollution from organic and inorganic sources impacted to great extent on diversity and distribution of fish**.** To mitigate these threats, site-specific conservation strategies are essential to safeguard rare and endangered fish species in this ecosystem.

Keywords

Biodiversity hotspot, endemism, conservation, Dhom Reservoir, anthropogenic activities, introduced species

Introduction

The Western Ghats of India is recognized as a global biodiversity hotspot due to its exceptional species richness and high endemism across various taxonomic groups, including amphibians and freshwater fish (Myers et al., 2000). This region harbors approximately 320 freshwater fish species, distributed across 11 orders, 35 families, and 112 genera, with ongoing discoveries of new taxa (Dahanukar & Raghavan, 2013). Among the major river systems originating in the northern Western Ghats, the Krishna River plays a pivotal role in sustaining aquatic biodiversity. The Krishna River originates from Mahabaleshwar in the Satara District of Maharashtra and follows an eastward course spanning approximately 290 km through the districts of Satara, Sangli, and Kolhapur before traversing into Karnataka and Telangana. The river's hydrological network is marked by several infrastructural interventions, with the Dhom Dam serving as the first major impoundment and Wai being the first prominent urban settlement along its trajectory. Despite the ecological importance of this riverine system, studies addressing freshwater fish diversity within the Krishna River at Wai and Dhom Reservoir remain sparse. The ichthyofaunal diversity of the Deccan Plateau has been historically documented since Sykes (1839) with more focused investigations on the Krishna and Godavari River systems conducted by David (1963). However, these studies did not furnish species-specific inventories for distinct river sections. A more comprehensive evaluation of the Krishna River's fish assemblages was performed by Jayaram (1995), though this assessment lacked an exclusive checklist for tributaries. Research efforts have predominantly centered on the tributaries within the Satara District.

Annandale (1919) recorded 18 fish species in the Yenna River at Medha, while Silas (1953) documented 14 species from Mahabaleshwar and Wai. Arunachalam et al. (2002) contributed further by identifying 14 species from the Dhom Reservoir. A more extensive ichthyofaunal survey was conducted by (Jadhav et al., 2011) who documented 58 species from the Koyna tributary. A study by Kharat et al. (2012) subsequently provided a significant update, reporting 51 species from the Krishna River at Wai and Dhom Reservoir. Despite these valuable contributions, research on the fish fauna of Krishna river at Wai has been scarce in recent years, with no updated studies published since 2012.

Additionally, the Krishna river has undergone substantial changes in the last decade, driven by growing tourism, industrialization, and recreational activities (Joshi and Chakravarty, 2025). These alterations, coupled with the increasing human footprint on the landscape, have the potential to affect the delicate balance of the aquatic ecosystems, including fish populations. Given the paucity of information on fish diversity in the Krishna river and Dhom dam, especially in the face of increasing anthropogenic pressures, it is imperative to revisit and reassess the ichthyofaunal of this critical waterbody. This study aims to provide a comprehensive overview of the current diversity and distribution of fish species in the Krishna river and Dhom dam, more than a decade after the last substantial survey. By documenting the present status of fish fauna, and making comprehensive comparative analysis with earlier reports, we provide baseline data that will aid in identifying key threats to fish populations and inform conservation efforts in the region.

Materials and Methods

Study area and duration of study

The study was conducted to assess the fish diversity of the Krishna river at Wai and Dhom dam over the period two years from January 2021 to December 2022.

Collection, preservation of fishes and identification

Fish specimens were collected with the help of local fishers using different mesh-sized gill nets and cast nets. Alternatively, fish samples were also procured from local fish markets at Wai. Collected fishes were stored in ice-containing insulated boxes and transported to the laboratory. In the laboratory small-sized fish were preserved in 4% aqueous formalin solution, while larger fish were preserved in 10% aqueous formalin solution. The specimens were stored in airtight plastic bottles to ensure proper preservation. In the laboratory, fish specimens were identified using recent published literature and standard taxonomic keys, including Jayaram (1981), Jayaram (1999), (Talwar & Jhingran, (1991) Jayaram & Jeyachandra Dhas (2000) and Jayaram,(2002). The online database FishBase was utilized for verification and authentication of scientific names (Froese & Pauly, 2024).

Results

The present study documented the freshwater fish diversity in the Krishna River at Wai and the upstream

Dhom Reservoir, recording 56 species distributed across 9 orders, 14 families, and 35 genera. The fish population in the Krishna River at Wai faces significant threats due to various factors, including excessive exploitation of fish resources, competition and predation from non-native species, and habitat deterioration caused by both organic and inorganic pollution (figure 1). Total number of 56 fish species were recorded in this study period, Cypriniformes was most abundant order with 36 species belonging to four families with cyprinidae dominant family having 23 species. Siluriformes is second dominant order with seven species belonging to it. Perciformes, Anabantiformes and Cichliformes have four, three and two species respectively. Beloniformes, Gobiiformes, Osteoglossiformes and Synbranchiformes have one species each (Table 1). The assessment, based on the IUCN Red List (2025), reveals that the majority of species are classified as Least Concern (LC), indicating their widespread distribution and stable populations. However, several species, such as *Hypselobarbus curmuca* (Curmuca Barb), *Labeo potail* (Deccan Labeo), and *Clarias magur* (Mangur Catfish), are categorized as Endangered (EN), highlighting the urgent need for conservation efforts due to habitat degradation, overfishing, and ecological changes. Additionally, species like *Cyprinus carpio* (Common Carp) and *Hypselobarbus kolus* (Kolus Barb) fall under the Vulnerable (VU) category (Figure 2), signifying a high risk of population decline if threats persist. Among the Cyprinidae family, which constitutes a major portion of the dataset, species such as *Labeo rohita* (Rohu), *Cirrhinus mrigala* (Mrigal), and *Puntius ticto* (Ticto Barb) are classified as Least Concern (LC), reinforcing their adaptability and stable population dynamics. However, the presence of Near Threatened (NT) species like *Hypophthalmichthys molitrix* (Silver Carp) suggests potential risks due to environmental disturbances. The Siluriformes (catfish group) also exhibit varying conservation statuses, with *Mystus malabaricus* (Jerdon's Catfish) and *Ompok bimaculatus* (Butter Catfish) marked as Near Threatened (NT), indicating possible future vulnerability due to habitat alterations and fishing pressures.

Interestingly, within the Cichlidae family, *Oreochromis mossambicus* (Mozambique Tilapia) is identified as Vulnerable (VU), likely due to its invasive nature affecting native ecosystems and competition with other species. In contrast, *Oreochromis niloticus* (Nile Tilapia) remains Least Concern (LC), reflecting its ecological resilience and adaptability. Similar patterns are observed in the Perciformes and Anabantiformes orders, where species such as *Channa marulius* (Great Snakehead) and *Parambassis ranga* (Indian Glassy Fish) are Least Concern (LC), suggesting minimal immediate threats to their survival.

Discussion

The study highlights the diversity and conservation status of freshwater fish species across different taxonomic groups, with a particular focus on Cypriniformes, Siluriformes, Perciformes, and other significant orders.Among these, the Cyprinidae family exhibited the highest species richness, a pattern consistent with previous ichthyofaunal surveys in the Western Ghats. The majority of species were classified as Least Concern (LC) under the IUCN Red List (2025), suggesting stable populations in the study area. However, a notable subset of species was found to be globally threatened, with three species classified as Endangered (EN) (*H.curmuca, L.potail,* and *S.nukta*) and four species as Vulnerable (VU) (*C.carpio, H.kolus, and O.mossambicus,*) (Figure 1). Additionally, three species were Near Threatened (NT) (*H. molitrix, M..malabaricus,* and *O.bimaculatus*), while *Puntius amphibious* was categorized as Data Deficient (DD), highlighting the need for further ecological studies.

A comparative analysis with previous studies Silas (1953) Arunachalam et al. (2002) and Kharat et al. (2012) revealed both similarities and deviations in species presence. Several species recorded in earlier studies were confirmed in the present study (*G. mullya, P.ticto, T.khudree, B.barna*), reinforcing their persistence in the ecosystem. However, some species were newly recorded or absent compared to past surveys, indicating possible population fluctuations influenced by habitat modifications, climatic variations, or anthropogenic pressures (Bunn & Arthington, 2002, Arunachalam et al., 2002, Kharat et al., 2012).

The presence of introduced and transplanted species in the study area poses significant threats to native ichthyofauna. *C. carpio* (Common Carp) and *H. molitrix* (Silver Carp), both introduced for aquaculture, have been implicated in habitat alteration and competition with native species**.**

Freshwater biodiversity is experiencing unprecedented and growing pressure from human activities such as overfishing, pollution (organic and inorganic), and habitat degradation were observed as key stressors affecting fish populations in the region (Dudgeon et al., 2006). The study underscores the urgent need for site-specific conservation strategies, particularly for threatened and endemic species.

Presence of additional species such as *Labeo calbasu* and *Labeo potail*, which were not recorded in earlier studies, highlighting potential changes in fish assemblages over time. The presence and distribution of species were compared with historical records, revealing that *Garra mullya*, *Pethia ticto*, and *Devario aequipinnatus* showed consistent presence across all studies, reinforcing their stable populations. However, species such as *Hypselobarbus curmuca*, which were absent in Arunachalam et al. (2002), were recorded in this study, indicating a possible resurgence or improved detection methods. *Mystus malabaricus* and *Ompok bimaculatus* were identified as Near Threatened (NT), consistent with previous assessments. These findings align with past research but also underscore the need for enhanced conservation measures, particularly for species that were previously data deficient or unrecorded. Our study suggests that habitat modifications, pollution, and overfishing might be contributing factors to population shifts. *Clarias magur*, categorized as Endangered, was absent in previous surveys, suggesting either a recent decline or historical underreporting. The proliferation of invasive species such as *Oreochromis mossambicus* and *Oreochromis niloticus* (previously unrecorded in certain studies) may pose competition threats to native species (Trewavas, 1983). The highly carnivorous *Clarias gariepinus*; African cat fish which is illegally introduced into freshwaters of India made severe damage to indigenous fish fauna. The union agriculture ministry has ordered killing of these fishes and preventing further culture of these fishes but this order did not have any impact as it lacked any specific guidelines to destroy this fish (Kumar, 2000).

Conclusions

The ichthyofaunal diversity of the Krishna River at Wai is facing significant threats due to multiple anthropogenic stressors. Intensive exploitation of fish resources, competition and predation by invasive species, and habitat degradation driven by organic and inorganic pollution are major concerns. A substantial portion of the river is impacted by agricultural runoff, leading to water quality deterioration. Given the global decline in freshwater biodiversity, particularly in ecologically sensitive regions such as the Western Ghats of India, which support a high number of endemic species, urgent conservation interventions are required. The presence of globally threatened species in this region further emphasizes the need for systematic monitoring, habitat restoration, and effective management strategies to ensure the long-term sustainability of native fish populations in the Krishna River system.

Acknowledgement

SS acknowledges the support of the CSIR-UGC Research Fellowship. The authors express their gratitude to the Head of the Department of Zoology and the Principal of YCIS, Satara, as well as YCM, Halkarni. Special thanks are also extended to R.B. More and all members of Team VYD's, Satara, for their valuable support.

Author's contributions

SS and VD were involved in designed the study, SS and RM involved in collection and analysis of the results and writing of the manuscript. RM and SS collected laboratory and field data.

Conflict of Interest

Authors have no conflict of interest to declare.

References

- **Arunachalam, M., A. Sankaranarayanan, A. Manimekalan, R. Soranam & J.A. Jonson** (2002). Fish fauna of some streams and rivers in the Western Ghats of Maharashtra. Journal of the Bombay Natural History Society 99(2): 337–341.
- **Bunn, S. E., & Arthington, A. H.** (2002). Basic Principles and Ecological Consequences of Altered Flow Regimes for Aquatic Biodiversity. *Environmental Management*, *30*(4), 492–507. https://doi.org/10.1007/s00267-002-2737-0
- **Dahanukar, N., & Raghavan, R.** (2013). Freshwater fishes of Western Ghats: Checklist v 1.0 August 2013. *MIN-Newsletter of IUCN SSC/WI Freshwater Fish Specialist Group-South Asia and the Freshwater Fish Conservation Network of South Asia (FFCNSA)*, *1*, 6–16.
- **Dudgeon, D., Arthington, A. H., Gessner, M. O.,**

Kawabata, Z.-I., Knowler, D. J., Lévêque, C., Naiman, R. J., Prieur-Richard, A.-H., Soto, D., & Stiassny, M. L. (2006). Freshwater biodiversity: Importance, threats, status and conservation challenges. *Biological Reviews*, *81*(2), 163–182.

- **Froese, & Pauly.** (2024). FishBase. World wide web electronic publication. *Http://Www. Fishbase. Org*. https://cir.nii.ac.jp/crid/1570291225439044352
- **Jadhav, B. V., Kharat, S. S., Raut, R. N., Paingankar, M., & Dahanukar, N.** (2011). Freshwater fish fauna of Koyna river, northern Western Ghats, India. *Journal of Threatened Taxa*, *3*(1), 1449–1455. http://threatenedtaxa.org/index.php/JoTT/article/view/1195
- **Jayaram, K. C.** (1981). *Freshwater fishes of India, Pakistan, Bangladesh, Burma and Sri Lanka*.
- **Jayaram, K.C.** (1995). The Krishna River System: A Bioresources Study. Occasional Paper No. 160. Records of Zoological Society of India, 167pp.
- **Jayaram, K. C.** (1999). *The freshwater fishes of the Indian region*. https://agris.fao.org/search/en/providers/122621/records/6473a56613d110e4e7a7a9bf
- **Jayaram, K. C.** (2002). *Fundamentals of fish taxonomy*. Narendra publishing house.
- **Jayaram, K. C., & Jeyachandra Dhas, J.** (2000). Revision of the Genus Labeo Cuvier from the Indian region with a discussion on its phylogeny and zoogeography (Pisces: Cypriniformes, Cyprimidae, Cyprininae). https://cir.nii.ac.jp/crid/1130000798300341632
- **Joshi, S., & Chakravarty, P.** (2025). An Assessment of Human Impact on Tropical Rivers: A Critical Review on Worship to Responsibility, Case of India. Remotely Sensed Rivers in the Age of Anthropocene, 607-635.
- **Kharat, S. S., Paingankar, M., & Dahanukar, N.** (2012). CEPF Western Ghats Special Series: Freshwater fish fauna of Krishna River at Wai, northern Western Ghats, India. *Journal of Threatened Taxa*, *4*(6), 2644–2652.
- **Kumar, A. B.** (2000). Exotic fishes and freshwater fish diversity. *ZOOS'PRINT JOURNAL*, *15*(11), 363–367. https://zoosprint.org/index.php/zpj/article/view/5881
- **Myers, N., Mittermeier, R. A., Mittermeier, C. G., Da Fonseca, G. A., & Kent, J.** (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853–858. https://www.nature.com/articles/35002501.;
- **Silas, E. G.** (1953). Notes on fishes from Mahabaleshwar and Wai (Satara district, Bombay state). *Journal of Bombay Natural History Society*, *51*(3), 579–589. http://eprints.cmfri.org.in/6945/
- **Sykes, Lieut. -Col. W. H.** (1839). On the Fishes of the Dukhun. *The Transactions of the Zoological Society of London*, *2*(5), 349–378. https://doi.org/10.1111/j.1469-7998.1839.tb00029.x
- **Talwar, P. K., & Jhingran, A. G.** (1991). *Inland fishes of India and adjacent countries* (Vol. 2). CRC press.
- **Trewavas, E.** (1983). *Tilapiine fishes of the genera Sarotherodon, Oreochromis, and Danakilia*. https://agris.fao.org/search/en/providers/122376/records/65119ef58ed6443ca193b87d

Table 1: List of Freshwater Fish from the Krishna River at Wai and Dhom Reservoir, Including Species Recorded in Previous Studies

Family/species[a]	Common Name	Threat status (As per IUCN 2017)[b]	Previous study status			Present study
			Silas (1953)	Arunachalam et al. (2002)	Kharat et al. (2012)	
Cyprinidae						
Cirrhinus mrigala (Hamilton, 1822)	Mrigal	LC	-	-	+	+
Cirrhinus reba (Hamilton, 1822)	Reba carp	LC	-	-	+	+
Cyprinus carpio (Linnaeus, 1758)	Common carp	VU	-	-	+	+
Garra mullya (Sykes, 1839)	Sucker fish	LC	+	+	+	+
Hypophthalmichthys molitrix (Valenciennes, 1844)	Silver Carp	NT	-	-	+	+
Hypselobarbus curmuca (Hamilton, 1807)	Curmuca Barb	EN	+	-	+	+
Hypselobarbuscf jerdoni (Day, 1870)	Jerdon's Carp	LC	+	-	+	+
Hypselobarbus kolus (Sykes, 1839)	Kolus Barb	VU	-	-	+	+
Labeo calbasu (Hamilton, 1822)	Orangefin Labeo	LC	-	-		+
Labeo catla (Hamilton, 1822)	Catla	LC	-	-	+	+
Labeo potail (Sykes, 1839)	Deccan Labeo	EN	-	-	+	+
Labeo rohita (Hamilton, 1822)	Rohu	LC	-	-	+	+
Osteobrama vigorsii (Sykes, 1839)	Bheemaosteobrama	LC	-	-	+	+
Puntius amphibius (Valenciennes, 1842)	Scarlet-banded barb	DD	-	-	+	+
Pethia conchonius (Hamilton, 1822)	Rosy barb	LC	-	+	-	+
Puntius sahyadriensis (Silas, 1953)	Khavli barb	LC	-	-	+	+
Systomus sarana (Hamilton, 1822)	olive barb	LC	-	-	+	+
Pethia ticto (Hamilton, 1822)	Ticto barb	LC	+	+	+	+
Rohtee ogilbii (Sykes, 1839)	Rohtee	LC	-	-	+	+
Schismatorhynchos nukta (Sykes, 1839)	Nukta	EN	-	-	+	+
Tor khudree (Sykes, 1839)	Deccan Mahseer	LC	-	+	-	+
Danionidae						
Barilius barna (Hamilton, 1822)	Barna baril	LC	+	-	+	+
Barilius bendelisis (Hamiton, 1807)	Indian Hill Trout	LC	+	-	+	+
Devario malabaricus (Jerdon, 1849)	Malabar danio	LC	-	-	+	+
Devario aequipinnatus (McClelland, 1839)	Giant danio	LC	-	+	+	+
Rasbora daniconius (Hamiton, 1822)	Slender rasbora	LC	-	+	+	+
Salmostoma boopis (Day, 1874)	Boopis razorbelly minnow	LC	-	+	+	+
Salmostoma novacula (Valenciennes, 1840)	Novacula razorbelly minnow	LC	-	-	+	+
Nemacheilidae						
Acanthocobitis mooreh (Sykes. 1839)	Maharashtra zipper loach	LC	-	-	+	+
Indoreonectes evezardi (Day, 1872)		LC	-	+		+
Nemacheilus anguilla (Annandale, 1919)	eel loach	LC			+	+
Nemacheilus rueppelli (Sykes, 1839)	Mongoose loach	LC	-	+	-	+

Schistura denisoni (Day, 1867)	Stone loach	LC	+	-	+	+
Cobitidae						
Lepidocephalichthys thermalis (Valenciennes, 1846)	Common spiny loach	LC	-	+	+	+
Bagridae						
Mystus cavasius (Hamilton 1822)	Gangetic mystus	LC	-	-	+	+
Mystus malabaricus (Jerdon, 1849)	Jerdon's catfish	NT	-	-	+	+
Mystus seengtee (Sykes, 1839)	Seengtee	LC	-	-	+	+
Sperata seenghala (Sykes, 1839)	Giant river catfish	LC	-	-	+	+
Clariidae						
Clarias gariepinus (Burchell, 1822)	North African catfish	LC	-	-	+	+
Siluridae						
Ompok bimaculatus (Bloch, 1794)	Butter catfish	NT	-	-	+	+
Ambassidae						
Chanda nama (Hamilton, 1822)	Elongate glassy perchlet	LC	-	-	+	+
Parambassis lala (Hamilton, 1822)	Highfin glassy perchlet	NT	-	-	-	+
Parambassis ranga (Hamilton, 1822)	Indian glassy fish	LC	-	-	+	+
Channidae						
Channa gachua (Hamilton, 1822)	Dwarf snakehead	LC	-	-	+	+
Channa marulius (Hamilton, 1822)	Great snakehead	LC	-	-	+	+
Channa punctata (Bloch, 1793)	Spotted snakehead	LC	+	-	+	+
Channa marulius (Hamilton, 1822)	great snakehead	LC	-	-	-	+
Cichlidae						
Oreochromis mossambicus (Peters, 1852)	Mozambique tilapia	VU	-	-	+	+
Oreochromis niloticus (Linnaeus, 1758)	Nile tilapia	LC	-	-		+
Belonidae						
Xenentodon cancila (Hamilton, 1822)	Freshwater Garfish	LC	-	-	+	+
Gobiidae						
Glossogobius giuris (Hamilton, 1822)	Tank goby	LC	-	+	+	+
Notopteridae						
Notopterus notopterus (Pallas, 1769)	Bronze featherback	LC	-	-	+	+
Mastacemebelidae						
Mastacembelus armatus (Lacepede, 1800)	Zig-zag eel	LC	-	+	+	+

[a]Taxonimc status as per FishBase

[b]IUCN (2017) status., EN - Endangered, NT - Near Threatened, LC - Least Concern, NE - Not Evaluated, DD - Data Deficient.

Key: + = present, - = absent.

Figure 1. Major threats to the fish fauna of Krishna River at Wai. (A). Pollution of the river stretch; (B and C): Heavy harvesting of threatened species and endemic fishes.

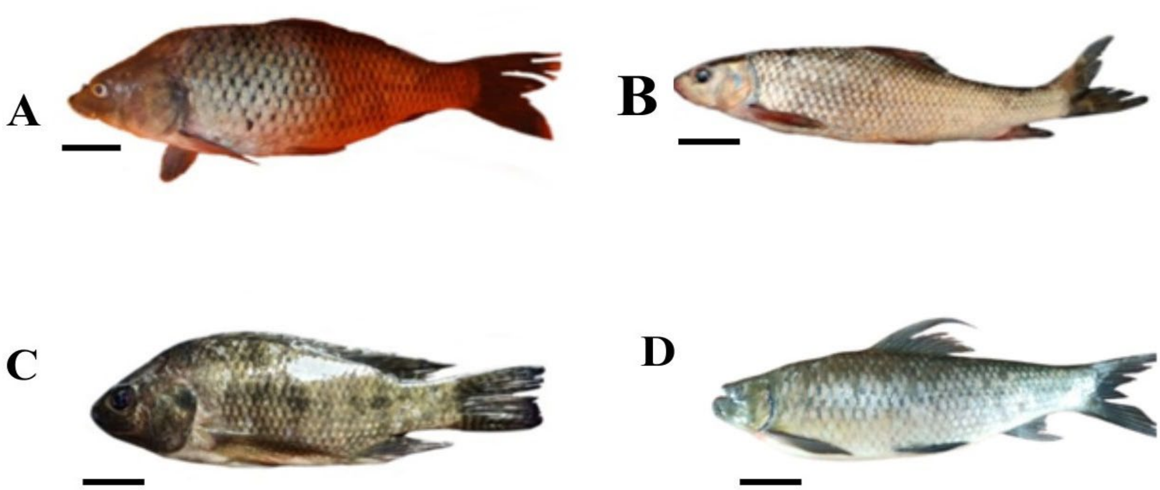


Figure 2. **A.** ***Cyprinus carpio*****, B.** ***Hypselobarbus kolus*** **, C.** ***Oreochromis mossambicus*** **, D.** ***Schismatorhynchos nukta***

Quantitative evaluation of proteins, carbohydrates and lipids in the leaves of *Tridax procumbens* L.

Patil Amol M.* and Pawar Sunil G.
Department of Botany, Yashwantrao Chavan College of Science Karad, Satara- 415-124.
Department of Botany, Yashwantrao Mohite College of Arts, Science and Commerce, Pune
*Corresponding Author: amolpatil7799@gmail.com, Mob.- 9116 9116 79.
Address: Yashwantrao Chavan College of Science Karad, Satara- 415-124. Maharashtra, India.

Citation: Patil Amol M. and Pawar Sunil G. (2025). Quantitative evaluation of proteins, carbohydrates and lipids in the leaves of *Tridax procumbens* L. *Ela Journal of Forestry and Wildlife*. 14(2): 1759-1763

Date of Publication: 30 June 2025

ISSN 2319-4361

Abstract

Tridax procumbens L. in marathi called kambarmodi, jakhamjudi or tantani is a trailing herb and is reported as a weed in India. (Reyes-Garcia et al., 2006). It has many bioactive molecules valuable in medicines and as food supplements. In this study phytochemical constituents from the crude extract from the leaves of *Tridax procumbens* collected from Vetal hill Dist. Pune have been studied during two consecutive years 2017 and 2018 throughout the year. Many investigators have reported only phytochemical constituents in the leaves of *Tridax procumbens*. The crude extract from the leaves of *T. procumbens* was subjected to methanol extraction. It was phytochemically analyzed for different qualitative and quantitative properties. This investigation revealed proteins, lipids, alkaloids, terpenoids, flavonoids, carbohydrates, glycosides, and phenols in the leaves. In this study we have focused on proteins, carbohydrates and lipids for further utility.

For both years, quantitatively protein contents were found highest as compared to carbohydrates and lipids during winter, monsoon and summer seasons, followed by carbohydrates as moderate and lipids were found lowest during the winters, monsoons and summers. The total annual average of Proteins (P), Carbohydrates (C) and Lipids (L) were found more during 2018 (P 19.10 mg/g, C 16.47 mg/g and L 4.87 mg/g respectively) and recorded less during 2017 (P 16.91 mg/g, C 15.83 mg/g and L 4.85 mg/g respectively). Utility of these findings may offer a clue for their isolation on large scale implementing vast cultivation for the farmers to yield some new edible products like protein chocolates, carbohydrate cakes and lipid syrups, some of which may have medicinal properties.

Keywords - Quantitative, phytochemical, seasonal, annual, variation, proteins, carbohydrates and lipids.

Introduction

Medicinal plants play an essential role in health care and are the major raw materials for both traditional and conventional medicinal preparations; and people choose herbal medicines to conventional medicines (WHO, 2002). *Tridax procumbens* is one of the important medicinal plants. (WHO, 2002). Medicinal plants attracted the attention of scientists due to their effectiveness, lower incidence of side effects, lack of current alternatives, increasing cost of modern medicines and cultural preferences (Heinrich et al., 2000; Tabuti et al., 2003). The quantitative ethnobotanical studies were used to identify the plant uses as food, (Pieroni et al., 2001) medicines for human health care, (, (Kim et al., 2013) veterinary medicine (Upadhyay et al, 2011) and economic importace due to their low cost (Reyes-Garcia et al., 2006).

Conventionally, *T. procumbens* is used in India as antifungal, insect repellent and anticoagulant medicine. In folk medicine, leaf extracts are used to treat skin infections and in Ayurvedic medicine as a remedy for liver complaints for its hepato-protective nature in addition to use in gastritis and heart burn (Wani et al., 2010). Hence, in this study we have focused on the seasonal and annual evaluation of phytochemical composition of *T. procumbens* leaves.

Fig A - Taluka - Haveli, District- Pun

Fig B - Vetal Hill collection spot

Material

Study Area

Vetal hill in Pune city has an elevation of 2600 ft. Geographically it is 18^0 30' to 18^0 32' N latitude and 73^0 48' to 73^0 59' E longitude covering an area of 10.5 square kilometers. It runs North-South with some spurs perpendicular extensions. Vetal hill runs across areas like MIT College, Y.M. College, Bharati Vidyapeeth, SNDT Women's University, ILS Law College, Gokhale Nagar, Symbiosis Society and Chattursrungi.

Fig: A and B: Study Area Vetal Hill, Taluka- Haveli, District- Pune, Maharashtra State, india.

Authentication

Botanical Survey of India (BSIP) Pune helped us in identification of *T. procumbens.* Subsequently, a sample of the plant with reference number No. BSI/WRC/IDEN.CER. / 2016/135 (A) specimen No.-- PAM 01FHI 1008876 was deposited in the same institute.

Extraction

Leaves *Tridax procumbens* were washed and sliced into small pieces, shade dried and then using an electrical blender ground into a powder. Five grams of powder was subjected to successive solvent extraction in 100 ml of methanol and kept on shaker for 24 hours to obtain homogenate, filtered by Whatman filter paper-1, and the extracts were stored separately in sterile bottles at 10 ^{0}C for phytochemical screening.

Fig. C- Root, stem leaves and inflorescence *T. procumbens*.

Fig. D- Leaves of *T. procumbens* (ventral and dorsal side), hairy, toothed and arrowhead-shaped.

Fig: E and F: Leaf Powder Extraction *T. procumbens*

Method

1) Determination of Total Protein Content *T. procumbens* (Lowry's Method)

Extraction is carried out with buffers used for the enzyme assay. 500 mg of the sample was taken and ground well with a pestle and mortar in 5-10 ml of the buffer, centrifuged and the supernatant was used for protein estimation.

a) **Procedure for estimation of Protein:**

1. Pipette out 0.2, 0.4, 0.6, 0.8 and 1.0 ml of the working standard into a series of test tubes.

2. Pipette out 0.1 ml and 0.2 ml of the sample extract in two other test tubes.

3. Make up the volume to 1.0 ml in all the test tubes. A tube with 1.0 ml of water serves as the blank.

4. Add 5.0 ml of reagent C to each tube including the blank. Mix well and allow to stand for 10 min.

5. Then 0.5 ml of reagent D was added, it was mixed well and incubated at room temperature in the dark for 30 min when blue colour is observed.

Take the reading at 660 nm. Draw a standard graph and calculate the amount of protein estimation in the sample.

2) Determination of Total Carbohydrate Content

The total carbohydrate content of all the extracts were quantified by using Anthrone method (1952). 100 mg of the *T. procumbens* plant sample was taken into a boiling tube and hydrolyzed by keeping it in a boiling water bath for three hours, with 5.0 ml of 2.5 N HCl and cooled to room temperature. It was neutralized with solid sodium carbonate until the effervescence ceased, made up the volume to 100 ml and centrifuged, collected the supernatant of 0.2 to 1.0 ml was taken for analysis.

Prepare the standards by taking 0.2-1.0 ml of the working standards. 1.0 ml of water serves as a blank, make up the volume to 1.0 ml in all the tubes with distilled water, then add 4.0 ml of anthrone reagent, heated for eight minutes in a boiling water bath, cool rapidly and read the green to dark green colour at 630 nm.

3) Estimation of Total Lipid Content (van Handel 1985)

For the estimation of total lipids, 100 mg per 100 ml of a commercial vegetable oil (Olive oil) in chloroform was used as standard. Aliquots of lipid extracts and standards in test tubes were placed in a water bath at 100° C to evaporate the solvent. 0.2 ml of sulfuric acid was added and heated for 10 min at 100° C. All the samples were made up to 5 ml with vanillin reagent and mixed well. Samples were cooled and kept for approximately 5 min till a reddish color developed. OD was measured at 625 nm within 30 minutes.

Results

Quantitative estimation of total Protein content of *T. procumbens* leaves was done during summer, winter and monsoon season, 2017 and 2018. *T. procumbens* leaves showed highest concentration of proteins during winter and monsoon season (22.18 ± 0.07 mg/g and 19.82 ± 0.13 in 2018), followed by winter and monsoon season (19.05 ± 0.98 mg/g and 18.25 ± 0.65 mg/g in 2017), and the minimum concentration during summer season (15.32 ± 0.19 mg/g in 2018 and 13.44 ± 0.01 mg/g in 2017).

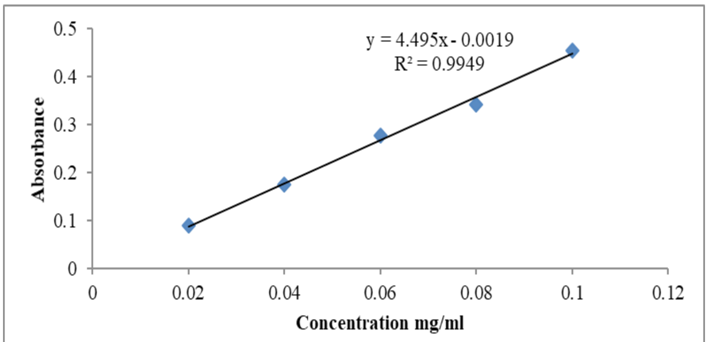
Phytochemical analysis of *T. procumbens* leaves revealed following results. The prominent results were recorded in summer, monsoon and winter seasons, 2017 and 2018. These results showed highest concentration of carbohydrates during monsoon and winter seasons (16.94 ± 0.21 mg/g and 16.54 ± 0.17 mg/g in 2018), comparatively less in monsoon and winter seasons (16.28 ± 0.50 mg/g and 16.12 ± 0.23 mg/g in 2017), and the lowest concentration during summer seasons (15.94 ± 0.25 mg/g in 2018 and 15.10 ± 0.02 mg/g in 2017).

T. procumbens leaves recorded highest concentration of lipids during monsoon seasons (6.12 ± 0.19 mg/g in 2018 and 5.95 ± 0.15 mg/g in 2017), followed by winter seasons (5.42 ± 0.09 mg/g in 2018 and 5.02 ± 0.09 mg/g in 2017), and the lowest concentration in summer seasons (3.60 ± 0.02 mg/g in 2017 and 3.09 ± 0.23 mg/g in 2018).

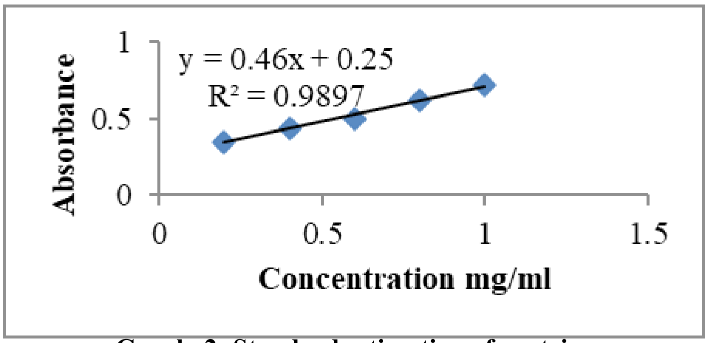
The total annual average of proteins, carbohydrates and lipids was more during 2018 (P 19.10 mg/g, C 16.47 mg/g and L 4.87 mg/g respectively) and less during 2017 (P 16.91 mg/g, C 15.83 mg/g and L 4.85 mg/g respectively).

Graph. 1 and 2: Observations of quantitative phytochemical compositions of *T. procumbens* leaves and stems depicted graphically.

Discussion



Graph. 1: Standard estimation of carbohydrates



Graph. 2: Standard estimation of proteins

Different disciplines like Ethnobotany, Unani medicine, Ayurveda and herbal treatment modalities use *T. procumbens* for treating a variety of diseases. The evaluation of total protein in the leaf extract *Tridax procumbens* revealed higher protein during winter, moderate during monsoon and minimum in summer during both the years 2017 and 2018. This study indicated that increased level of proteins during winter naturally protect the plant from diseases and offer and opportunity to produce edible products. The carbohydrate content is more in monsoon and it gradually decreased in winter and was lowest in summer in both 2017 and 2018. It supports the hypothesis of plant vegetative growth (Jing Zhang et al., 2012) which is maximum in favorable conditions i.e. monsoon periods followed by winter and summer season. The lipid contents were maximum during monsoon period for both years, moderate during winter, while minimum in summer.

We may cultivate *Tridax procumbens* on large scale in our agricultural country for economic benefits through the department of agriculture. Proteins and carbohydrates can be obtained on large scale for the manufacture of different edible foodstuffs with high protein contents in some and higher carbohydrate contents in others.

Conclusion

Different disciplines like ethnobotany, Unani medicine, Ayurveda and herbal treatment modalities use *T. procumbens* for treating a variety of diseases. These investigations reveled higher concentration of proteins and carbohydrates *Tridax procumbens* in all seasons in both the years 2017 and 2018. The utility of these constituents may be useful in our agricultural country for the economic and all-round progress of our farmers as well as for research in physiology and pharmacological.

Acknowledgement

We are thankful to Principal, Yashwantrao Chavan College of Science Vidyanagar, Karad, Dist. Satara for support in research. We are also thankful to Principal, Yashwantrao Mohite College of Arts, Science and Commerce, Erandwane, Pune.

References

- **Deshmukh, M. H, Pai SR, Nimbalkar MS, Patil RP** (2009) "Biochemical Characterization of Banana CultivarsFromSouthern India", *International Journal of Fruit Scienc*e, 9: 4, 305-322. DOI: 10.1080/15538360903241336.
- **Heinrich M. Ethnobotany and its role in drug development. *Phytother Res*.** 2000;14: 479–488.
- **Jing Zhang, Ke Yuan, Wen-Long Zhou, Jian Zhou And Ping Yang** (2012) "Antioxidant Activity of Ethanol Extracts from Tridax procumbens" Asian Journal of Chemistry; 24, 1, 58-62.
- **Kim H. Song M.J.**(2013) "Ethnomedicinal practices for treating liver disorder of local communities in the southern regions of Korea" J Evid Based Complement Altern Med Article ID, 2013;869176:11. doi:10.1155/2013/869176.
- **Okereke S. C., Nwaogwugwu, J. C., and Chukwudoruo C. S.** (2017) "In vitro antioxidant activity of methanolic leaf extract of *Tridax procumbens* and *Tithonia diversifolia*" *JMSCR* 05(05):21783-21789.
- **Pieroni A.** (2001) "Evaluation of the cultural significance of wild food botanicals traditionally consumed in Northwestern Tuscany, Italy" *J Ethnobiol*. 21:89–104.
- **Reyes-Garcia V. Huanca T. Vadez V. Leonard W. Wilkie D.** (2006) "Cultural, practical, and economic value of wild plants: a quantitative study in the Bolivian" *Amazon. Econ Bot* 60:62–74.
- **Suseela L. Sarasvathy A. and Brindha P.** (2002) "Pharmacognostic studies on *Tridax procumbens* L. (Asteraceae)*" Journal of Phytological Research* 5(2):141–147.
- **Singh D. K. Srivastva B. Sahu A.** (2004) "Spectrophotometric determination of Rauwolfia alkaloids, estimation of reserpine in pharmaceuticals" *Analytical Sci*., 20:571-573.
- **Tabuti J.R.S. Lye K.A. Dhillion S.S.** (2003) "Traditional herbal drugs of Bulamogi, Uganda: plants, use and administration" *J Ethnopharmacol* 88:19–44.
- **Upadhyay B. Singh K.P. Kumar A.** (2011) "Ethnoveterinary uses and informants consensus factor of medicinal plants of Sariska region, Rajasthan, India" *J Ethnopharmacol* 133:14–25.
- **Wani SA. Ahmad F. Zargar SA. Amin A. Dar ZA, Dar PA.** (2010) "Intestinal helminthiasis in children of Gurez valley of Jammu and Kashmir State, India" *J Global Infect Dis* 2:91-4.
- **WHO, World Health Organization** (2002) "*World Health Organization, Traditional Medicine Strategy Report"* Document WHO/EDM/TRH/2002.1.

Conservation of Biodiversity – Review of the Present Status of Remote Sensing Based Mechanisms and Future Applications

Rohan Bhagat[1] and Sushilkumar Chaudhari[2]
[1]Department of Environmental Sciences, The Institute of Science, 15, Madame Cama Road, Fort, Mumbai, Maharashtra 400032, India.
[2]Department of Zoology, The Institute of Science, 15, Madame Cama Road, Fort, Mumbai, Maharashtra 400032, India.

Citation: Bhagat Rohan and Chaudhari Sushilkumar. (2025). Conservation of Biodiversity - Review of the Present Status of Remote Sensing Based Mechanisms and Future Applications.
Ela Journal of Forestry and Wildlife. 14(2): 1764-1782

Date of Publication: 30 June 2025

ISSN 2319-4361

Abstract

The emergence of advanced mechanisms like remote sensing (RS) systems has added more value to biodiversity conservation analysis. This paper provides a succinct overview of biodiversity conservation and explains the prominence of RS-based mechanism in analyzation of data for conservation of biodiversity. It describes the diverse RS technologies, their types and characteristics for acquisition of imperative data for analysis. This work reviews well-known and advanced technologies like machine learning, computational intelligence, ensemble methods and deep learning adopted by researchers for safeguarding biodiversity. It describes the application of RS and fusion of RS with machine learning (ML) and deep learning (DL) schemes in existing research works for biodiversity protection and explains the significance of these technologies and their advancements for educating the readers regarding their benefits and encouraging further research in this domain with an intent of developing better strategies for achieving biodiversity conservation.

Keywords

Biodiversity conservation, Remote sensing, Machine learning, Ensemble method, Deep learning

Introduction

Remote sensing (RS) mechanism has loomed as a prominent tool for mapping and conserving remote and widespread regions (Albalawi & Kumar 2013; Ouellette & Getinet 2016). In the biodiversity protection domain, RS has attracted tremendous interests and is employed in diverse ways (Petrou et al. 2015; Prasad et al. 2015; Alleaume et al. 2018). The RS technology plays an instrumental part in protecting natural features and natural habitat. The prominent applications of RS technology in conservation of biodiversity include data collection, map generation, protection of forested areas, natural resource region monitoring, change detention, animal conservation, land-cover protection and categorization and environmental conservation (Geller et al. 2017).

This paper provides a detailed review on utilization of RS mechanism and other evolving methods in the analysis of biodiversity conservation research.

Conservation of Biodiversity

Biodiversity conservation indicates the protection, monitoring, management and upliftment of biodiversity for deriving sustainable benefits for current and future generations (Byjus n.d.). Its vital objectives include preservation of species diversity, sustainable exploitation of ecosystem and species and maintenance of imperative ecological processes and life-supporting mechanisms. A region with greater amount of species richness possesses a highly stable environment compared to a region with lesser amount of species richness. Currently, biodiversity is being lost owing to over-usage of resources, loss of habitat, pollution, climatic variations, hunting, deforestation, poaching, diseases, invasive external species, etc. (Fletcher et al. 2011). Since biodiversity offers diverse ethical and economic benefits, it is indispensable for conserving the biodiversity.

Biodiversity Monitoring by Remote Sensing

The United Nations (UN) declared the period 2010-2020 as the decade on biodiversity. However, the goal of minimizing the biodiversity loss was not met. Though the in-situ campaigns are considered as the most reliable way of monitoring different aspects of biodiversity,

Table 1. Application of RS technology in biodiversity conservation

Application	Description
Data collection	RS is deemed to be a useful tool for gathering information. For simplifying biodiversity conservation procedure, remote sensors can be employed for acquiring and recording environmental data, which is indispensable for further surveys and analysis.
Map generation	Remote sensors, typically are airborne devices and therefore they are useful in generation of terrestrial ecosystem maps. Further, these maps can be utilized for identifying non-forested and forested areas as well as other physical attributes.
Protection of forested areas	Biodiversity conservation can be achieved through protecting and preventing deforestation in forested zones. As monitoring the dense forest areas from earth's region is tedious, exploitation of RS technologies aids in capturing images at a greater altitude, covering all regions of interest and can be supportive in monitoring forest areas and their conservation.
Natural resource region monitoring	For biodiversity conservation, natural resources must be efficiently utilized. RS technology can be employed for monitoring sites involving resources and regulating activities of over-utilization of resources.
Change detection	As RS has wide coverage, it possesses the potential to recognize environmental variations. Thus, it plays a cardinal part in species and ecosystem services.
Animal conservation	Domestic and wild animals are imperative entities of biodiversity. RS technology aids in monitoring illegal activities like poaching and animal killings.
Land-cover protection and categorization	It assists in monitoring vegetation and it's conservation. Moreover, remote sensor information is useful in categorizing plants as per their families.
Environment conservation	Remote sensors aid in environment conservation; air quality monitoring and pollution minimization

they suffer from numerous challenges and have various limitations such as high execution cost, time consuming, and require more effort to execute the process. Remote sensing (RS) is considered as the potential solution for the conventional campaigns. Unlike these campaigns, RS incorporates the data collected from satellites and airborne sensors which accurately collects the data for biodiversity monitoring (Nagendra et al. 2013). The data collected from remote sensing can provide cost efficient and repetitive monitoring of larger regions and provides additional information which is may not be possible using conventional field assessment campaigns.

Several studies have been presented in the existing literary works that use RS data for monitoring (Wang & Gamon 2019; Luque et al. 2018; Reddy 2021). However, most of the existing studies have not incorporated any biodiversity indicator which can be used directly or indirectly to extract any information. Various indicators have been presented in the existing works which results in several incompatible monitoring systems. Furthermore, despite the growing significance of RS data, the relation between the parameters measured by RS and indicators required for monitoring biodiversity is not analyzed in depth. Hence, it becomes essential to use a fundamental set of indicators which can be beneficial to biodiversity using RS.

However, there are certain critical issues which challenges the potential adoption of RS indicators and techniques. Some of the prominent challenges are summarized below (Mairota et al. 2015):

- It is difficult to deal with image corrections and to register image data for detecting changes in biodiversity and for the retrieval of biophysical data along with proper registration of multiple source datasets with multiple dates.
- Incorporating novel and advanced technologies for interpreting images which are currently exploited in the RS area, such as object oriented image analysis (OBIA) and knowledge-driven information mining.
- Defining exact type of habitat and determining its quality can be a complex task.
- Assessing the quality of the habitat and standard of biodiversity from RS is challenging considering the dynamic behavior of RS systems.
- It is highly difficult to accurately map the habitats based on the RS data considering the uncertainties associated with RS systems.
- It requires proficient knowledge related to RS and ecology along with an appropriate ground truth for monitoring of biodiversity.
- Selecting relevant time and space related applications for RS based monitoring.
- There is a need to analyze the interrelationships between habitat quality, distribution and structure of biodiversity.

It can be inferred from existing works that RS experts must try to bridge the gap between the ecologists and space engineers by precisely defining and interpreting the terms (Rocchini et al. 2016). In addition, the experts should also provide feasibility analysis of relevant satellite observation parameters which can validate the accuracy of RS biodiversity products based on in situ observations or ground proofing. This is one of the prominent requirements which needs to be considered to achieve a proper tradeoff between the technical requirements of RS systems and ecological demands of biodiversity (Rocchini et al. 2016; Skidmore et al. 2021). The above mentioned problems necessitate the need for an empirical analysis of biodiversity conservation and the implementation of remote sensing for biodiversity monitoring.

Paper Organization

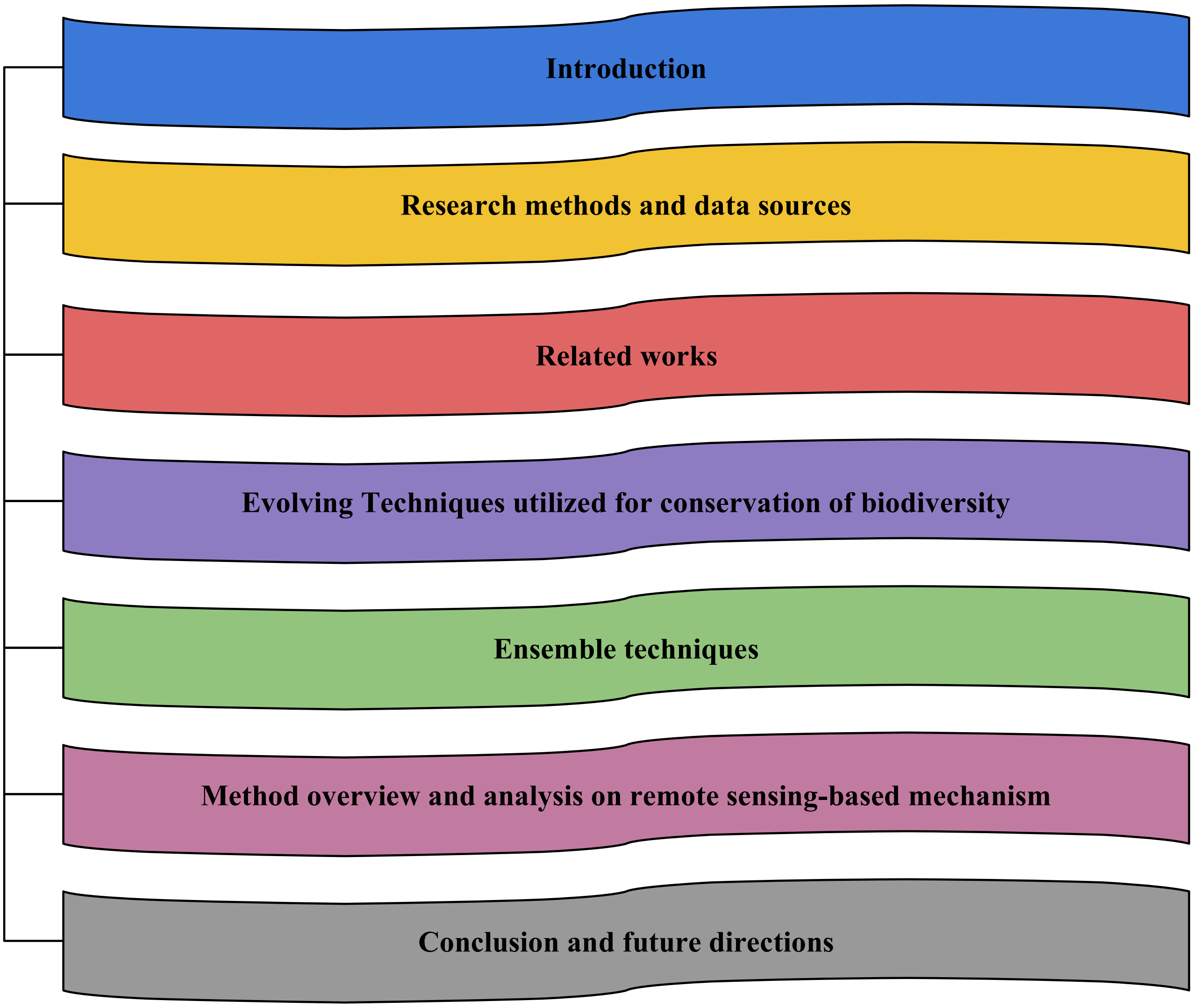


Fig. 1 Paper Structure

Contributions of Survey

The cardinal contributions of this survey include:

Investigation of emerging techniques employed for conserving biodiversity.

Exploration of ensemble methods adopted for conserving biodiversity.

Investigation of remote-based mechanisms for analysis, understanding and future developments.

Research Methods and Data Sources

The well-known technologies for data acquisition include satellite imagery or remote sensing method (Randin et al. 2020). These technologies aid in acquiring images of study areas considered for investigation. Currently, multispectral imagery has been extensively applied for capturing high resolution analysis images of interest. RS systems include a heterogeneous array of platforms and sensors. The sensors include active sensors and passive sensors, while platforms range mainly from planet observation satellites, helicopters, planes to drones with rotaries and fixed wings. The popular sensor employed in RS includes an optical imaging mechanism which is capable of capturing information beyond the thermal and infrared wavelengths (visible wavelengths) across the spectrum. Optical sensors include hyperspectral sensors (possess innumerable narrower bands) and multispectral sensors (possess limited amount of bands) (Randin et al. 2020). Passive sensors mainly include thermal systems and optical systems that depend on emitted thermal or reflected sunlight energy and thereby cannot penetrate smoke or clouds. These sensors cannot be utilized during night time. Active sensors mainly include synthetic aperture radar (SAR) and light detection and ranging (LiDAR) systems (Randin et al. 2020). These sensors can penetrate through smoke and clouds and can be operated at night. Depending on sensor wavelength, the signal can easily penetrate soil, canopy and vegetation. Recently, with the colossal advancements in sensor mechanisms, the mountable active sensor and passive sensor versions have been introduced, which can be easily mounted on drones (UAV), larger planes and satellites. The other sorts of sensors include spaceborne sensors and airborne sensors. Spaceborne sensors make consistent estimations at definite time periods as per the time needed for its revisit to the same location. Airborne platforms can be flown in relation to particular events like fire. They can even be flown under clouds (specifically drones) (Randin et al. 2020). Airborne platforms like drones can capture extremely-high-distance spatial-resolution information. After desired data acquisition via these sensors, the analysis can be conducted using advanced technologies like artificial intelligence or computational intelligence schemes.

Related Works

In Holloway & Mengersen (2018), the RS mechanism was adopted for biodiversity monitoring. The authors in this work explored the cardinal biophysical procedures underlying the species distribution including land cover variations, disturbances and climate variability. The work also described the prospective synergies between RS communities and ecological modeling for determining the conceptual gaps hindering the application of RS for modeling and monitoring ecological systems. In Holloway & Mengersen (2018), RS and statistical ML schemes for achieving sustainable growth were explored. The authors defined the four cardinal classes of statistical machine learning schemes for investigating RS information namely regression, clustering, dimension diminution and classification. The study further declared that the method selection for analyzing RS data relies on numerous parameters including the amount and nature of training data, inferences needed, and availability of computing power and software and category of estimates. This work also suggested the necessity of advanced approaches and ensemble techniques for performing effective RS analyses. In Silveira et al. (2021), spatio-temporal RS indices were employed for identifying biodiversity conservation hotspots. Here, indices capturing the spatial and inter-annual variability of surface temperature and vegetation greenness were generated for identifying regions of low, medium and high biodiversity conservation interest. This work indicated that the elevated inter-annual variability posed a huge threat in northeastern parts and southern Argentina regions owing to low spatial variability. This work further declared that in regions with high spatial variability, protection must be strongly considered for maintaining the region's original biodiversity heritage.

Performance of distinct ML methods on categorizing three distinct multispectral and spatial satellite images was described in Rahman (2020a). For categorization, a group of fine and moderate resolution images of Planet, Sentinel-2 and Landsat-8 possessing similar phenological phases were obtained and processed for determining appropriate techniques that offer better performance with regard to land use land cover (LULC) categorization. The classifiers like support vector machine (SVM), random forest (RF) and stacking methods were applied mainly on Planet, Sentinel-2 and Landsat-8 images separately for assessing individual and total class accuracy. Furthermore, two unique training sets were generated for categorizing the imagery. It was identified that the Sentinel-2 performed better compared to all the employed images and SVM outperformed the RF and stacking methods. Results substantiated that the SVM exhibited 0.968 Kappa value and 98.3% overall accuracy. Findings of this work are useful for planners, decision-makers and RS scientists in monitoring briskly changing, diverse and segregated landscape. In Bojamma & Shastry (2021), automated identification of plant species based on ML was described with an intent of biodiversity conservation. This work aimed at resolving the intricacies involved in recognizing distinct plant species through classical techniques for conservation. This work declared that the inclusion of exhaustive and large databases would aid in attaining greater accuracy and identification rates. The study further suggested the necessity for developing identification mechanisms that are capable of functioning even in natural settings. The study Varotsos et al. (2021) discussed the contribution of RS in investigation of ultraviolet radiation effects on biodiversity, ecology and conservation. Findings of this study signified that the optimized fusion of improved RS instrumentation and ground-based system would aid in better investigation of ultraviolet radiation effects and the associated uncertainties. The work Randin et al. (2020) described the applications of RS in forest bionomics and management. This work provided the prominence of RS in forest surveillance and discussed the distinct sorts of RS platforms and sensors for mapping the variety of forest parameters. This study declared the RS as a promising technology for forest conservation and management around the globe.

Potential for application of ML and artificial intelligence (AI) in managing forests, related services and achieving biodiversity conservation in India was discussed in Shivaprakash et al. (2022). This work discussed the adoption impediments of AI in biodiversity and Indian forestry domains. The study revealed that AI has been less adopted in existing works for forest management and biodiversity conservation. Thus, exploitation of big data, cloud computing, satellite and digital technology would aid in the adoption of AI with regard to forest management and biodiversity conservation. This study declared that challenges like limited accessibility to existing big data or better data unavailability and computation and technical hurdles of employing AI technologies have led to the constrained application of AI technology in biodiversity and Indian forestry domains. Thus, this study suggested the necessity for a) interdisciplinary associations between forest ecologists, forest officials, conservation practitioners, technologists and academicians for facilitating long-run exploitation of AI, b) cost-effective and cheap computational resources, c) ceaseless augmentation of data collection abilities and d) development of fast processing and less intensive algorithms for data examination. The work Diez et al. (2021) investigated and discussed the prominence of DL and RS technology in forest monitoring. It emphasized on studies employing RGB images acquired through RS mechanism and DL method for settling real-world forest research issues. This work stressed on three crucial topics namely forest anomaly identification (insect infestation and forest fires), tree species categorization and individual tree identification from the viewpoint of forest conservation. This study declared the necessity for additional research on identification and categorization of insect infested trees and exploitation of DL schemes in reviewed articles. It further stated that the cause for limited research on these topics was mainly owing to intricacy of individual tree recognition in dense forests and also the relatively limited amount of available samples for infested or sick trees. Thus, it declared that the exploitation of a strong and publicly existing expert annotated dataset could bring about crucial improvements.

The work Amarasingam et al. (2022) described the prominence of drone-based RS mechanism for crop health enhancement and management. The study concentrated on adoption of RS technology for crop disease and pest management, phenotypic measurement, yield estimation, nutritional status assessment and soil moisture evaluation for achieving environmental sustainability and boosting productivity. This work concluded that drone-based crop RS would be an extremely effective approach for ameliorating the quality and yield and leading to environmental, social and economic benefits. The work Murray et al. (2018) discussed the value of satellite RS in assessing ecosystem risks. It declared that unstructured utilization of RS information for evaluating ecosystem dynamics would introduce substantial uncertainty and error. The authors investigated the usefulness of RS data in evaluating the degradation of terrestrial, aquatic and marine ecosystem types. This work provided a valuable framework and desired guidance for integrating RS information into ecosystem threat assessment. This study highlighted that the RS information should possess fine temporal resolutions and spatial resolutions for representing biome dynamics and enabling the detection of brisk changes, closely correlating with suitable in situ ecosystem degradation indicators and facilitating ecosystem monitoring.

Evolving Techniques Utilized for the Conservation of Biodiversity

In Chaves et al. (2020), ML approach was adopted for mapping tree's floristic patterns through exploiting RS data. The authors utilized RF regression scheme for prediction. Through integrating field information of Peruvian national forest, ML and remotely sensed information, a map indicating the forecasted patterns in the community composition of trees was derived. Comparison with previously-reported works illustrated that the presented RF regression scheme exhibited robustness and could be applied to other tropical areas for recognizing suitable regions for conservation. In Rousset et al. (2021), DL methods were employed for land use land cover (LULC) categorization in a subtropical, complex setting. In this work, a specific database was created using SPOT6 satellite information for LULC data analysis. The LULC categorization performance of the presented DL approach was compared with the XGBoost ML classifier. It was identified that the presented DL method performed better than the XGBoost classifier, achieving 63.61%

amelioration in overall accuracy. In Barrett et al. (2014), performance of distinct ML methods like SVM, RF and highly randomized trees was evaluated for distinguishing the grassland categories over two widespread regions of Ireland through employing ancillary spatial, multi-sensor radar and multi-temporal datasets. The detailed assessment conducted in this work demonstrated the effectiveness of SVM, RF and highly randomized trees in categorizing distinct sorts of grasslands. Experiments indicated that the employed ML schemes attained $\geq$ 88.7% overall accuracies for single frequency categorizations and 97.9% maximum accuracies for combined frequency categorizations. Findings also highlighted the suitability of ML technology for biodiversity protection.

In Kafy et al. (2021), seasonal surface temperature variation and LULC prediction via RS data was performed using ML schemes. This work adopted Landsat bands and SVM technique for retrieving surface temperature variation and LULC patterns of 2019, 2009 and 1999. Furthermore, it employed neural networks and cellular automata scheme for determining surface temperature variation and LULC patterns for 2039 and 2029. Results manifested that the cellular automata scheme offered better accuracy with 0.82 Kappa value. Experimental LULC analysis results illustrated a substantial augmentation in the suburban built-up regions by 13.59% (2039) and 9.23% (2029) compared to 2019. Experimental summer surface temperature data analysis illustrated that 35.02% and 31.30% region would likely to experience greater than 36^0 C surface temperature, followed by 29.53% and 1.28% region in winter season for 2039 and 2029. Moreover, the seasonal surface temperature conditions in distinct LULC manifested comparatively elevated temperatures in urban zones. The findings indicated the possibility of larger heat zones owing to augmentation of urban region and diminution of green cover in future. This work further recommended the necessity for natural resource conservation with sustainable and eco-friendly future urban advancement plans through ensuring greater urban-plantation. In Anand et al. (2021), prediction of regional dissemination of a therapeutic plant species (*Rhododendron arboreum*) was achieved using a deep learning (DL) scheme. The employed DL scheme utilized atmospheric and ecological parameters which were resampled statistically and were further employed in establishing a nonlinear and linear relationship for determining the occurrence conditions of the species. Results clarified that the presented DL scheme outperformed the existing competing method with regard to species occurrence prediction. The work Saha et al. (2022) aimed at detecting deforestation probable regions at Jaldapara protected area and its neighboring zones with an intent of biodiversity preservation. This work adopted five ML algorithms namely RF, decision trees (DT), Naive Bayes (NB), neural networks and support vector machine (SVM) for detection. This study revealed that the middle and northern sections suffered extreme deforestation owing to massive timber trafficking, poaching and human encroachment. It was clearly observed from experimental outputs that the SVM approach outperformed the RF, neural networks, NB and DT schemes through providing 0.90 AUC value. It further stated that deforestation probability region analysis together with proper management policies and daily monitoring would aid in forest sustainability. Moreover, creation of unnatural forest buffer region near the protected forest area would promote the livelihood of forest fringe folks and forest dwellers. Additionally, this work suggested the necessity for enforcing restriction on non-timber product usage for forest fringe folks and forest dwellers and timber trafficking and wild animal trafficking with an intent of biodiversity conservation.

With the intent of biodiversity conservation, the Da Silveira et al. (2021) exploited the RS mechanism and ML scheme. The authors integrated Landsat-8 and WorldView-3 imagery along with ML schemes for mapping appropriate habitats pertinent to the existence of *Millepora alcicornis*, a hydrocoral species in coral reefs of Northeast Brazil's marine protected regions. The ML schemes were employed for determining the species distribution and habitat mapping. This work stated that human activities strongly inhibited coral growth. Findings of this work reinforced the significance of taking safety measures for local biodiversity maintenance. The work Vega Isuhuaylas et al. (2018) discussed Peruvian forest mapping using ML technology for biodiversity conservation. It aimed at determining the best framework for categorizing shrubland and Andes forest using land cover information and Landsat-8 satellite data. The authors employed three distinct ML methods like RF, SVM and K-Nearest Neighbor (KNN) for categorization. Experiments ascertained that the SVM exhibited better classification performance than the RF and KNN. In Choe et al. (2021), a DL scheme was employed for mapping prospective plant species richness along the Korean peninsula. Initially, the richness of South Korean plant species was estimated through fusing the probability-dependent species distribution framework outputs and plant surveys were employed for validation of proposed prospective species abundance maps. Experiments substantiated that the presented DL scheme showed better estimation potential for species richness compared to the extensively employed RF scheme.

For biodiversity conservation, the work Guirado et al. (2020) estimated the tree cover in drylands through exploiting a DL framework. Findings of this work declared that the adopted DL-based tree cover categorization framework exhibited 23% amelioration in accuracy compared to visual manual interpretation. In DeLancey et al. (2019), DL method was employed for categorizing widespread wetland via RS technology. This work validated a DL-oriented landcover categorization scheme against a classical XGBoost method for mapping an intricate set of landcover types and wetland classes. It was substantiated from experimental observations that the presented DL scheme superseded the XGBoost method with regard to wetland classification through exhibiting 80.2% accuracy and thereby proved its effectiveness for diverse landcover mapping operations. In Kalantar et al. (2020), ML frameworks like regression tree, multivariate regression and SVM were employed for predicting forest fire vulnerability using RS data. This study employed distinct fire predictors acquired from climatic variables, vegetation indices, topographical features and environmental factors. Experimenting with distinct optimization schemes boosted the frameworks' performances providing better prediction accuracy at 0.91, 0.90 and 0.89 for regression tree, multivariate regression and SVM schemes. In Ahmed et al. (2021), ML schemes were adopted chiefly for wetland classification. Analysis was performed through employing the Landsat optical information as input to ML frameworks. It was noticed from experiments that the employed ML schemes effectively categorized the wetlands with less error and high accuracy. In Bland et al. (2015), ML schemes were utilized for forecasting conservation level of data-insufficient species. The work employed geography, threat data and life history of species for predicting their conservation status. The adopted ML schemes were trained using known status of species. The authors utilized distinct ML schemes including KNN, neural networks and SVM for prediction. Experiments substantiated that the ML schemes displayed extremely high species categorization accuracy (92%) and exhibited greater potential with reference to correct identification of endangered species richness hotspots. The employed ML schemes forecasted 313 out of 493 species which were at the threat of extinction that in turn augmented the calculated proportion of endangered terrestrial species from 22 to 27%. The analysis further stated that the sites forecasted to comprise numerous threatened species were given conservation priorities beforehand, however species specifically in these sites showed relatively greater levels of threat than previously identified. Although the attine results left general mammalian protection priorities typically unaffected, they recommended that threat levels in these mammals were relatively underestimated. The study concluded that unless targeted directly for monitoring, the species categorized as data-inadequate had high possibilities of extinction. Moreover, it declared that through considering information pertinent to data-inadequate species would assist in alleviating gaps in conserving deficiently known biodiversity and biodiversity indicators.

In Ayhan et al. (2020), a DL method was adopted for vegetation recognition. This work employed testing and training databases acquired from distinct geographical regions with distinct image resolutions. The authors in this work applied the vegetation recognition techniques to high-resolution color images containing near-infrared and RGB bands. Experimental observations explicitly confirmed that the DL framework employing the RGB bands exhibited acceptable performance in terms of vegetation detection than the classical DL schemes. The work Smoliński & Radtke (2017) employed ML-based schemes for spatial forecasting of Baltic Sea's fish diversity. The analysis employed six imperative predictors namely sea depth, bottom salinity, seabed sediments, growth season underside temperature and annual average underside current velocity. This work highlighted the capability of ML-based schemes in diminishing the prediction error while modelling fish diversity. In Mayfield et al. (2017), deforestation prediction with an intent of biodiversity conservation was achieved using the ML technology. The authors employed freely accessible databases for creating deforestation threat maps, considering the Madagascar and Mexico study zones. Results clearly revealed the potential of ML schemes with regard to effective deforestation prediction and confirmed the suitability of these schemes for conservation of biodiversity. The work Rehush et al. (2018) utilized both ML and DL schemes for detecting tree-linked microhabitats (TliMs). This work aimed at assessing the capability of terrestrial close-range laser scanning mechanism for recognizing distinct TliMs such as bark, cavities, mosses, fungi, ivy and bark pockets. The proposed ML scheme employed local geometric attributes for distinguishing the 2D structures like mosses and bark from 3D structures like fungi, ivy and cavities. However, these attributes were incapable of discriminating the concave stem structures (cavities) and convex structures (fungi and ivy). The proposed DL scheme employed rasterized multi-point orthographic projections, suitable for discriminating the stem structures. The ML approach offered 70% overall accuracy whereas the DL scheme exhibited 83% overall accuracy. Findings illustrated that the proposed approach would be promising for forest monitoring tasks.

In Carbonneau et al. (2020), DL techniques were utilized for classifying RGB fluvial environments. The authors employed a RGB image database comprising 5 land-cover categories namely roads, senescent vegetation, green vegetation, dry sediment and water. The conducted experiments manifested that the adopted DL techniques effectively categorized the RGB fluvial environments and outperformed the ML schemes with regard to fluvial scene categorization. In Cao et al. (2018), ML methods were employed for identifying eight distinct mangrove species in China's Qiao island. For mangrove species identification, hyperspectral imaging data was employed as input. Furthermore, waveband selection techniques namely stepwise discriminant investigation, successive projections method and correlation-directed feature selection were applied chiefly for dimensionality diminution and effective waveband selection. Then, distinct ML approaches like SVM, KNN and RF were used for mangrove species categorization. Experimental evaluations ascertained that the SVM classifier provided 93.54% accuracy and superseded the ML approaches in mangrove species recognition. Findings of this work would be promising for forest conservation and management. In Naderpour et al. (2021), a spatial DL-oriented model was built for forecasting forest fire threat in Sydney's northern beach region. The authors selected thirty-six prominent key determinants contributing to fire threat. Further, they spatially mapped this information considering distinct contexts like topography, human-induced, climate, morphology, physical and social viewpoints as input. The developed DL approach followed a stepwise process for executing several scenarios in order to estimate the fire threat probability with neoteric input contributing variables. It generated fire threat levels depending on vulnerability and susceptibility frameworks. Here, diverse geospatial variables were employed for modeling susceptibility and diverse socio-economic variables were employed for physical and social vulnerability modeling. Finding of this work substantiated the presented DL model's efficacy with regard to fire threat prediction, making it an appropriate and favorable candidate for biodiversity protection.

ML with satellite imagery was exploited in Jackson & Adam (2021) for categorizing jeopardized tree species of submontane forest. The work employed an imbalanced database and evaluated its effect in mapping and detecting tree species under risk in a chosen sub-montane diversified tropical forest by utilizing SVM, RF classifiers and multispectral imagery. The analysis illustrated that among the recognized species, *Zanthoxylum gilletii and Syzygium guineense* were most precisely mapped while *Newtonia buchananii* was least precisely mapped. The presented methodology exhibited greater potential for forest biodiversity conservation. In Tian et al. (2020), DL scheme was employed for acquiring phenological-spectral features necessary for understanding the *Spartina alterniflora* species, which has led to severe degradation to biodiversity and ecosystem. The phenological features greatly assisted in boosting the DL scheme's performance with regard to *Spartina alterniflora* detection. Furthermore, the regional scale and long-term maps of *Spartina alterniflora* served as a baseline information for the evaluation, conservation and management of diverse ecosystem services like climate change, carbon storage, biodiversity richness and biological invasion. In Mosebo Fernandes et al. (2020), a ML approach for conservation of biodiversity through locating habitat regions for irreproachable species like sage-grouse depending on existing climate conditions and further pinpoint future habitat regions depending on climate projections was described. For analysis, data pertinent to wildlife location, vegetation cover, precipitation, normal temperature and remaining ecosystem-related information was used. Furthermore, ML schemes were crucially applied for locating the current wildlife habitat sites and forecasting appropriate future regions where wildlife would probably migrate to, depending on the impact of climate variation. The conducted experiments explicitly illustrated that the RF approach outperformed the available competing models through attaining 88.5% specificity, 91.7% sensitivity and 89.7% accuracy. Moreover, it exhibited better potential in modeling species distribution for providing necessary vision into habitat forecasting. The presented methodology revealed that the Utah's sage-grouse habitats would continue to diminish over the succeeding years owing to climate variation, producing an extremely segregated habitat and inducing a loss of nearly 70% of their existing habitat. Findings of this work highlighted that the protected sites and priority regions of conservation might be considered inadequate for preventing the habitat loss and therefore more effort would be needed for conserving sage-grouse population.

Table 2. Evolving Techniques used for conservation

References	Publication year	DL/ML techniques	Evaluation Parameters
Chaves et al. (2020)	2020	ML	RMSE = 0.467
Rousset et al. (2021)	2021	ML	Accuracy = 63.61%
Barrett et al. (2014)	2014	ML	Accuracy = 97.9%
Kafy et al. (2021)	2021	ML	MSE = 0.523, Correlation coefficient (R) = 0.796
Anand et al. (2021)	2021	DL	AUC = 0.917
Saha et al. (2022)	2022	ML	Efficiency = 90.7%, Sensitivity = 88.5%, Specificity = 84.6%
Silveira et al. (2021)	2021	ML	Accuracy = 79%
Vega Isuhuaylas et al. (2018)	2018	ML	AUC = 0.81
Choe et al. (2021)	2021	DL	Accuracy = 98%
Guirado et al. (2020)	2020	DL	Accuracy = 79%
DeLancey et al. (2019)	2019	DL	Accuracy = 80.2%
Kalantar et al. (2020)	2020	ML	AUC = 0.90
Ahmed et al. (2021)	2021	ML	Accuracy = 99%
Bland et al. (2015)	2015	ML	Classification Accuracy = 92%
Ayhan et al. (2020)	2020	DL	Accuracy = 82.98%
Smoliński & Radtke (2017)	2017	ML	RMSE = 0.08, Mean = 1.39, Standard Deviation = 0.66
Mayfield et al. (2017)	2017	ML	AUC = 0.85
Rehush et al. (2018)	2018	ML	Accuracy = 70%
Carbonneau et al. (2020)	2020	DL	F1 Score = 91%
Cao et al. (2018)	2018	ML	Accuracy = 93.54%
Naderpour et al. (2021)	2021	DL	ROC = 95.1%, k coefficient = 94.3%
Jackson & Adam (2021)	2021	DL	F1 Score = 68.56 %
Tian et al. (2020)	2020	DL	Accuracy = 96.22 %
Mosebo Fernandes et al. (2020)	2020	ML	Accuracy = 89.7%

AUC = area under the curve, MSE = Mean Square Error, RMSE = Root Mean Square Error, F1 score = harmonic mean, ROC = Receiver-operating characteristic curve

Table 2 summarizes the application of different ML and DL techniques for monitoring different biodiversity regions. These techniques are highly suitable for predicting the tropical patterns and helps in identifying suitable areas for conservation. A ML based XGBoost classification is used to obtain cartographic information for environmental monitoring Rousset et al. (2021). However, ML techniques are more complex to handle while processing large scale environmental data. In this context, DL models simplify the process. Several research works have implemented DL models in their monitoring process (Anand et al. 2021; Saha et al. 2022; Choe et al. 2021; Guirado et al. 2020; DeLancey et al. 2019; Ayhan et al. 2020; Carbonneau et al. 2020; Naderpour et al. 2021; Jackson & Adam 2021; Tian et al. 2020. The work mentioned in DeLancey et al. (2019) distinguished the effectiveness of deep learning and shallow learning processes. Observations show that, shallow learning cannot provide satisfactory results in terms of image recognition Landover classification, and different remote sensing applications. This is mainly due to the fact that shallow learning cannot analyze contextual information such as complex data patterns and habitats, vegetation, marshes and water bodies etc. However, DL models need more labelled samples for training and more investigation is required for analyzing different wetland or land cover mapping studies. This constitutes as one of the prominent research gaps and needs to be addressed.

Ensemble Techniques

In Muthoka et al. (2021), ensemble ML techniques were employed for detecting *Opuntia stricta* which poses a threat for biodiversity. This work utilized RS imagery data and ensemble techniques like random forest (RF) and extreme gradient boost (XGBoost) for detection. It was identified that the RF and XGBoost techniques offered 92.4% and 89.2% overall accuracies. Experimental findings manifested the efficacy of RS imagery information and ensemble techniques with regard to detection and mapping Opuntia stricta for conserving biodiversity. In Halmy & Gessler (2015), ensemble schemes were adopted for categorizing land-cover in arid regions. The authors employed the Landsat5 mapper data acquired for an Egyptian desert landscape with ancillary parameters for categorizing 13 distinct LULC classes. The employed ensemble schemes classified the land-covers accurately and exhibited greater than 85% overall accuracy and 0.83 Kappa coefficient.

Ensemble modeling framework was employed in Rather et al. (2022) for identifying appropriate regions for restoring habitats of endangered biodiversity. The authors adopted ensemble techniques for mapping the current possible distribution and forecasting the prospective appropriate habitats for species, considering the likely climate variation scenarios. The community data results declared that the considered Himalayan Trillium was positively linked with four shrubs, two tree species and a herbaceous species. The developed ensemble approach provided a nature-dependent panacea in guiding habitat restoration activities in Himalaya and across the world. In Rew et al. (2020), an ensemble approach was employed for estimating the habitat suitability. This work employed environmental and observational data for seven species of birds and four species of amphibians for analysis. It was viewed from results that the presented ensemble approach offered accurate habitat suitability estimation compared to earlier-reported schemes. In Mohamed et al. (2018), RS and ML-based ensemble approach was adopted for monitoring benthic cover and mapping. Initially, videos pertinent to benthic habitats were collected using a towed camera, and were transformed to geo-located habitat images. Further, these habitat images were labeled for grouping the habitats manually. The attributes for classifying these images were automatically extracted using the bag of attributes algorithm. Then, benthic cover classes were automatically detected using a majority voting ensemble of KNN, bagging and SVM classifiers. The accurately classified geo-located images offered ground truth instances for mapping benthic cover using satellite imagery. Testing of presented methodology over Ishigaki island of Japan manifested that the presented ensemble approach offered 89% accuracy in classifying algae, sediments, corals and seagrass species. Additionally, the presented ensemble technique provided 92.7% accuracy in benthic cover mapping using the satellite image. Experimental outputs substantiated the amelioration in automatic monitoring of benthic habitats and mapping accuracies.

The work Stohlgren et al. (2010) adopted an ensemble approach for identifying invasive plant habitats. In this work, five individual ML frameworks namely logistic regression, multivariate regression splines, regression trees, maximum entropy framework and RF schemes were adopted and compared with the presented ensemble approach for a chosen plant species recognition. Analysis was performed using the field information gathered from

Table 3. Ensemble Techniques used for conservation

References	Publication year	Evaluation Parameters
Muthoka et al. (2021)	2021	Accuracy = 90.8%
Halmy & Gessler (2015)	2015	Accuracy = 85%
Rather et al. (2022)	2022	High Predictive Accuracy
Rew et al. (2020)	2020	True skill statistic (TSS) score = 0.886
Mohamed et al. (2018)	2018	Accuracy = 92.7%
Stohlgren et al. (2010)	2010	High risk analysis and robustness
Chakraborty et al. (2016)	2016	Accuracy = 70%

the park members, combined with vegetation, climatic and topographic predictors acquired from satellite information. Experimental outputs ascertained that the presented ensemble approach performed better than the individual ML frameworks and exhibited greater robustness. In Chakraborty et al. (2016), a tree-directed ensemble classification scheme was adopted chiefly for mapping LULC variation in Himalayan region. For handling high temporal and high spatial variability and sophisticated multi-signature categories, this work presented an ensemble classification method. The authors used multi-seasonal data using temporal signatures in diverse spectral sites and heterogeneous environmental variables for recognizing twenty LULC categories, focusing on discriminating geographically predominant forest types. This work employed a knowledge-dependent decision level combination for producing annual fusion maps and RF classifier for creating seasonal maps. Results demonstrated that this approach offered nearly 70% accuracy. This methodology could be extended to distinct RS databases for further assisting in widespread forest site mapping and forest type monitoring, thereby supporting in developing forest conservation strategies and realistic field inventories.

The works reviewed in Table 2 and Table 3 based on publication year are depicted in Fig. 2. From Fig. 2, it could be observed that in most of the recent works (published in 2020 and 2021) DL techniques have been largely utilized compared to ML and ensemble techniques.

The works reviewed in Table 2 and Table 3 based on techniques employed for analysis are depicted in Fig. 3. The techniques adopted for biodiversity monitoring and conservation in existing works are comprehensively categorized as ML, DL and ensemble methods. From Fig. 3, it could be noted that ML techniques are largely adopted in reviewed works than the DL and ensemble techniques.

The works reviewed in Table 2 and Table 3 based on achieved accuracy percentages are depicted in Fig. 4. From

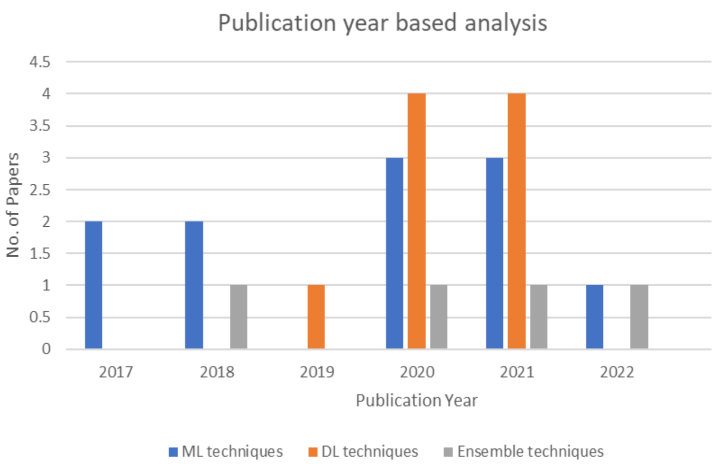


Fig. 2 Analysis of reviewed works based on publication year.

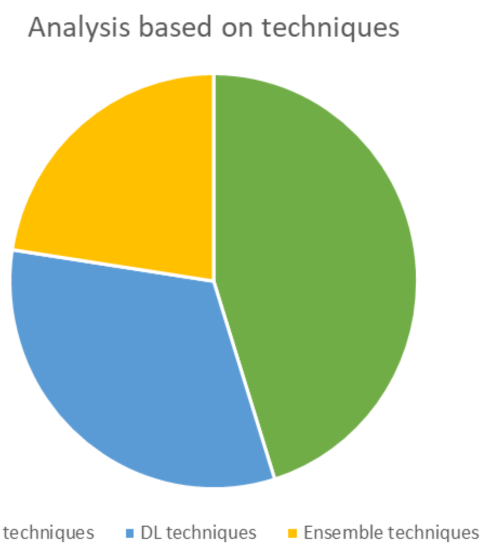


Fig. 3 Analysis of reviewed works based on techniques.

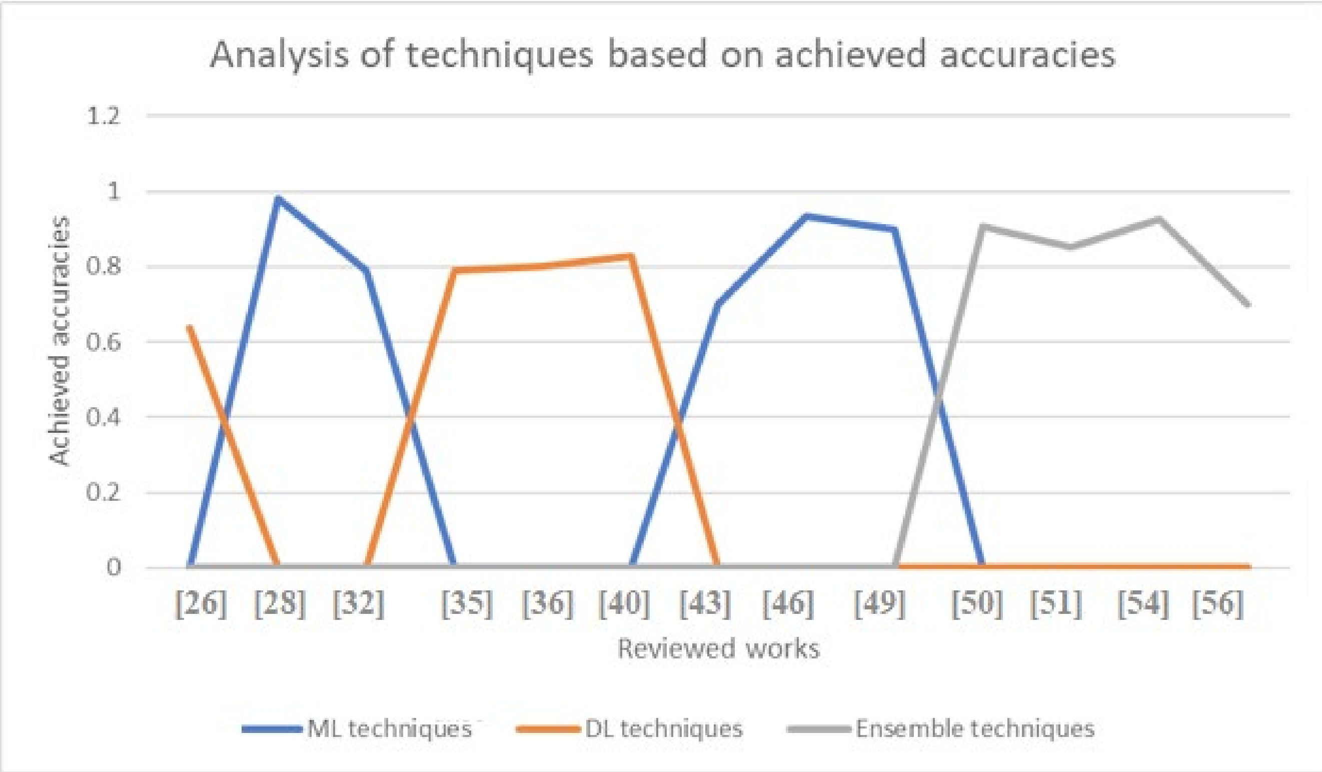


Fig. 4 Analysis of reviewed works based on achieved accuracies

Fig. 4, it could be inferred that among the reviewed studies, the ML technique employed in work Barrett et al. (2014) offered highest accuracy of about 97.9%. The DL method utilized in work Ayhan et al. (2020) provided the highest accuracy of 82.98% and the ensemble technique employed in work Mohamed et al. (2018) provided the highest accuracy of 92.7%.

Method Overview and Analysis on Remote-sensing based Mechanism

In Rahman et al. (2020b), RS-based mapping of carbon to nitrogen ratio (CNR) of senescent leaf using ML schemes was presented. The ML schemes were employed for validating the predictability of employing the Landsat8 and Landsat TM5 for mapping temporal and spatial distribution of CNR of leaves in Bangladesh's Sundarbans Forest. Findings clarified that the remote sensing information, namely Landsat TM5 effectively mapped the CNR of leaves with acceptable accuracy. In Traganos et al. (2018), RS based mechanism was employed for widespread, temporal and high spatial mapping and surveillance of seagrasses and optically shallow sites. The employed RS based mechanism aimed at providing the cardinal seasonal to annual baseline mapping, surveillance of seagrass habitats on a widespread basis for identifying threat regions, assisting management planning, coastal conservation and finally climate variation mitigation. In Wang et al. (2020), RS-based mechanism was integrated with landscape characteristics for soil salinity estimation. This work derived an overall 35 indices such as terrain attributes, salinity spectral, and vegetation spectral along with RS classifiers and correlated them with soil salinity. Findings clarified that the farmland reclamation influenced the soil salinity distribution. In Ortega Adarme et al. (2020), RS imagery was employed for detecting deforestation in Cerrado and Amazon biomes of Brazil via DL-directed strategies. Experimentation was conducted using two Landsat 8 images captured at distinct dates. Results ascertained that the fusion of RS-based mechanism with DL technology exhibited greater effectiveness with regard to deforestation detection and reduced the time spent in the visual investigation of deforested regions.

In Arruda et al. (2021), a RS-based mechanism was integrated with the DL scheme for identifying burned regions in the Brazilian Cerrado biome. This work reported that 67% and 31% of the overall burned region occurred in native vegetation and farming lands. Experiments substantiated that the adopted approach offered 97% overall accuracy in terms of burned region prediction. Moreover, the research findings revealed that the presented approach could be applied successfully to the RS domain using huge RS databases and requiring low labor demand and time. The work Nguyen et al. (2021) combined the RS technology with ML technique for evaluating land usage variation and environmental monitoring. The authors employed Sentinel-2 images and RF method for map generation. Results revealed that the employed RS and ML technology fusion exhibited acceptable efficiency with regard to evaluation of land usage variation and environmental monitoring. In Tuanmu et al. (2010), a RS mechanism was utilized for detecting understory vegetation. This work employed phenology features derived from the RS approach for spatial distribution mapping of bamboo. Owing to its extensibility, flexibility and generality, this approach constituted an amelioration with regard to remote identification of vegetation, confirming its efficacy for mapping distinct understory species in heterogeneous geographic settings. Findings of this study declared that both the wildlife ecosystem management and biodiversity conservation would be benefitted by the detailed understory vegetation data via the application of presented approach.

In Pontoglio et al. (2021), RS technology was integrated with ML approach for identifying automated features in fluvial settings. The analysis was executed through acquisition of several photogrammetric images. Further, an algorithm was developed for identifying the water table. The presented approach successfully identified distinct patterns such as vegetation, gravel bars, water and ground categories in specific geomatics and hydraulic conditions and provided 11% amelioration in accuracy and 13.5% amelioration in F1-score mean values. This work also suggested the suitability of applying this approach in diverse fluvial scenarios for monitoring distinct fluvial regions and preventing catastrophic incidents induced by climate change. In Ye et al. (2019), DL with RS-based mechanism was applied mainly for detecting landslides. In this work, hyperspectral RS data was used for landslide recognition. Initially, the spatial-spectral attributes of the landslide were extracted. Further, the high-level attributes were inserted into the DL classification framework for landslide identification. It was clearly found from experimental outputs that the RS-DL technology fusion helped in precise landslide detection with about 97.91% precision when compared to customary hyperspectral image categorization techniques. In Meng et al. (2021), the RS mechanism was integrated with ML approach for mapping *Kobresia pygmaea*, a meadow grassland community. In this work, ML techniques were integrated with topographic indices and satellite images for categorizing the grassland community. Findings indicated that for the considered field regions, the alpine vegetation communities illustrated an acceptable spatial heterogeneity. Moreover, the employed ML approach with texture attributes, topographic indices and vegetation indices displayed superior performance achieving 83.92% overall accuracy and 0.80 Kappa coefficient. Results manifested the feasibility of ML and RS mechanism with regard to categorization of vegetation community.

In Wagner et al. (2020), RS technology combined with DL method was applied chiefly for examining spatial distribution and regional mapping of canopy palms of Amazonian forest. The regional mapping was executed for investigating spatial dissemination of palms and their relation to edaphic and human disturbance conditions. It was found that this approach offered 95.5% overall mapping accuracy and 0.7 F1-score. The palm distribution analysis revealed that the abundance of palms was naturally controlled by soil water level, avoiding both waterlogged and flooded regions near dry areas and rivers. Moreover, their distribution indicated a considerable pristine landscape which is severely endangered owing to illegal cutting and deforestation. Furthermore, this work declared that the new species distribution information would aid in documenting the species distribution and understanding species spatial diversity and distribution. In Doyle et al. (2021), RS and ML technologies were employed for identifying patterns in land-cover, land-use variation and the augmenting loss of wetlands and forests. In this work, a RF classifier was adopted chiefly for mapping land-cover and land-use across the complete Landsat record. Furthermore, the seasonal and multiyear composites were utilized for acquiring good coverage and discriminating distinct land-cover and land-use types. The employed RS and ML technological fusion exhibited acceptable performance with regard to interpretation of crucial trends in land-cover, land-use variation and the expanding loss of wetlands and forests. In Abeysinghe et al. (2019), RS and ML technology was employed for mapping an invasive plant species known as *Phragmites australis*. The RS technology was adopted for acquiring invasive plant images. Further, pixel-based schemes (SVM, neural networks and classical parametric optimum likelihood classifier) and object-based schemes (SVM and KNN) were utilized for detecting *Phragmites* in Estuary. It was identified that the pixel-oriented NN offered 94.80% overall detection accuracy. Moreover, this work provided an approach for identifying invasive plant species with greater accuracy in a limited region with just a constrained amount of samples. In Knopp et al. (2020), RS mechanism was integrated with DL technology for burned region segmentation. The authors employed a U-Net structure-based neural network and shortwave infrared, near infrared and visual spectral bands for analysis. Results indicated that this methodology offered 0.94 Kappa coefficient and 98% overall accuracy. In Huerta et al. (2021), DL method and RS-based mechanism was applied chiefly for mapping metropolitan green spaces with the cardinal goal of ameliorating the urban management, necessary for natural resource conservation. The authors utilized a U-Net structure for analysis. Experimental outputs indicated that the adopted DL methodology precisely mapped the metropolitan green spaces and exhibited 0.94 Kappa value, 0.80 recall, 0.57 dice coefficient and 0.97 overall accuracy. In Miyoshi et al. (2020), a RS with DL methodology was described for recognizing a tree species specifically in the extremely-dense areas. For analysis, a Brazilian biome's semi-deciduous forest images were utilized. This work then employed a DL architecture for recognizing a tree species. The employed architecture considered the probability of each image pixel to be analogous with an original tree-species, as this was imperative for providing accurate outputs in an extremely-dense scene. Experiments confirmed that the presented methodology offered notable performance with reference to identification and geolocation of trees in RS-dependent hyperspectral images, offering 0.945 recall, 0.973 precision and 0.959 F-measure values. Experimental outputs and findings demonstrated the DL architecture's effectiveness in terms of forest monitoring and accurate recognition of single-trees. The work Morin et al. (2021) applied RS-ML technological fusion for mapping deforestation, forest degradation and LULC changes in Armenia's Dilijan national reserve. The authors employed high resolution imagery for measurement and validation of forest density and related variations. Analysis of study outputs clarified that the majority of degradation and deforestation occurred before 2000 with a considerably constant period until 2006 when both degradation and deforestation started to augment again. From the LULC map analysis it was identified that the chief reasons for forest cover variations were linked to agriculture, human settlements and transformation to other sorts of vegetation. This study served as an imperative decision-making tool for developing sustainable forest policies and management.

In Wu & Liang (2018), a RS-dependent biodiversity index was exploited for forecasting animal species abundance. This work introduced a neoteric biodiversity index through fusing diverse highly correlated RS metrics. It was identified that the evapotranspiration metrics highly influenced the richness of species at global levels. Moreover, the RS metric in texture group exhibited higher dependency with species abundance at regional level. The temperature and radiance metric showed a greater effect on bird richness distribution, compared to their effects on distributions of mammals and amphibians. The results attained in this work demonstrated the efficacy of RS mechanism with regard to biodiversity conservation analysis.

Conclusion

This paper provided an overview of RS technology and its crucial role in biodiversity conservation, discussing its distinct components and their features for desired data acquisition. The study investigated previously reported research works on the adoption of RS mechanisms for ecosystem monitoring and biodiversity protection, exploring popular technologies like ML, computational intelligence, DL and ensemble methods employed in existing studies for conservation. Furthermore, this review article investigated the utilization of integrated frameworks exploiting hybrid mechanisms involving RS and AI technologies in existing research studies to determine their efficacy towards biodiversity conservation. The review concluded that the development and adoption of appropriate hybrid frameworks through integrating RS with AI technologies would be significantly more effective for biodiversity conservation analysis than their individual exploitation. This review has highlighted various RS and ML techniques presently preferable for different types of biodiversity analysis: for burnt forest analysis, RS combined with DL techniques like U-Net excels in segmenting burnt regions with high precision; ocean beds for corals benefit from RS combined with ML techniques such as RF and SVM for habitat mapping and species distribution; tree species identification is best achieved using DL models, particularly CNNs, even in dense forests; species richness can be predicted using both ML and DL techniques, with DL models being particularly useful for large-scale and complex data patterns; sick trees can be detected using RS combined with ML algorithms like SVM and RF, effective for identifying anomalies such as insect infestations and diseases; LULC classification benefits from DL models providing high accuracy in environmental monitoring; wetland classification is effectively performed using ML algorithms like RF and SVM; forest fire prediction is best achieved using ML models, including regression trees and SVM, which predict susceptibility based on various environmental factors; invasive species detection is effectively performed using ensemble ML techniques like

RF and XGBoost; and lastly, habitat suitability estimation benefits from ensemble ML models, providing accurate estimations by combining multiple ML algorithms. These summaries will aid researchers in selecting the appropriate technology for their specific biodiversity analysis needs. Moreover, the utilization of evolving technologies like ML, DL, and computational intelligence would significantly aid policymakers and ecosystem conservation authorities in sustainable environmental resource management, as well as wild habitat and species conservation. Additionally, the implementation of effective environment or ecosystem management policies and the enforcement of rules for natural resource usage would assist in ameliorating environmental health and in conserving unblemished natural resources.

Declaration

Acknowledgement: We thank Prof. Shrinivas B. Kulkarni, Director, The Institute of Science, Mumbai & Dr. (Mrs) Gayatri Rajendra Barabde, HoD, Department of Environmental Sciences, The Institute of Science, Mumbai for their support. We extend our gratitude to the Department of Zoology, The Institute of Science, Mumbai for constant support.

Funding: No funding was received for conducting this study.

Conflicts of interest/Competing interests: The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

- **Abeysinghe T, Simic Milas A, Arend K, Hohman B, Reil P, Gregory A, Vázquez-Ortega A** (2019) Mapping invasive Phragmites australis in the Old Woman Creek estuary using UAV remote sensing and machine learning classifiers. *Remote Sensing* 11(11):1380
- **Ahmed KR, Akter S, Marandi A, Schüth, C** (2021) A simple and robust wetland classification approach by using optical indices, unsupervised and supervised machine learning algorithms. *Remote Sensing Applications: Society and Environment* 23:100569
- **Albalawi EK, Kumar L** (2013) Using remote sensing technology to detect, model and map desertification: A review. *Journal of Food, Agriculture & Environment* 11(2):791-797
- **Alleaume S, Dusseux P, Thierion V, Commagnac L, Laventure S, Lang M, Féret JB, Hubert-Moy L, Luque S** (2018) A generic remote sensing approach to derive operational essential biodiversity variables (EBVs) for conservation planning. *Methods in Ecology and Evolution* 9(8):1822-1836
- **Amarasingam N, Salgadoe S, Powell K, Gonzalez LF, Natarajan S** (2022) A review of UAV platforms, sensors, and applications for monitoring of sugarcane crops. *Remote Sensing Applications: Society and Environment.* 100712
- **Anand A, Pandey MK, Srivastava PK, Gupta A, Khan ML** (2021) Integrating multi-sensors data for species distribution mapping using deep learning and envelope models. *Remote Sensing* 13(16):3284
- Arruda VL, Piontekowski VJ, Alencar A, Pereira RS, Matricardi E A (2021) An alternative approach for mapping burn scars using Landsat imagery, Google Earth Engine, and Deep Learning in the Brazilian Savanna. *Remote Sensing Applications: Society and Environment* 22:100472
- **Ayhan B, Kwan C, Budavari B, Kwan L, Lu Y, Perez D, Li J, Skarlatos D, Vlachos, M** (2020) Vegetation detection using deep learning and conventional methods. *Remote Sensing* 12(15):2502
- **Barrett B, Nitze I, Green S, Cawkwell F** (2014) Assessment of multi-temporal, multi-sensor radar and ancillary spatial data for grasslands monitoring in Ireland using machine learning approaches. *Remote sensing of environment* 152:109-124
- **Bland LM, Collen BEN, Orme CDL, Bielby JON** (2015) Predicting the conservation status of data-deficient species. *Conservation Biology* 29(1):250-259
- **Bojamma AM, Shastry C** (2021) A study on the machine learning techniques for automated plant species identification: current trends and challenges. *International Journal of Information Technology* 13(3):989-995
- **Byjus (n.d.)** Biodiversity Conservation. https://byjus.com/biology/biodiversity-conservation/
- **Cao J, Liu K, Liu L, Zhu Y, Li J, He Z** (2018) Identifying mangrove species using field close-range snapshot hyperspectral imaging and machine-learning techniques. *Remote Sensing* 10(12):2047
- **Carbonneau PE, Dugdale SJ, Breckon TP, Dietrich JT, Fonstad M.A, Miyamoto H, Woodget AS** (2020) Adopting deep learning methods for airborne RGB fluvial scene classification. *Remote Sensing of Environment* 251:112107
- **Chakraborty A, Sachdeva K, Joshi PK** (2016) Mapping long-term land use and land cover change in the central Himalayan region using a tree-based

ensemble classification approach. *Applied Geography* 74:136-150

- **Chaves PP, Zuquim G, Ruokolainen K, Van Doninck J, Kalliola R, Gomez Rivero E, Tuomisto H** (2020) Mapping floristic patterns of trees in Peruvian Amazonia using remote sensing and machine learning. *Remote Sensing* 12(9):1523
- **Choe H, Chi J, Thorne JH** (2021) Mapping Potential Plant Species Richness over Large Areas with Deep Learning, MODIS, and Species Distribution Models. *Remote Sensing* 13(13):2490
- **Da Silveira CBL, Strenzel GMR, Maida M, Gaspar ALB, Ferreira BP** (2021) Coral Reef Mapping with Remote Sensing and Machine Learning: A Nurture and Nature Analysis in Marine Protected Areas. *Remote Sensing* 13(15):2907
- **DeLancey ER, Simms JF, Mahdianpari M, Brisco B, Mahoney C, Kariyeva J** (2019) Comparing deep learning and shallow learning for large-scale wetland classification in Alberta, Canada. *Remote Sensing* 12(1):2
- **Diez Y, Kentsch S, Fukuda M, Caceres MLL, Moritake K, Cabezas M** (2021) Deep learning in forestry using uav-acquired rgb data: A practical review. *Remote Sensing* 13(14):2837
- **Doyle C, Beach T, Luzzadder-Beach S** (2021) Tropical forest and wetland losses and the role of protected areas in northwestern belize, revealed from landsat and machine learning. *Remote Sensing* 13(3):379
- **Fletcher Jr RJ, Robertson BA, Evans J, Doran PJ, Alavalapati JR, Schemske DW** (2011) Biodiversity conservation in the era of biofuels: risks and opportunities. *Frontiers in Ecology and the Environment* 9(3):161-168
- **Geller GN, Halpin PN, Helmuth B et al** (2017) Remote sensing for biodiversity. *In The GEO handbook on biodiversity observation networks*. Springer, Cham, pp 187-210
- **Guirado E, Alcaraz-Segura D, Cabello J, Puertas-Ruíz S., Herrera, F, Tabik S** (2020) Tree cover estimation in global drylands from space using deep learning. *Remote Sensing* 12(3):343
- **Halmy MWA, Gessler PE** (2015) The application of ensemble techniques for land-cover classification in arid lands. *International Journal of Remote Sensing* 36(22):5613-5636
- **Holloway J, Mengersen K** (2018) Statistical machine learning methods and remote sensing for sustainable development goals: a review. *Remote Sensing* 10(9):1365
- **Huerta RE, Yépez FD, Lozano-García DF, Guerra Cobián VH, Ferriño Fierro AL, de León Gómez H, González RAC, Vargas-Martínez A** (2021) Mapping Urban Green Spaces at the Metropolitan Level Using Very High-Resolution Satellite Imagery and Deep Learning Techniques for Semantic Segmentation. *Remote Sensing* 13(11):2031
- **Jackson CM, Adam E** (2021) Machine Learning Classification of Endangered Tree Species in a Tropical Submontane Forest Using WorldView-2 Multispectral Satellite Imagery and Imbalanced Dataset. *Remote Sensing* 13(24):4970
- **Kafy AA, Faisal AA, Shuvo RM, Naim MNH, Sikdar MS, Chowdhury RR, Islam MA, Sarker MHS, Khan MHH, Kona MA** (2021). Remote sensing approach to simulate the land use/land cover and seasonal land surface temperature change using machine learning algorithms in a fastest-growing megacity of Bangladesh. *Remote Sensing Applications: Society and Environment*, 21:100463
- **Kalantar B, Ueda N, Idrees MO, Janizadeh S, Ahmadi K, Shabani, F** (2020) Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data. *Remote Sensing* 12(22):3682
- **Knopp L, Wieland M, Rättich M, Martinis S** (2020) A deep learning approach for burned area segmentation with Sentinel-2 data. *Remote Sensing* 12(15): 2422
- **Luque S, Pettorelli N, Vihervaara P, Wegmann M** (2018) Improving biodiversity monitoring using satellite remote sensing to provide solutions towards the 2020 conservation targets. *Methods in Ecology and Evolution* 9(8):1784-1786
- **Mairota P, Cafarelli B, Didham RK, Lovergine FP, Lucas RM, Nagendra H., Rocchini D, Tarantino C** (2015) Challenges and opportunities in harnessing satellite remote-sensing for biodiversity monitoring. *Ecological Informatics* 30:207-214
- **Mayfield H, Smith C, Gallagher M, Hockings M** (2017) Use of freely available datasets and machine learning methods in predicting deforestation. *Environmental modelling & software* 87:17-28
- **Meng B, Yang Z, Yu H, Qin Y, Sun Y, Zhang J, Chen J, Wang Z, Zhang W, Li M, Lv Y, Yi S** (2021) Mapping of *Kobresia pygmaea* community based on unmanned aerial vehicle technology and gaofen remote

sensing data in alpine meadow grassland: A case study in eastern of Qinghai–Tibetan Plateau. *Remote Sensing* 13(13):2483

- **Miyoshi GT, Arruda MDS, Osco LP, Marcato Junior J, Gonçalves, DN, Imai NN, Tommaselli AMG, Honkavaara E, Gonçalves WN** (2020) A novel deep learning method to identify single tree species in UAV-based hyperspectral images. *Remote Sensing* 12(8):1294
- **Mohamed H, Nadaoka K, Nakamura T** (2018) Assessment of machine learning algorithms for automatic benthic cover monitoring and mapping using towed underwater video camera and high-resolution satellite images. *Remote Sensing* 10(5):773
- **Morin N, Masse A, Sannier C, Siklar M, Kiesslich N, Sayadyan H, Faucqueur L, Seewald M.** (2021) Development and Application of Earth Observation Based Machine Learning Methods for Characterizing Forest and Land Cover Change in Dilijan National Park of Armenia between 1991 and 2019. *Remote Sensing* 13(15):2942
- **Mosebo Fernandes AC, Quintero Gonzalez R, Lenihan-Clarke MA, Leslie Trotter EF, Jokar Arsanjani J** (2020) Machine learning for conservation planning in a changing climate. Sustainability 12(18):7657
- **Murray NJ, Keith DA, Bland LM, Ferrari R, Lyons MB, Lucas R, Pettorelli N, Nicholson E** (2018) The role of satellite remote sensing in structured ecosystem risk assessments. *Science of the Total Environment*, 619:249-257
- **Muthoka JM, Salakpi EE, Ouko E, Yi ZF, Antonarakis AS, Rowhani P** (2021) Mapping Opuntia stricta in the arid and semi-arid environment of kenya using sentinel-2 imagery and ensemble machine learning classifiers. *Remote Sensing* 13(8):1494
- **Naderpour M, Rizeei HM, Ramezani F** (2021) Forest fire risk prediction: a spatial deep neural network-based framework. *Remote Sensing* 13(13):2513
- **Nagendra H, Lucas R, Honrado JP, Jongman RH, Tarantino C, Adamo M, Mairota P** (2013) Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators* 33:45-59
- **Nguyen HAT, Sophea T, Gheewala SH, Rattanakom R, Areerob T, Prueksakorn K** (2021) Integrating remote sensing and machine learning into environmental monitoring and assessment of land use change. *Sustainable Production and Consumption* 27:1239-1254
- **Ortega Adarme M, Queiroz Feitosa R, Nigri Happ P, Aparecido De Almeida C, Rodrigues Gomes A** (2020) Evaluation of deep learning techniques for deforestation detection in the Brazilian Amazon and cerrado biomes from remote sensing imagery. *Remote Sensing* 12(6):910
- **Ouellette W, Getinet W** (2016) Remote sensing for marine spatial planning and integrated coastal areas management: Achievements, challenges, opportunities and future prospects. *Remote Sensing Applications: Society and Environment* 4:138-157
- **Petrou ZI, Manakos I, Stathaki T** (2015) Remote sensing for biodiversity monitoring: a review of methods for biodiversity indicator extraction and assessment of progress towards international targets. *Biodiversity and conservation* 24(10):2333-2363
- **Pontoglio E, Dabove P, Grasso N, Lingua AM** (2021) Automatic features detection in a fluvial environment through machine learning techniques based on UAVs multispectral data. *Remote Sensing* 13(19):3983
- **Prasad N, Semwal M, Roy PS** (2015) Remote sensing and GIS for biodiversity conservation. In Recent advances in lichenology. *Remote Sensing and GIS for Biodiversity Conservation*, New Delhi. pp 151-179
- **Rahman A, Abdullah HM, Tanzir MT, Hossain MJ, Khan BM, Miah MG, Islam I** (2020a) Performance of different machine learning algorithms on satellite image classification in rural and urban setup. *Remote Sensing Applications: Society and Environment*, 20:100410
- **Rahman MM, Zhang X, Ahmed I, Iqbal Z, Zeraatpisheh M, Kanzaki M, Xu M** (2020b) Remote sensing-based mapping of senescent leaf C: N ratio in the sundarbans reserved forest using machine learning techniques. *Remote Sensing* 12(9):1375
- **Randin CF, Ashcroft MB, Bolliger J et al** (2020) Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models. *Remote sensing of environment* 239:111626
- **Rather ZA, Ahmad R, Khuroo AA** (2022) Ensemble modelling enables identification of suitable sites for habitat restoration of threatened biodiversity under climate change: A case study of Himalayan Trillium. *Ecological Engineering* 176:106534
- **Reddy CS** (2021) Remote sensing of biodiversity: what to measure and monitor from space to species? *Biodiversity and Conservation* 30(10):2617-2631
- **Rehush N, Abegg M, Waser LT, Brändli UB** (2018) Identifying tree-related microhabitats in TLS point

clouds using machine learning. *Remote Sensing* 10(11):1735

- **Rew J, Cho Y, Moon J, Hwang E** (2020) Habitat suitability estimation using a two-stage ensemble approach. *Remote Sensing* 12(9):1475
- **Rocchini D, Boyd DS, Féret JB, Foody GM, He KS, Lausch A, Nagendra H, Wegmann M, Pettorelli N** (2016) Satellite remote sensing to monitor species diversity: Potential and pitfalls. *Remote Sensing in Ecology and Conservation* 2(1):25-36
- **Rousset G, Despinoy M, Schindler K, Mangeas M** (2021) Assessment of deep learning techniques for land use land cover classification in Southern New Caledonia. *Remote Sensing* 13(12):2257
- **Saha S, Bhattacharjee S, Shit PK, Sengupta N, Bera B** (2022) Deforestation probability assessment using integrated machine learning algorithms of Eastern Himalayan foothills (India). *Resources, Conservation & Recycling Advances* 14:200077
- **Shivaprakash KN, Swami N, Mysorekar S, Arora R, Gangadharan, A, Vohra K, Jadeyegowda M, Kiesecker JM** (2022) Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India. *Sustainability* 14(12):7154
- **Silveira EMO, Radeloff VC, Martinuzzi S, Pastur GJM, Rivera LO, Politi, N, Lizarraga L, Farwell LS, Elsen PR, Pidgeon AM** (2021) Spatio-temporal remotely sensed indices identify hotspots of biodiversity conservation concern. *Remote Sensing of Environment* 258:112368
- **Skidmore AK, Coops NC, Neinavaz E et al** (2021) Priority list of biodiversity metrics to observe from space. *Nature ecology & evolution* 5(7):896-906
- **Smoliński S, Radtke K** (2017) Spatial prediction of demersal fish diversity in the Baltic Sea: comparison of machine learning and regression-based techniques. *ICES Journal of Marine Science* 74(1):102-111
- **Stohlgren TJ, Ma P, Kumar S, Rocca M, Morisette JT, Jarnevich CS, Benson N.** (2010). Ensemble habitat mapping of invasive plant species. *Risk Analysis: An International Journal* 30(2):224-235.
- **Tian J, Wang L, Yin D, Li X, Diao C, Gong H, Shi C, Menenti M, Ge Y, Nie S, Ou Y, Song X, Liu X** (2020) Development of spectral-phenological features for deep learning to understand *Spartina alterniflora* invasion. *Remote Sensing of Environment* 242:111745
- **Traganos D, Aggarwal B, Poursanidis D, Topouzelis K, Chrysoulakis N, Reinartz P** (2018) Towards global-scale seagrass mapping and monitoring using Sentinel-2 on Google Earth Engine: The case study of the aegean and ionian seas. *Remote Sensing* 10(8):1227
- **Tuanmu MN, Viña A, Bearer S, Xu W, Ouyang Z, Zhang H, Liu J** (2010) Mapping understory vegetation using phenological characteristics derived from remotely sensed data. *Remote Sensing of Environment* 114(8):1833-1844
- **Varotsos C, Mazei Y, Xue Y** (2021) On the Contribution of Remote Sensing to the Investigation of the Effects of UV-B on Mechanisms of Ecology, Biodiversity, and Conservation. In 2021 *IEEE International Geoscience and Remote Sensing Symposium IGARSS*. IEEE pp 6240-6243
- **Vega Isuhuaylas LA, Hirata Y, Ventura Santos LC, Serrudo Torobeo N** (2018) Natural forest mapping in the Andes (Peru): A comparison of the performance of machine-learning algorithms. *Remote Sensing* 10(5):782
- **Wagner FH, Dalagnol R, Tagle Casapia X, Streher AS, Phillips OL, Gloor E, Aragão LE** (2020) Regional mapping and spatial distribution analysis of canopy palms in an amazon forest using deep learning and VHR images. *Remote Sensing* 12(14):2225
- **Wang N, Xue J, Peng J, Biswas A, He Y, Shi, Z** (2020) Integrating remote sensing and landscape characteristics to estimate soil salinity using machine learning methods: a case study from Southern Xinjiang, China. *Remote Sensing* 12(24):4118
- **Wang R, Gamon JA** (2019) Remote sensing of terrestrial plant biodiversity. *Remote Sensing of Environment* 231:111218
- **Wu J, Liang S** (2018) Developing an integrated remote sensing based biodiversity index for predicting animal species richness. *Remote Sensing* 10(5):739
- **Ye C, Li Y, Cui P, Liang L, Pirasteh S, Marcato J, Goncalves WN, Li J** (2019) Landslide detection of hyperspectral remote sensing data based on deep learning with constrains. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12(12):5047-5060

Rescue and re-wilding of Lesser Adjutant Stork *Leptoptilos javanicus* after ringing and tagging at Solapur, Maharashtra, India: A Case Report

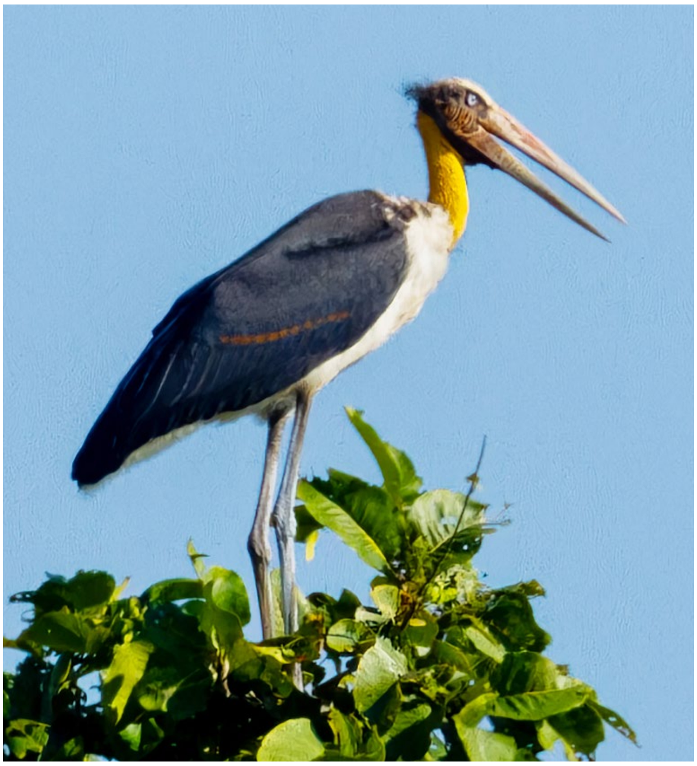
Satish Pande*, Bharat Cheda#, Rahul Vanjari#, Rahul Lonkar*, Rohitkumar Gangurde, Ajit Shinde**, Tushar Chavan**, Mahadev Mohite** and N.R.Praveen****

(Ela Foundation, Pune; Nature Conservation Circle, Solapur; Maharashtra Forest Department)

Citation: Pande Satish, Cheda Bharat, Vanjari Rahul, Lonkar Rahul, Gangurde Rohitkumar, Shinde Ajit, Chavan Tushar, Mohite Mahadev and Praveen N.R. (2025). Rescue and re-wilding of Lesser Adjutant Stork *Leptoptilos javanicus* after ringing and tagging at Solapur, Maharashtra, India: A Case Report. *Ela Journal of Forestry and Wildlife*. 14(2): 1783-1784

Date of Publication: 30 June 2025

ISSN 2319-4361



An exhausted Lesser Adjutant Stork *Leptoptilos javanicus* was found on the road at the IIT College Chowk on 29th April 2025 in Solapur. It was not flying and therefore was rescued by the members of Nature Conservation Circle, Solapur. Examination after rescue revealed that there was no external injury. It was weak and dehydrated as indicated by dry mucous membranes and eyes. The stork was admitted to TTC Solapur of Maharashtra Forest Department (MFD). It was kept in a separate enclosure and there was no disturbance. TTC of Ela Foundation at Pingori, Taluka Purandar, Pune, of MFD and Ela Foundation was requested for treatment advice. The stork was offered fresh clean water and fresh fish (Rohu *Labeo rohita*, Catla *Catla catla*, Eel *Mastacembelus armatus,* and Tilapia *Oreochromis mossambicus*) in a shallow pond in the housing aviary, which it consumed voluntarily. It was monitored 24x7 with a CCTV camera. The stork gained strength and started flying and was seen perching on the high horizontal artificial perch in the tall aviary where it was housed.

This stork is distributed in South and SE Asia with patchy distribution in India[1,2]. It is listed as Vulnerable in IUCN Red Data Book since 2020[3]. Hence, this rescue is an important conservation measure.

Permission (dated 8/5/2025) was granted by N. R. Praveen, IFS, CCF-T, Pune, to TTC of Ela Foundation and MFD, Pingori, to ring and tag this rescued and treated Lesser Adjutant Stork prior to rewilding to monitor the stork in the future. The procedure was successfully carried out at TTC Solapur on 15th May 2025, by ornithologists and experts from Ela Foundation [Dr. Satish Pande (Hon. WLW), Rahul Lonkar, Shrikant Kulkarni and Vivek Kelkar] in collaboration with Solapur ACF (Ajit Shinde) and RFO (Rohitkumar

Experts after ringing and tagging of Lesser Adjutant Stork in the aviary of forest department, Solapur

Gangurde), veterinary doctor of TTC Solapur, Forest Department Maharashtra and Nature Conservation Circle, Solapur led by Bharat Cheda, Hon. WLW. The stork was found to be alert, strong and able to fly with strong wing beats. Hence, a decision was taken to release the stork near a water body on the next day.

The details of tagging are as follows:

- **Wing Tag** – Red, B 17-03 (right and left wings); upper and under wing-U shaped
- **Ring** – Yellow, Right tibia, No. 360; (Contact numbers mentioned)
- **Small overlay tag** – Orange No. 21 and 22

The details of morphometry are as follows:

- **Biometry:** Biomass: 4770 gm; Stretched wing: 1090 mm; Wing chord: 640 mm; Beak: 255 mm; Tarsus: 300 mm; Middle toe: 122 mm; Middle talon: 167 mm; Body temperature: 35 deg C;

Laboratory tests: (Done at Dr. Bharat Mulay's Pathology Laboratory, Solapur)

- **Fecal (stool) examination:** No parasites. No blood. White splash and central GIT pellet.
- **Haematology**: Hb 17.5 g/d
- **Serology**: CRP 1.75 mg/L
- **Biochemistry**: BSL:210.8 mg/dL; TChol: 160 mg/dl; TG: 54 mg/dl; HDL Chol: 71.4 mg/dl; S. Amylase: 2282IU/L.
- **Liver Function Tests:** TBl: 0.4 mg/dl; DBl: 0.3 mg/dl; In Bl: 0.1 mg/dl; SGOT: 592 IU/L; SGPT: 57.9 IU/L; S. ALP: 99 U/L; TPr: 3.2 g/dl; Alb: 1.2 g/dl; Glob: 2 g/dl; A:G ratio: 0.6
- **Renal (Kidney) Function Tests:** B Urea: 15.6 mg/dl; S Cr: 0.4 mg/dl; S. Uric acid: 16.7 mg/dl; S Ca: 9.7 mg/dl; S P: 4 mg/dl; S Na: 153 mmol/L; S Cl: 102 mmol/L.

Above parameters indicated mild stress induced pancreatitis after sun stroke, which is expected to regress after rewilding. Stork was active, alert flying, eating fish (Tilapia, Catla, Rohu, Eel), drinking water and defecating. The stork was successfully released on the banks of Hipparga Lake, Solapur, and flew to freedom in the presence of ACF and RFO, Solapur and the flight was recorded on both still and video digital cameras. The stork was not sighted again. It is requested to the birding community to inform the author SP if it is sighted again (Phone: 9822193707).

References

- **Pande Satish, Tambe Saleel, Clement Francis M. and Sant Niranjan.** *Birds of Western Ghats, Kokan and Malabar (including Birds of Goa)*. Ela Foundation, Pune; Bombay Natural History Society, Mumbai and Oxford University Press, New Delhi, c2003. 371 pp.
- **Hancock, James A.; Kushan, James A.; Kahl, M. Philip.** (1992) *Storks, Ibises and Spoonbills of the World*. Princeton University Press. ISBN 978-0-12-322730-0
- **BirdLife International** (2017). *"Leptoptilos javanicus". IUCN Red List of Threatened Species.* ***2017***: *e.T22697713A110481858. doi:10.2305/IUCN.UK.2017-1.RLTS.T22697713A110481858.en. Retrieved 12 November 2021.*

ISSN 2319 - 2461
Journal for Private Circulation only

Table of Contents

Cover : Vivek Kelkar (Lesser Adjutant Stork)
Back cover : Pramod Deshpande (Lesser Adjutant Stork)

You can contribute to conservation : Please send your reports and research papers to the Editor EJFW (ejfwmanuscript@gmail.com)
Ela Foundation
Nature Conservation through Education, Research and 'One Health'